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Research Article

Cutting Tools Assignment and Control Using Neutrosophic Case-Based Reasoning and Best Worst Method

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Cutting tools management is one of the major issues in metal cutting operations. Most of the problems in cutting tools management were mostly addressed using optimization, heuristic, and simulation techniques. This important problem was not studied using decision-based approaches. This study proposed a decision support system (DSS) that can perform part-cutting tools assignment and control decisions by integrating a neutrosophic case-based reasoning and the best-worst method (BWM) in metal cutting processes. Specifically, this study utilized the integration of case-based reasoning (CBR) and single-valued neutrosophic set (SVNS) theories in artificial intelligence (AI). Furthermore, the proposed DSS applies the BWM to determine optimal weights for case attributes from multicriteria decision-making (MCDM). The system retrieves the most similar historical cases using a neutrosophic CBR and the BWM to adapt their cutting tool requirements to the current product orders. In addition, it revises retrieved cases (tool sets) depending on attribute differences between new and retrieved cases using rule-based reasoning (RBR) from experts. This study provided new insights regarding the application of a neutrosophic CBR and its integration with the BWM. Specifically, the integration of SVNS, CBR, and BWM was not articulated in cutting tools management problems. A numerical example was illustrated in a computer-simulated environment to show the applicability of the proposed DSS using lathe machine operations.

1. Introduction

The contemporary manufacturers are characterized by frequent changes in production requirements such as flexibility, responsiveness, improved quality, and resources utilization [1]. Cutting tools are one of the major components and current issues for metal cutting industries to meet the stated requirements [2–4]. Cutting tools planning and control in machining processes is a crucial task to increase productivity by making available the necessary tools [5]. Managing the flow of these components is as significant as managing the flow of parts in contemporary manufacturing systems [5–10]. These authors suggested that cutting tools management strategies should be integrated with system design, planning, and control activities to improve resources utilization and reduce operational costs.

Cutting tools can contribute to 30–50% of the potential savings of the total operating costs in machining processes, although its cost contribution is nearly from 2 to 4% of the total production cost [5]. To address this problem, several studies were proposed in the past. These were reviewed in different studies [6, 11–14]. The proposed approaches to cutting-tools management were dependent upon pure optimization techniques [13, 15, 16], heuristics [11], domain knowledge-based expert systems [17, 18], computer-aided process planning (CAPP)-based optimization [12, 19–21]. Optimization models are computationally intractable as the number of input variables increases. Heuristic algorithms are unable to find the global optimum solution. In rule-based expert systems, it is impossible to represent the complex domain knowledge from experts in the form of rules alone [22, 23]. In addition, these previous methods are static in nature to accommodate knowledge uncertainties, vagueness, and inconsistencies in dynamic situations where much is unknown and solutions are open-ended [24].

To accommodate these situations, this study proposed an intelligent decision support system (DSS) by integrating the single-value neutrosophic versions of a case-based reasoning (CBR) component and the best-worst method (BWM). This study represented cases using an SVNS-based object-oriented (OO) approach to construct cases for their cutter requirements. The proposed DSS uses a neutrosophic CBR method to represent uncertain, vague, and inconsistent data of part attributes for part-cutter assignment. The BWM was applied to determine the optimal weights of case attributes for case retrieval operations. In the BWM, when a large number of attributes are considered in multi-criteria decision-making (MCDM), the attributes must be hierarchically clustered into different classes using different parameters [25]. This feature of the BWM is very useful to handle the increasing machining complexity and product variants in real industrial situations. This is illustrated using the numerical example of this study.

As a new contribution, a new approach of problem solving in cutting tools planning and management was synthesized in this study by integrating the current complex theories in AI and MCDM. The CBR part of the proposed DSS was constructed in a neutrosophic environment, and the BWM was applied to find the optimal weights of case attributes for the case retrieval process. This kind of integration was not applied in past studies to solve cutting tools management problems. This implies that the proposed DSS in this paper has a useful contribution to the current literature/body of knowledge in DSS research using advanced versions of CBR and MCDM approaches.

According to this study, retrieved cases with their assigned tool sets can be adapted as solutions for new order arrivals. This is used to plan parts together with the required cutting tools in an interactive and an automated way. Cutters can be enumerated and the purchase of missed cutters can be scheduled in advance. This kind of approach was not applied to cutting tools management problems. This study illustrated a numerical example of machining operations using a computer-simulated environment. It incorporated four data categories such as nominal, numerical, verbal, and binary data for hybrid case construction and similarity measures.

This paper is structured into six sections. Section 2 reviews previous studies in cutting tools management. Section 3 elaborates the proposed DSS, including its methodological approach. In Section 4, the applicability of the DSS is analyzed using a numerical example. Section 5 describes the results of the study. The conclusions are addressed in the final section.

2. Related Literature

In the past, cutting tool management approaches were largely focused on optimization and heuristic methods, as stated in the introductory section. This part reviews optimization, heuristic, and AI methods proposed to address the problems of cutting tool management.

Buyurgan et al. [11] presented a heuristic approach in FMS using tool life over tool size (L/S) ratio for tools selection and allocation by considering the highest ratio of tool alternatives assigned to the operations of each machine. Rahimifard and Newman [10] proposed a simulation-based multi-flow scheduling system for planning workpieces, cutting tools, and fixtures simultaneously. They applied a tool-dominated strategy to optimize the number of required cutting tools. In addition, Rahimifard and Newman [26] proposed an integrated planning and control system to generate short-term schedules for part, fixture, and cutter assignments. Zhao et al. [21] presented an integrated system of CAD and expert systems to select cutting tools and conditions for turning operations. Meseguer and Gonzalez [12] proposed a methodology for tool management integrated with computer-aided process planning and scheduling for the use of alternative tools.

Petruse and Brîndaşu [5] proposed an augmented reality system for effective cutting tool management. Arunachalam et al. [27] applied fuzzy multiple-attribute decision-making methods to select complaint-polishing tools. Sun et al. [28] developed a methodology for cutting-tool delivery using two models such as a cutting-tool demand prediction model and a just-in-time cutting-tool delivery model using a genetic algorithm (GA) to minimize delivery time. Li et al. [29] used the analytic hierarchy process (AHP) to judge the importance of material properties and to weigh their criterion for the selection of cutting tool materials. Saranya et al. [30] developed a cutting-tool selection system using artificial neural networks (ANNs), fuzzy theory, and genetic algorithms to select appropriate tools from a huge tool database for turning and milling operations.

Zhou et al. [14] proposed an ontology-based cutting tool configuration to reduce carbon emissions in machining process. In addition, the authors reviewed different cutting tool configuration methods. Tomelero et al. [4] presented a lean environmental benchmarking (LEB) method for cutting tool management using strategic, technical and logistical aspects. Özbayrak and Bell [9] presented a knowledge-based DSS for short-term scheduling of part-cutting tools assignment used rule-based reasoning (RBR). Kasie et al. [8] proposed a theoretical decision support framework for stabilizing the flows of cutters, fixtures, and jigs using CBR, discrete-event simulation (DES), and relational database management tools.

The review of related studies indicated that cutting tool management problems were addressed using different optimization, MCDM, heuristics, simulation and AI (e.g. ANNs, GA, and RBR) and CAPP tools. As reviewed in the previous section, optimization models (both linear and nonlinear) are computationally intractable when the number of input variables is large. Heuristic algorithms are vulnerable to a local optimum solution. In rule-based expert systems, it is difficult to represent complex domain knowledge using rules alone. In addition, these previous methods are static in nature to accommodate knowledge uncertainties, vagueness, and inconsistencies in dynamic situations. This indicates that the problem of cutting-tools management requires additional studies to make the

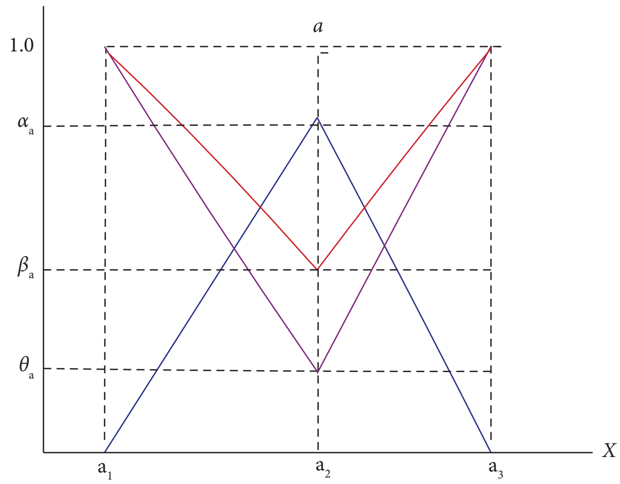

FIGURE 1: Single-valued triangular neutrosophic fuzzy number "a".

solution approach more intelligent and dynamic to address uncertainties, vagueness, and consistencies in a natural decision-making process. This research is intended to bridge this knowledge gap using neutrosophic CBR systems and the BWM in this problem domain. Specifically, the application of SVNF-CBR systems and its integration with the BWM was not researched in previous studies, as the survey of the literature indicated.

3. Proposed DSS and Methodological Approach

This section presents the theories and methodological approaches applied in this study. Similar methods were applied in Kasie [7] and Kasie and Bright [31] by integrating fuzzy CBR and AHP for part-fixture assignment and control problems. This study extended and advanced the methodological approach to the integration of a neutrosophic CBR and the BWM in part-cutting tool management problems.

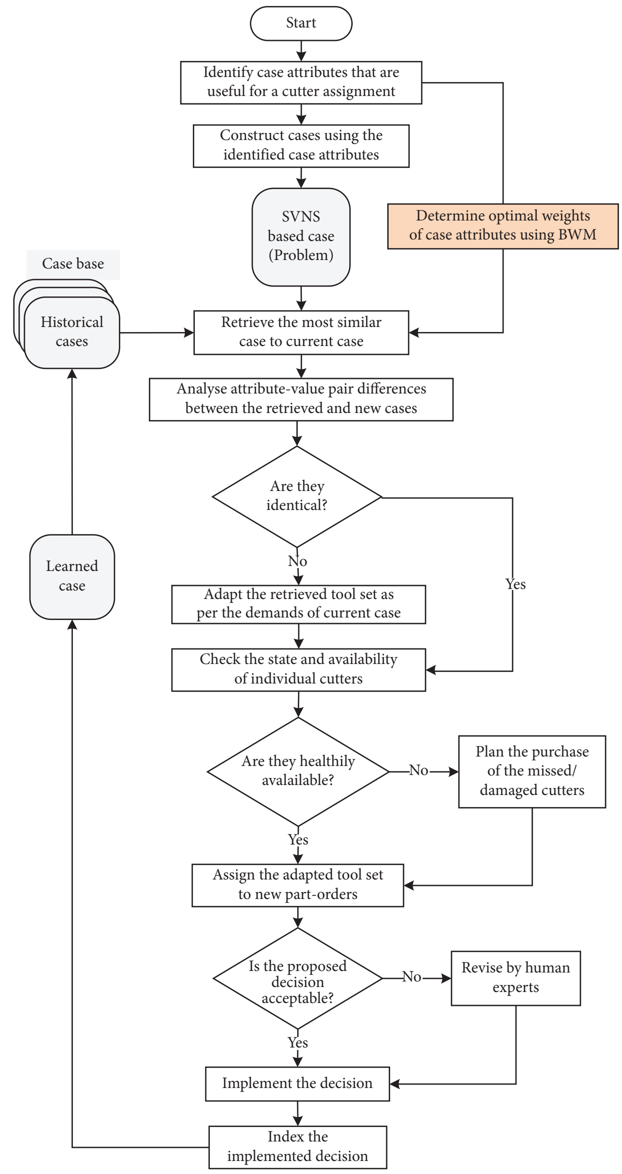

FIGURE 2: Methodological approach of the proposed DSS (adapted from [7]).

3.1. CBR in Neutrosophic Environment. Intelligent industries take the advantage of advanced information to achieve flexible, smart, and reconfigurable processes to address dynamic and stochastic markets [32, 33]. Case-based reasoning is one of the useful methodologies in artificial intelligence (AI) to solve a new problem using the experience of similar problems in the past [22, 23]. As a machine learning paradigm, CBR can be trained with a small number of training data as compared with other machine-learning approaches [34]. Different numerical examples are illustrated in different studies (see Kasie et al. [1]; Kasie and Bright [31, 35]). CBR systems have recently been advanced to address complex situations by integrating them with other problem-solving approaches, as reviewed in Zhang et al. [36] and Zhao et al. [37]. For example, Zhao et al. [37] combined the CBR with attribute feature mining techniques for predicting posting popularities on social media networks for the online automobile community. Moreover, Zhang et al. [36] proposed a CBR method for the judgment debtor's hidden property analysis using four types of case attributes such as crisp symbols, crisp numbers, interval numbers, and fuzzy variables.

Aamodt and Plaza [22] described their CBR methodology using its four cycles, such as: retrieving the most similar prior case; reusing the knowledge and experiences in the retrieved case; revising the retrieved case for adapting as a solution to a new problem; and finally, retaining the current solution as a learned case for future retrieval. Because many decision-making environments are usually uncertain, vague, and inconsistent [38], in such regard, knowledge can be reasonably expressed in neutrosophic sets (NS), which are the generalizations of fuzzy sets (FS) and intuitionistic fuzzy sets (IFS) [24, 39]. A case is said in such environments, it must contain at least one of its attributes must be described in verbal terms [40]. FS was introduced by Zedah [41] to determine true-membership levels within [0, 1]. An extension of FS was introduced by Atanassov [42] as IFS to address the degree of nonmembership or false membership in addition to the true-membership. An NS was introduced by Smarandache [43] to incorporate the degree of indeterminacy membership as an independent component in addition to the truth and falsified memberships. Single-valued neutrosophic sets (SVNS) were defined by Wang et al. [44]. SVNS systems have been widely applied in decision-making for decision support systems [45–48].

SVNS theory can be considered in CBR for describing product quality features such as surface roughness, tolerance limit, surface treatment, etc. For example, suppose that ten customers are asked to respond to a given level of surface roughness; five customers accept, three reject, and the remaining two are indifference about the given surface quality. This situation can be represented by a dependent SVNS as (0.5, 0.3, and 0.2) and the survey result may vary though time from one survey to another due to uncertainty of survey results [39]. This implies these memberships in SVNS are fuzzy and can be expressed using FS and such kinds of parameters are best-described using single-valued neutrosophic fuzzy sets (SVNSFS). The membership values are usually rated independently by an individual or group of experts in an uncertain, indeterminacy, and inconsistent decision-making environment [44]. These concepts of SVNFS were applied in different recent applications of multicriteria decision-making (MCDM) (e.g. see [39, 45–49]).

The following preliminary definitions of neutrosophic set and its extensions are applicable to this study.

Definition 1. As Smarandache [43]; a neutrosophic set (NS) A is in a universe (space of points/objects) X whose elements are generically denoted by x i.e. $x \in X$, then, A is characterized by a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$ and a falsity-membership function $F_A(x)$. The functions $T_A(x)$, $I_A(x)$, and $F_A(x)$ of X are real standard or nonstandard subsets of $]^-0, 1^+[$ such that $T_A(x)\colon X \longrightarrow]^-0, 1^+[$, $I_A(x)\colon X \longrightarrow]^-0, 1^+[$, and $F_A(x)\colon X \longrightarrow]^-0, 1^+[$. There is no restriction on the sum of $T_A(x)$, $I_A(x)$, and $T_A(x)$, so that, $^-0 \le \sup\ T_A(x) + \sup\ I_A(x) + \sup\ F_A(x) \le 3^+$.

Definition 2. According to Wang et al. [44] and Chai et al. [50]; a single-valued neutrosophic set (SVNS) A in a universe X is characterized by $T_A(x)$, $I_A(x)$, and $T_A(x)$. An SVNS A is defined as $A = \{x,\ T_A(x),\ I_A(x)$, and $F_A(x)/x \in X\}$ where $T_A(x), I_A(x), F_A(x) \in [0, 1]$. Then, $0 \le T_A(x) + I_A(x) + F_A(x) \le 3$. For an SVNS A in X, the triplet $T_A(x)$, $I_A(x)$ and $F_A(x)$ is known as a single-valued neutrosophic number (SVNN), which is a core element in an SVNS.

Definition 3. As Abdel–Basset et al. [49]; a single-valued triangular neutrosophic number (SVTNN) in Figure 1 is defined as $a = ((a_1, a_2, a_3); \alpha_a, \theta_a, \beta_a)$, that is, $\alpha_a, \theta_a, \beta_a \in [0, 1]$ and $a_1, a_2, a_3 \in R$ where $a_1 \le a_2 \le a_3$. The number $a = ((a_1, a_2, a_3); \alpha_a, \theta_a, \beta_a)$ is a special neutrosophic number that combines a triangular fuzzy number (a_1, a_2, a_3) and SVNN, which is considered as a single-valued neutrosophic fuzzy number (SVNFN). Then, its truth, indeterminacy and falsity-membership functions are calculated as follows:

$$
T_A(x) = \begin{cases} \alpha_a\left(\dfrac{x - a_1}{a_2 - a_1}\right), & [a_1 \le x < a_2], \\[2ex] \alpha_a & [x = a_2], \\[2ex] \alpha_a\left(\dfrac{a_3 - x}{a_3 - a_2}\right), & [a_2 < x \le a_3], \\[2ex] 0, & \text{otherwise}, \end{cases}
$$

$$
I_A(x) = \begin{cases} \dfrac{(a_2 - x) + \theta_a(x - a_1)}{a_2 - a_1}, & [a_1 \le x < a_2], \\[1ex] \theta_a, & [x = a_2], \\[1ex] \dfrac{(x - a_2) + \theta_a(a_3 - x)}{a_3 - a_2}, & [a_2 < x \le a_3], \\[1ex] 1, & \text{otherwise}, \end{cases}
$$

$$
F_A(x) = \begin{cases} \dfrac{(a_2 - x) + \beta_a(x - a_1)}{a_2 - a_1}, & [a_1 \le x < a_2], \\[1ex] \beta_a, & [x = a_2], \\[1ex] \dfrac{(x - a_2) + \beta_a(a_3 - x)}{a_3 - a_2}, & [a_2 < x \le a_3], \\[1ex] 1, & \text{otherwise}, \end{cases} \tag{1}
$$

where α_a, $\theta_a\, an\, d\, \beta_a$ are the degree of maximum truth-membership, minimum indeterminacy-membership, and minimum falsity-membership values, respectively.

3.2. BWM for CBR.

In CBR, cases are usually regarded as multiple-attribute decision-making (MADM) problems [51]. The roles of MADM in CBR are well articulated in Kasie et al. [1] and Kasie and Bright [31,35]. The BWM was initially proposed by Rezaei [52] and improved by Rezaei [25]. Nowadays, this method is recognized as a popular pairwise comparison method in MADM. It has many advantages over the analytic hierarchy process (AHP). It was shown that the BWM could perform better than the AHP in consistency ratio, minimum violation, total deviation, and conformity [52].

According to Rezaei [52] and Rezaei [25], the five steps of BWM are briefly explained as follows:

(1) Select a set of n decision criteria $\{c_1, c_2, \ldots, c_n\}$.

(2) From a set of criteria, find the best B and the worst W criteria.

(3) Find the preference vector of the best-to-others in a 1–9 scale, $A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn})$, where a_{Bj} is the preference of the best criterion B over j th criterion.

(4) Find the preference vector of others-to-worst using a 1–9 scale, $A_W = (a_{1W}, a_{2W}, \ldots, a_{nW})^T$, where a_{jw} is the preference of the jth criterion over the worst one W.

Table 1: Linguistic to triangular SVNFN conversion scale (adapted from Abdel–Basset et al. [46]).

Linguistic terms	Triangular neutrosophic scale
Very low (VL)	((0.0, 0.1, 0.2); 0.35, 0.45, 0.3)
Low (Lo)	((0.1, 0.2, 0.3); 0.45, 0.7, 0.65)
Fairly low (FL)	((0.2, 0.3, 0.4); 0.5, 0.85, 0.6)
Moderately low (ML)	((0.3, 0.4, 0.5); 0.55, 0.4, 0.35)
Moderate (Mo)	((0.4, 0.5, 0.6); 0.75, 0.2, 0.25)
Moderately high (MH)	((0.5, 0.6, 0.7); 0.8, 0.35, 0.2)
Fairly high (FH)	((0.6, 0.7, 0.8); 0.85, 0.2, 0.15)
High (Hi)	((0.7, 0.8, 0.9); 0.9, 0.15, 0.1)
Very high (VH)	((0.8, 0.9, 1.0); 0.95, 0.1, 0.1)

(5) Find the optimal weights of each criterion $(w_1^*, w_2^*, \ldots, w_n^*)$.

To find the optimal weights, Rezaei [52] presented a min-max optimization model as follows:

$$\begin{gathered} \text{MinMax}_j = \left\{ \left| \frac{w_B}{w_j} - w_j \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\}, \\ \text{subject to} \sum_{j=1}^{n} w_j = 1,\ w_j \geq 0 \text{ for all } j, \end{gathered} \tag{2}$$

Rezaei [25] developed an equivalent linear programing model for equation (2) as shown below:

$$\begin{aligned} &\text{Min} && \xi^L, \\ &\text{subject to} && \left| w_B - a_{Bj} w_j \right| \leq \xi^L \text{ for all } j, \\ & && \left| w_j - a_{jW} w_W \right| \leq \xi^L \text{ for all } j, \\ & && \sum_{j=1}^{n} w_j = 1,\ w_j \geq 0, \end{aligned} \tag{3}$$

where ξ^L is a linear consistency index for a pairwise comparison. A value of ξ^L close to zero indicates a good level of consistency.

3.3. Methodological Approach. The methodological integration among CBR, SVNS, and BWM to develop the proposed DSS are discussed in this section (Figure 2). This integration was used to make the proposed DSS more intelligent. Different types of case attributes such as numerical, symbolic, categorical, and verbal attributes were selected by experts to characterize parts for their cutting tools requirements. The researchers constructed prior and current cases using the identified case attributes. In this study, researchers constructed SVNF cases using hierarchical multiple attributes, which are useful for finding distances between new and prior cases for part-cutter assignments. The pairwise preference of attributes at all levels was determined using the BWM i.e. applying Equation (3).

Similar approaches were applied in Kasie and Bright [31,35] using fuzzy CBR and AHP for other problem domains. However, this study advanced the concept of CBR by integrating SVNFN, CBR, and the BWM into the problems of part-cutting tools planning and management. Verbal terms were converted into triangular SVNFNs using the conversion scales proposed in Table 1. The ideas from Figure 1 and definitions from 1 to 3 were applied during the development of this conversion scale. Triangular SVNFNs were implemented for simplifying the illustration in the simulated environment. In the case of triangular SVNFNs, similarity measurement functions and crisp score (de-neutrosophic) functions are relatively easy for illustration. In addition, different arithmetic theories are well established for such numbers in the current literature in this area. Hoverer, trapezoidal and other complex neutrosophic fuzzy numbers can be applied in real situations depending upon the characteristics of manufacturing processes.

For case retrieval, there are several distance-based retrieval methods in the current literature such as Hamming distance, Manhattan distance, Euclidean distance, Minkowski distance, and so on. Among these, the weighted Euclidean distance is the most popular method [7, 35]. This study used the weighted Euclidean distance to measure the distance between new and prior cases. The weighted Euclidean distance is capable to measure the shortest regular distance between any two objects in an n-dimensional space as compared with other methods [53]. In addition, it is relatively robust (less sensitive) method for parametric changes due to environmental dynamism [35]. This is the reason why this method is widely applied for calculating distances or similarities between prior and new cases. The method finds the distance between a target (new case) x and a prior case y,$\text{dis}(x, y)$ as follow:

$$\begin{gathered} \text{dis}(x, y) = \left(\sum_{j=1}^{n} \left(w_j \left(\text{dis}\left(a_j^x, a_j^y\right) \right) \right)^2 \right)^{1/2}, \\ \text{dis}\left(a_j^x, a_j^y\right) \in [0, 1], \end{gathered} \tag{4}$$

where n is the number of case attributes, w_j is a normalized weight for jth attribute, $\text{dis}(a_j^x, a_j^y)$ is an individual distance of jth attribute of cases x and y, a_j^x and a_j^y are jth attribute values.

For numerical, symbolic and categorical case attributes, the method proposed in Kasie and Bright [35] was applied. In the case of neutrosophic attributes, a different approach was applied to convert triangular SVNFNs into their equivalent crisp values. Similar conversion approaches were used in different studies (e.g. see [45, 54]). The crisp score of an SVNFN, $a = ((a_1, a_2, a_3); \alpha_a, \theta_a, \beta_a)$ was estimated as:

$$Sc(a) = \frac{(a_1 + 2a_2 + a_3)(2 + \alpha_a - \theta_a - \beta_a)}{12}. \tag{5}$$

This crisp score was treated as any standardized numerical value in the case retrieval process.

Because distance and similarity measures are inversely related, the similarity between two cases x and y, was found as follows [53]:

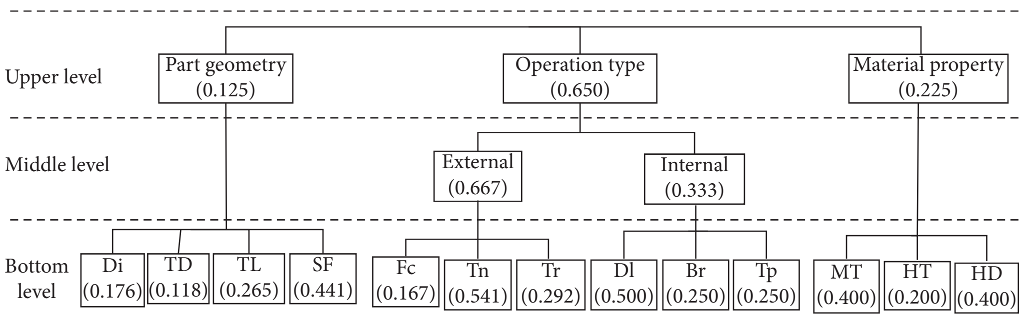

Figure 3: BWM based hierarchical evaluation of case features.

$$\operatorname{sim}(x, y) = \frac{1}{1 + \alpha(\operatorname{dis}(x, y))}, \tag{6}$$

where α is a positive constant. Its value depends on the inverse proportionality of similarity and distance. In this case, $\alpha = 1.0$ was used by assuming that the inverse proportionality ratio is one to one (1 : 1).

Once the retrieval process is completed, a case revision is required to propose a solution to the current order arrival. Depending upon the case attribute differences between the retrieved and new cases, some cutters can be added to or removed from retrieved tool sets for adaptation. The researchers presented many (If..., Then,....) rules from the general domain knowledge of experts to reinforce the case-reasoning process. All algorithms presented in Figure 3 were coded as rules in the Java platform. Some of the implemented rules are presented as follows using the similarity between new and retrieved cases.

If the current and retrieved cases are identical ($\operatorname{sim}(x, y) \approx 1$), then, the retrieved tool set should be temporarily accepted for reuse without any revisions. Under this decision, the DSS checks the availability and healthiness of all cutters in the cutting tool database. If all are healthily available, then, the proposed system recommends direct reuse of cutting tools, otherwise it recommends a purchase plan for missed/damaged cutters.

If the two cases are not identical ($\operatorname{sim}(x, y) < 1$), then, revisions with reference to the differences in attributes should be undertaken. The same rules can be applied as stated before for checking the availability and healthiness of individual retrieved cutters. This rule was extended to include new cutting tools or replace/remove existing cutters to adapt retrieved cutter sets for new arrivals. For example, when new attributes are required for a new order, then, additional cutters must be included into the retrieved tool sets by the recommendations of exert systems. The same was also done for the removal of attributes from retrieved cases. In both situations, a database was designed to present the availability of individual cutters.

After a solution is proposed for every order arrival, the solution must be retained for future retrieval and adaptation. The case retaining operation was done in a similar approach with the one proposed by Kasie and Bright [35].

4. Numerical Example

This numerical analysis was simulated in an artificial environment of turning/lathing operations. This operation center can produce several cylindrical shafts depending upon various product order arrivals.

4.1. Case Attributes Selection and Their Optimal Weight. Experts selected thirteen product attributes, which are useful for case representation with the help of an object-oriented method. These attributes were considered that they could strongly influence part-cutting tool assignment and control activities in a specific metal cutting operation. The attributes were hierarchically evaluated to determine systematically their importance using the BWM. The evaluation results are presented in Table 2 and Figure 3. The upper part of the hierarchy includes primary feature such as part geometry, material property and operations types. These major features are branched into different secondary features. The middle levels are also branched into bottom level attributes. The optimal weights of all attributes at specific levels were evaluated using the BWM. This evaluation was done using the model presented in Equation (3).

For example, the primary attributes were weighted using the BWM using the following five steps. Table 3 indicates the preference vector of the best-to-others and Table 4 shows the preference of others-to-the worst criterion.

(1) Three decision criteria ($n = 3$) such as part geometry (c_1), material property (c_2) and operation type (c_3) were selected.

(2) From the three criteria, c_3 and c_1 were selected as the best B and the worst W criteria respectively.

(3) The preference vector of the best-to-others using a 1–9 scale was evaluated as: then, $A_B = (a_{B1} = a_{BW} = 5, a_{B2} = 3, a_{B3} = a_{BB} = 1)$.

(4) Similarly, the preference vector of others-to-the worst was evaluated as: then, $A_W = (a_{1W} = a_{1W} = 1, a_{2W} = 2, \ldots, a_{3W} = a_{BW} = 5)^T$.

(5) The optimal weights of each criterion ($w_1^* = w_w^*, w_2^*, w_3^* = w_B^*$) and the minimum

Table 2: Hierarchical BWM based weighting of case attributes.

Attribute			Weight	
Upper	Middle	Bottom	w_j calculation	w_j
Part geometry (0.125)	—	Di (0.176)	(0.125) (0.176)	0.022
		TD (0.118)	(0.125) (0.118)	0.017
		TL (0.265)	(0.125) (0.265)	0.033
		SF (0.441)	(0.125) (0.441)	0.055
		(ξ^{L*} = 0.088)		
Material property (0.225)	—	MT (0.400)	(0.225) (0.400)	0.090
		HT (0.200)	(0.225) (0.200)	0.045
		HD (0.400)	(0.225) (0.400)	0.090
		(ξ^{L*} = 0.000)		
Operation types (0.650)	External (0.667)	Fc(0.167)	(0.650) (0.667) (0.167)	0.072
		Tn (0.541)	(0.650) (0.667) (0.541)	0.234
		Tr (0.292)	(0.650) (0.667) (0.292)	0.126
		(ξ^{L*} = 0.042)		
	Internal (0.333)	Dl (0.500)	(0.650) (0.333) (0.500)	0.108
		Br (0.250)	(0.650) (0.333) (0.250)	0.054
		Tp (0.250)	(0.650) (0.333) (0.250)	0.054
(ξ^{L*} = 0.025)	(ξ^{L*} = 0.00)	(ξ^{L*} = 0.000)		

Table 3: Best-to-others comparison.

	c_1	c_2	c_3 = B
c_3	5	3	1

Table 4: Others-to-worst comparison.

	c_1 = W
c_1	1
c_2	2
c_3	5

consistence index ξ^{L*} were determined using Equation (5) as follows:

$$\begin{aligned}
&\operatorname{Min}\xi^{L},\\
&\text{subject to}
\begin{aligned}[t]
&\left|w_B - 5w_1\right| \le \xi^{L},\\
&\left|w_B - 3w_2\right| \le \xi^{L},\\
&\left|w_2 - 2w_W\right| \le \xi^{L},\\
&\left|w_3 - 2w_W\right| \le \xi^{L},\\
&\sum_{j=1}^{n} w_j = 1,\ w_j \ge 0 \text{ for } j = 1, 2, 3,
\end{aligned}
\end{aligned} \tag{7}$$

The optimal weights were found as $w_1^* = 0.125, w_2^* = 0.225,\ w_3^* = 0.650$, and $\xi^{L*} = 0.025$, is very close zero to indicate the consistence index is acceptable. The authors applied the same procedure to all attributes on their corresponding levels. The optimal weights are shown in parentheses, and the minimum consistency index is found at the bottom of the column of each attribute category (Table 2). The normalized optimal weights of all attributes were proportionally calculated and presented.

4.2. Case Construction in a Neutrosophic Environment. In this example, cases/part orders were constructed using thirteen attributes, which incorporate nominal, numeric, binary and linguistic data (see Table 5), which is the hybrid of four types of attribute/features. The diameter (*Di*) and turn-depth (*TD*) of parts were measured in millimeter (numeric values). The tolerance (*TL*) and surface finish (*SF*) of finished parts, and the hardness (*HD*) of workpieces were described in verbal terms. The linguistic terms were converted into triangular SVNFNs using the conversion scales presented in Table 1. Finally, the triangular SVNFNs were converted into their estimated crisp scores with the help of Equation (5) before they were used to calculate distance measures between cases. The material type (*MT*) and heat treatment type (*HT*) of workpieces were described nominal values such as carbon steel, aluminum, stainless steel, and so on for material compositions. Similarly, heat treatments were typically classified as normalized, annealed, and so on. Machining operation types were presented in binary measures of {0, 1} to indicate whether a particular operation is required to machine a part. These important operations are turning (*Tn*), facing (*Fc*), threading (*Tr*), drilling (*Dl*), boring (*Br*), and tapping (*Tp*).

The authors generated four order arrivals, OA1-OA4, (new cases) and two training cases, TC1 and TC2, in a simulated environment as shown in Table 5 for illustration. The numbers of simulated cases are small in number for the sake of demonstration; however, the proposed DSS can handle any size of cases and case attributes.

Table 5: Constructed case with their 13 case attributes.

Order arrival	Case/part order attributes													TC
	MT	*HT*	*TD*	*Di*	*TL*	*SF*	*HD*	*Tn*	*Fc*	*Tr*	*Dl*	*Br*	*Tp*	
*OA*1	Carbon steel	Normalize	35	120	MH	VH	Mo	1	0	1	0	1	0	—
*OA*2	Alloy steel	Anneal	45	160	FH	MH	Hi	1	0	1	1	0	1	—
*OA*3	Carbon steel	Normalize	30	120	MH	Hi	FH	1	0	1	0	1	1	—
*OA*4	Alloy steel	Anneal	43	170	Hi	MH	Hi	1	1	1	1	0	1	—
*TC*1	Alloy steel	Anneal	40	150	Hi	FH	FH	1	0	0	1	0	1	*TC*1
*TC*2	Carbon steel	Normalize	25	110	FH	VH	ML	1	1	1	0	1	0	*TC*2

Table 6: Case retrieval results from proposed DSS.

Order arrival	Retrieved case	Best similarity	Cases in case-library	
			When *OA* arrived	Immediately as *OA* served
*OA*1	*TC*2	0.8948	2	3
*OA*2	*TC*1	0.9903	3	4
*OA*3	*TC*3 (learned OA2)	0.9532	4	5
*OA*4	*TC*4 (learned OA1)	0.9464	5	6

4.3. Distance-Based Similarity Measure between Target and Prior Cases. After determining the normalized weights of case attributes using the BWM, the similarity between new and prior cases $\mathrm{sim}(x, y)$ was calculated using Equations (4) and (6). The standardized weighted similarity measures between new order arrivals and retrieved cases are presented in Table 6. For the case retrieval operation, several Java in-built, static, and instance functions were created in the Java platform, NetBeans IDE 12.6.

As new orders from *OA*1 to *OA*4 arrived at the proposed DSS, the number of cases in the case-base increases by one as a new order arrival is served, as shown in Table 6.

4.4. Case Revision/Adaptation. The proposed DSS can present attribute differences between new and retrieved cases for revisions. The rules proposed in the previous section were applied in detail using attribute differences. For example, in the case of *OA*3, the best similarity measure was calculated as $sim(OA3, TC3) = 0.9532 < 1.0$. This indicates that the two cases are not identical, and then, revisions are required. From the DSS, variations were presented in the *HD*, *SF,* and *Tp* attributes of the current case and training cases. During a case adaptation, some cutters can be removed, replaced, or added. In this case, a new cutter for the tapping operation was added into the retrieved/learned tool set *TC*3, which is the revision of TC2. Similarly, *PC*4 was the revisions of *PC*1 (see Table 6). In addition, a database was designed to present the availability of individual cutters.

4.5. Case Indexing. The case indexing operation was used to retain the current implemented solution/decision for the future case retrieval process. For example, in Table 6, the solutions for the third and the fourth order arrivals (OA3 and OA4) were adapted from the indexed solutions of the second and the first order arrivals (OA2 and OA3), respectively.

5. Discussion

This section discusses the new insights or contributions of the study to the current literature in the DSS research and the managerial implication of this study.

5.1. Comparison with Previous Studies. This study provided a new insight regarding a neutrosophic CBR and its integration with the BWM of MCDM. The uncertainty, vagueness, and inconsistency associated with the human reasoning process were articulated using neutrosophic set theory, which is the generalization of FST and IFST. As compared with other studies, this study provided two major new insights into the current literature in DSS research. (1) From the stand point of CBR systems, the current CBR systems usually incorporate fuzzy sets to articulate uncertainties in the human reasoning and decision-making processes. However, this study incorporated vagueness and inconsistency factors, which are very useful in addition to uncertainty issues in neutrosophic environments. (2) From the MCDM perspective, the BWM was integrated with the CBR component for the first time with its advantages in consistency ratio, minimum violation, total deviation, and conformity as compared with other similar methods like the AHP [52].

It was reviewed that part-cutting tool assignment and control is one of the most complex issues in manufacturing when a new order is received. Several analytical, heuristic, AI, CAPP, MCDM, linear, and nonlinear optimization approaches were proposed to solve cutting tools planning and control problems. These models were very complex and intractable to solve these open-ended problems in real industrial situations. In this regard, the proposed DSS is highly flexible and dynamic to solve such kinds of open-ended problems for part-cutting tools assignment and control using machine-learning algorithms.

The proposed system continuously updates the number of cases in its case base to improve its performance through time, as shown in Table 6. This kind of characteristic of the proposed DSS was presented in other similar studies such as Oh and Kim [34]; Chang et al. [51]; Kasie et al. [1]; Kasie and Bright [31, 35] in other problem domains. This study combined CBR, SVNFS, and BWM approaches for the first time in case retrieval and adaptation activities. This combination is very essential to make the proposed DSS flexible and evolutionary to articulate dynamisms in the contemporary manufacturing. Four different forms of case features (numerical, categorical/nominal, binary, and verbal terms) were included in case construction as indicated in Table 5; however, the proposed DSS can include other forms of knowledge and experience using the demands of its users. In the numerical example, lathe machine operations were illustrated in a computer-simulated environment. However, the proposed DSS can incorporate other machining operations depending upon the needs of its customers.

5.2. Managerial Implication. From a managerial view, planning and control managers can align the required cutting tools with their production/part plans of their predetermined customer orders for specific production periods. From this, the managers can enumerate the available and missed cutting tools in advance. In addition, they can purchase or manufacture the required cutting tools in planning phases depending upon the status and availability of cutters from cutting tool databases. This will be useful to minimize excess cutting tools holding costs and downtime costs due to the shortages of the required cutting tools. Because of stabilized flows of cutting tools during given production window periods, the utilization of resources will be highly improved by implementing the proposed DSS in this study.

6. Conclusions

In this study, a novel DSS was proposed to articulate the problems of cutting tool assignment and control using a single-valued neutrosophic CBR and the BWM as the principal methodologies. These two approaches were not applied in previous CBR studies. In general, CBR methodologies were not applied to cutting tool management problems, as reviewed in Section 2. The proposed DSS could be an alternative approach to solve cutting tool planning and control problems in metal cutting industries.

An object-oriented approach was utilized to represent SVNS cases using the combination of different attributes with the SVNF attributes. This hybrid case representation is very crucial to accommodating the flexibility required in the current DSS. An SVNF CBR methodology was used to represent uncertain, imprecise, and inconsistent knowledge using truth, indeterminacy and falsified memberships, respectively, in the case representation (see Table 5). In the numerical example, it was meaningful to describe some case features with the help of linguistic terms rather than measuring them using numeric values. These linguistic terms were converted into triangular SVNFN to address uncertainty, vagueness, and insistency issues in natural human thinking and decision-making processes. In addition, the BWM was used to elicit the knowledge and judgements of experts to determine the optimal weights of different case features. This method was not applied in the CBR methodology in the past. This implied that the concept of applying a neutrosophic CBR and its integration with the BWM is a novel contribution of this study in the CBR methodology and DSS research. In addition, the application of the CBR methodology in cutting tool assignment and control problems can be regarded as a new solution approach to the current literature.

In the future, the proposed DSS can be tested in industrial environments using historical data from several metal cutting operation centers to validate its accuracy. In this regard, detailed information can be required for a group of experts to represent part orders as cases. Depending on the pattern of industrial situations, this approach can be applied to classify or cluster cases. In this case, a k-NN algorithm can be used rather than retrieving a single past case. In addition, detailed knowledge-based rules will be included to make the case retrieval process more effective and efficient.

Data Availability

No underlying data were collected or produced in this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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