A Novel Software Package Selection Method Using Teaching–Learning Based Optimization and Multiple Criteria Decision Making

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Abstract—**Software packages that meets the requirements of an organization should be appropriately investigated and evaluated. Picking up a wrong software package may adversely influence the business process and working function of an organization. Inappropriate software selection can turn out to be costly and it is a time-consuming decision-making process. This paper aims to provide a base for selecting the open source software packages based on analytic hierarchy process and technique for order preference similarity to ideal solution methodologies. In addition, the priority weights are generated and optimized by using teaching–learning based optimization approach. A well-organized algorithmic procedure is given in detail and a numerical example is examined to illustrate the validity and practicability of our proposed methodologies.**

Index Terms—**Analytic hierarchy process (AHP), multicriteria decision making (MCDM), open source software (OSS) packages, teaching–learning based optimization (TLBO), technique for order preference similarity to ideal solution (TOPSIS).**

I. Introduction

THE necessity of reliable and qualitative software packages is tremendously increasing. In response to this growing demand, software firms are intended to produce diverse amount of distinct software packages. Open source software (OSS) may offer better opportunity at cost reduction, quality, and efficiency improvement. Various software packages are furnishing uncountable customizable features to meet the needs of an organization. In addition, this diversity will create chaos among all the decision makers to decide on which software to use. Inappropriate software selection may result in flawed strategic decisions and consecutive economic loss of an organization. Such decision problems have grasped the attention on the industry and academia. Decision making plays a prerequisite role in all the aspects of our daily lives. Multicriteria decision making (MCDM) exemplifies that extracting the finest viewpoint in the existence of numerous conflicting decision criteria by considering all the feasible alternatives.

Analytic hierarchy process (AHP) is a popular and traditional MCDM tool that assists the decision maker in decomposing a given complex problem into various subproblems, such as criteria, subcriteria, and alternatives. It is a multilevel hierarchical structure that offers a comprehensive framework of evaluating various different alternatives to the considered problem. In response to the hierarchical structured technique, goal or objective of the given problem, criteria, subcriteria, and the alternatives are placed in the subsequent levels. Once the formation of hierarchical structure is done, it is necessary to evaluate different criteria by performing comparison of one another. Pairwise comparison technique was done in order to evaluate different alternatives by determining the relative importance of alternatives with respect to each criterion. It helps in measuring the performance of each alternative and is intended to transform these assessments into the numerical values of estimating the priorities. The final decisions were made by using these priorities. The strategy has issues of commonality amongst criteria and options. On account of the methodology from/to pairwise connections, it can even be at risk to abnormalities in judgment and positioning criteria and it doesn't enable people to survey one instrument in disengagement, in any case as differentiated and the remainder of, not perceiving weaknesses and characteristics. One in the entirety of its greatest reactions is that the last sort of AHP square measure inclined to rank inversion. On account of the character of examinations between/of rankings, the expansion of other options to the highest point of the strategy may make a definitive rankings flip or turn around.

Teaching and learning mimics the fact that any individual may strive hard to learn something from the other to improve their intelligence. The most classical and conventional teaching–learning environment in a school is one of the inspired and motivated processes through which the students can gain knowledge from the teachers. Based on this scenario, Rao *et al.* [13] has developed an interesting teaching–learning based optimization (TLBO) approach by giving a better quality solution in minimum time. TLBO is a powerful and efficient population based optimization technique that was inspired by the philosophy of the traditional school teaching and learning based approach. This optimization methodology was based on the influence of a

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teacher on the outcome of fellow students in a class. It does not require any algorithm-specific parameters rather it uses common controlling parameters such as population size and number of generations.

Technique for order preference similarity to ideal solution (TOPSIS) was one of the renowned multicriteria decision making methods proposed by Kwangsun Yoon and Hwang Ching-Lai [27]. This popular ranking method can be used to evaluate multiple different alternatives in contrast to the chosen criteria. The basic theory of this algorithm was that the most preferable and chosen alternative should have shortened distance from the positive ideal solution (PIS) and far away from the negative ideal solution (NIS). It was popularly meant to allot scoring measures based on the geometric distance from the PIS and NIS. PISs were supposed to maximize the beneficial criteria and to minimize the cost criteria. The contrary aspects of PIS were NIS where it maximizes the cost criteria and minimizes the beneficial criteria. TOPSIS was treated as the best technique in order to avert huge number of pairwise comparisons. A disadvantage is that its utilization of Euclidean separation does not consider the correlation between attributes. It is difficult to weight attributes and keep consistency of judgment, especially with additional attributes. The working principle of this paper comprises three blocks. In the first block, the computation of geometric mean was done by using AHP and it should be given as an input to TLBO as the population of the first learner. In Block 2, TLBO comes into play for generating the optimized priority weights by carrying out maximum iterations. Finally, TOPSIS can be estimated by providing these optimized weights to the weighted normalized matrix and the rank should be determined based on the closeness coefficient.

The rest of this paper is organized as follows. Section II describes the literature review that plays a significant role in data collection. Section III represents the proposed method. Section IV briefly explains our novice idea/concept with the help of numerical example of the selection of software packages. Section V describes the results and discussion. Finally, Section VI concludes this paper.

II. Literature Review

The literature review is organized into three different categories. The first category explores an overview and survey of AHP. The second category describes the significance of TLBO for generating the optimized weights. The last category demonstrates the usage of TOPSIS for the rank generation. These three categories assure an improved understanding of the theory of the title.

A. Analytic Hierarchy Process

Many research scholars have paid their attentions toward the selection of first-rated software packages using the traditional AHP approach.

Lai *et al.* [5] explored a description of the multimedia processing environment where the AHP was applied in order to select a better qualified multimedia authorizing system (MAS) application for a group decision making environment. This paper was targeted to amalgamate AHP and multimedia environment together by creating the MAS decision structure. Alanbay [6] presented a brief description of the Expert Choice (EC) software to select the most leading enterprise resource planning (ERP) system applications. It was considered to be the first and foremost software for solving all the AHP-related applications. A multiattribute ERP selection decision model was proposed based on the hypothesis of AHP but it is not limited to the software selection. In addition to that, AHP can also be applied to many fields of decision making environment with multiple attributes and alternatives.

Kull and Talluri [37] have addressed the decision process architecture. The middle philosophies used in the Supply Risk Reduction Model are AHP and Goal Programming (GP). The AHP–GP blend has been used for provider choices, office area choices, and cost administration. In this paper, the AHP assessment process is used to operationalize the multidimensional hazard build, to survey providers along these hazard measurements, and to infer chance scores. The GP show is used to assess numerous providers dependent on an assortment of hazard objectives and other hard limitations, for example, lead time, quality, provider limit, least request amounts, and request fulfillment. The noteworthy impediment is that the AHP system is not prepared powerfully. This will be defeated by means of autofixing the inclination grid.

Jadhav and Sonar [7] exemplified a comparative study on various traditional methodologies for the selection of best renowned software packages. The ranking score produced by the hybrid knowledge based system (HKBS) is analogous to AHP and weighted scoring method (WSM) scoring measure and thus can be utilized as a tool for evaluation and selection of the software components. Abohamad and Arisha [8] conceded a framework of the selection of an outstanding optimization packages for solving some complicated business related problems. This may reduce the cycle time required for the entire process. This can be achieved by integrating the structured and well-organized web database with the selection criteria. The motivation behind the usage of database will help us to systemize all the criteria terminology during the selection process.

Dong *et al.* [38] explored a consensus building in a local context for the AHP-GDM with the individual numerical Scale and prioritization method. The center methodologies utilized in the group decision making are AHP and 2-tuple etymological portrayal show. The AHP-GDM display is connected to get an aggregate need vector from the individual pairwise examination lattices. The execution of the AHP-GDM in a nearby setting includes three methods. They are prioritization process, AHP determination show, and AHP accord demonstrates. The 2-tuple semantic portrayal show permits a consistent portrayal of the etymological data on its space; in this way, it can speak to any including of data acquired in a conglomeration procedure. The etymological data are communicated by methods for 2-tuples, which are made out of a phonetic term and a numeric esteem. The real downside is that the AHP agreement measure flops in a nearby setting. This can be overwhelmed by fixing the agreement edge esteem and it relies on the specific issue to be proposed.

Triantaphyllou and Mann [43] addressed the validation of the preference matrix consistency. AHP calculates a consistency ratio (CR) comparing the consistency index (CI) of the matrix (the one with our judgments) versus the consistency index of a random matrix. A random matrix is one where the judgments have been entered randomly and therefore expected to be highly inconsistent. More specifically, random index (RI) is the average CI of 500 randomly filled in matrices. In AHP, the Consistency Ratio is defined as CR where CR = CI/RI. A Consistency Ratio of 0.10 or less is worthy to proceed with the AHP examination. On the off chance that the consistency proportion is more noteworthy than 0.10, it is important to overhaul the decisions to find the reason for the irregularity and right it.

Mustafa and Albahar [42] suggested that AHP is a flexible and easily understood way to analyze project risks. It is a multicriteria decision analysis methodology that allows subjective as well as objective factors to be considered in the process which is precisely what is needed. The AHP gives managers a more rational basis on which to make decisions.

Angelou and Economides [44] explored the AHP and integer goal programming as to provide the decision maker with an effective and efficient decision support process that also models constrained resource environment. One of the AHP's strengths is the value it places on a decision maker's opinions and the crucial role these opinions play in the decision-making process. Moreover, AHP is fit for incorporating both subjective and quantitative criteria into the basic leadership process. Finally, through the pairwise comparison process, AHP decomposes large, complex decisions and allows the decision maker to focus his attention on every criterion.

Jadhav and Sonar [9] provided a description of the evaluation and selection of various software packages. In addition to that, they have added some keynotes of generic methodology, evaluation criteria terminologies, and HKBS approach. Simultaneously, they have accomplished a comparative study between HKBS, AHP, and WSM and concluded in a precise manner. Eldrandaly and Naguib [10] illustrated the fact that the most expensive GIS software packages can be selected by adopting the knowledge-based system. This system was a combinatorial representation of expert system (ES) and AHP. The component object model (COM) technology was widely used for this integration process. The usage of Visual Rule Studio and Microsoft Visual Basic 6.0 turns to be very effective in producing the outcome more precisely. Kutlu *et al.* [11] determined the scope of selecting the most preferable project management software packages using AHP. Many academicians and the research scholars have spent their time scrutinizing the complete list of available software packages in the market. Finally, they have discovered three peculiar software packages, namely HP-PPM, MS-Project, and Primavera. Amidst all these tools, HP-PPM was regarded as more superior when compared with other tools.

Sun *et al.* [41] explored AHP as user friendly since users can directly input judgment data without the in depth knowledge of mathematics. AHP, the scale of absolute values of 1–9 is used for making the pairwise comparison judgments. Under group decision making environment, the AHP can keep the consistency of group when individual DMs are consistent by using the weighted geometric mean method.

Lima *et al.* [35] addressed consensus-seeking, IT decision support model that internally blends interval algebra, utility theory, and an extended analytic hierarchy process method to account for uncertainty, risk and multiple criteria, respectively. Consensus seeking is supported by the Delphi technique. Raw metric values for all (criterion, alternative) pairs must be used to find the final priority vector. The next conceptual step in the decision making model is to introduce utility. The reasons for that are twofold: decision makers have an *attitude toward risk*: some are more risk averse and would prefer a lower expected return, as long as the risk is lower. Others are risk seeking, and others yet are risk neutral. The preference that a decision maker has for a particular range of metric values may be highly nonlinear. The concept of utility accommodates these issues by providing a mapping mechanism. The utility of a particular value for a given criterion reflects "how good" the decision maker feels about the value.

Nguyen and Gordon-Brown [34] have addressed the portfolio selection literature. In applications identified with portfolio selection, AHP requires decisions including evaluations of different resources as for decided criteria. The AHP approach, as widely applied in complex multicriteria decision making, is usually conducted with a tree structure of criteria and subcriteria. It is essential to take note of that peripheral effects of advantages on portfolio return are resource anticipated returns, which are crisp numbers. It is utilized to diminish the business sectors multifaceted nature and make a short rundown of advantages to invest. The fundamental target is to designate an ideal resource to contribute and to configure hedging with derivatives. The hindrance is that there is intricacy vulnerability in reality portfolio management context. Decision makers might be reluctant and sometimes unable to provide such precise judgments.

B. Teaching–Learning Based Optimization

TLBO was mainly meant to discover the global optimization solutions. It was used in diverse application areas, such as engineering and science, etc. The following manifests the survey of TLBO that was tested for distinct benchmark functions that depict the significance of this proposed methodology.

Crepinsek *et al.* [12] and Lin *et al.* [36] demonstrated the dreadful insight report on TLBO and have identified a few significant misconceptions when compared with other metaheuristics, such as Genetic Algorithm (GA) for the selection process. Finding states that this algorithm uses only less computational effort for solving the optimization problems. It is worth noticing that the results obtained from the qualitative and quantitative investigations find some mismatches regarding the abovementioned conclusion. Furthermore, there were some discrepancies related to the fitness function evaluations. Rao *et al.* [13] delivered a precise description of the TLBO approach. In addition to that, they have synopsized the step-by-step running strategy using the flow diagrams illustration. They have utilized Rastrigin as their benchmark function to achieve an outstanding performance with less computational efforts of continuous nonlinear large-scale problems.

Rao and Patel [14] illustrated the fact that the elitism concept was implemented newly in TLBO algorithm and the repercussion of their performance was examined properly. This algorithm was tested under 35 benchmark functions of the constrained optimization problem and their performance was compared with many other population-based algorithms. Satapathy *et al*. [15] proposed an upgraded version of TLBO, i.e., Weighted TLBO algorithm. The inclusion of adding “weight” parameter to the traditional TLBO however seems to increase the complexity of the algorithm but it may ease the task and yields better result when compared with the traditional TLBO approach. In this modernized technique, the part of its previous values is taken into consideration and they are determined by a weight factor “w” during the computation of new Learner values.

Rao and Patel [16] epitomized the concepts regarding the traditional TLBO and they have extended this algorithm to Improved TLBO (ITLBO) approach. In case of TLBO, the outcome produced by the learners in a class room was enhanced by a single teacher or by collaborating with other learners. In contrast to the traditional TLBO approach, ITLBO can make use of multiple numbers of teachers for the entire learners. The efficiency and performance of the ITLBO was comparatively better when compared with the traditional TLBO. Satapathy *et al*. [17] elucidated the facts regarding Orthogonal Teaching Learning Based Optimization (OTLBO), an improved version of the basic TLBO. If the problems are separable, nonseparable, unimodal, and multimodal, then the better option is to use OTLBO for attaining the results of a faster convergence time. During the performance evaluation, this method outperforms the best among all the other methods such as TLBO, particle swarm optimization (PSO), differential evolution, artificial bee colony, etc.

Lim and Isa [18] presented an outline description of Teaching and Peer-Learning Particle Swarm Optimization (TPLPSO) algorithm. The particle fails to improve their fitness function of the exploration process due to the unavailability of alternative learning strategy. In response to that, most of the researchers have spent their attentions toward integrating the basic TLBO with PSO algorithm. Finally, the utilization of stagnation prevention strategy (SPS) will improve the algorithm’s robustness toward the earlier convergence problems. Patel and Savsani [19] suggested a solution to solve multiobjective optimization problems by using an efficient and powerful Multiobjective Improved Teaching Learning Based Optimization (MO-ITLBO) methodology. The learners can enrich their knowledge by extracting the solutions to the external archive. MO-ITLBO uses a grid-based approach from handling the diversification amidst over the archive. The performance metric was compared with the other state-of-the-art algorithms and it was tested using Friedman’s rank test and Holm post hoc procedure.

Zou *et al*. [20] combined the efficient ITLBO with dynamic group strategy (DGS) and have proposed novice DGSTLBO approaches for solving optimization problems. The motivation behind this innovative algorithm is that instead of learning from the mean result of the entire class, each learner gains intelligence from the mean result of their corresponding group. Feasible regrouping is done dynamically to maintain the diversification of the population and to avoid the premature convergence. Rao and Waghmare [21] devised a comparative study of TLBO on the multiobjective optimization problems and these can be either constrained or unconstrained functions. The comparison was made between TLBO and other renowned optimization methods, such as AMGA, Clustering MOEA, DECMOSA-SQP, DMOEADD, GDE3, LiuLi algorithm, MOEAD, MOEADGM, etc. The results showed that the TLBO algorithm outperforms the best among all the abovementioned methodologies.

Chen *et al*. [22] discussed deeply on ITLBO to improve the performance and efficiency of TLBO by mixing up the local and global search methodologies. This paper proposes two distinct kinds of learning strategies such as local learning and self-learning methods to improve the search capabilities of TLBO. The ITLBO algorithm was considered as the first-rated technique amidst all the other well-known optimization approaches. Sahu *et al*. [23] focused on the robust fuzzy- Proportional–Integral–Derivative (PID) controller for measuring the performance of automatic generation control. Many practitioners and research scholars majestically said that this powerful TLBO algorithm was implemented in this area for the first time to acquire the parameters of the PID controller. The performance and their robustness were tested and compared with many other algorithms, such as Lozi map based chaotic optimization algorithm, GA, Pattern Search, and Simulated Algorithm.

Zou *et al*. [24] introduced a potent and impressive LETLBO (TLBO with learning experience of others) technique to improve the effectiveness of TLBO. In order to increase the learning speed of each individual learner, we are in need to extract and implement the area copying operator from the Producer–Scrounger model. This will greatly influence the performance of each learner. Finally, the researchers proved that this will suit best for the optimization problems. Venkata Rao [2] contributed a scrutinized list of applications for TLBO algorithm for solving the large-scale optimization problems. In addition to that, they have also illustrated some numerical examples using different benchmark functions of our better understanding. Many of the research scholars have suggested and proved that this algorithm will be the outstanding one when compared with all the other optimization-based algorithms.

C. Technique for Order Preference Similarity to Ideal Solution

The software package selection has grasped the decision maker’s attention on the investigation into the best ranking technique for implementation. The following section shows the survey on TOPSIS methodology and differentiates how this ranking technique suits the best in various application areas.

Dagdeviren *et al*. [25] elucidated the facts regarding the selection of an appropriate weapon for the defense industries. The traditional AHP technique mainly classifies the given decision-making problem of various considerations and helps in understanding the structure to derive an optimal priority weights. Furthermore, TOPSIS plays a vital role in ranking the alternatives (i.e., weapons) to suit the best for the industry. Amiri [26] devised a new methodology to select the best candidate by evaluating the basic investment measures. This is accomplished for the National Iranian Oil Company and it can be achieved by using AHP and TOPSIS methodology. The priority weights generated by AHP are given as input to the TOPSIS methodology to rank the alternatives.

Chandra and Varghese [39] addressed the role of decision tree for selection process. They developed a fuzzy decision boundary instead of a crisp decision boundary. Size of the decision tree built is another essential parameter in decision tree algorithms. Huge and more profound decision tree results in unfathomable acceptance rules. The disadvantage is that the decision tree algorithms do not give rules that are easy to understand and are inefficient due to sharp boundary problems. In a crisp decision tree, the split point is picked as the midpoint of progressive qualities where the class data changes. At whatever point a part quality is picked with a specific esteem, there is no certification that this is the precise incentive at which the split needs to happen. The cumulative normalized membership values of the dataset on the directly of the root node are more noteworthy than the threshold value. None of the ceasing criteria is valid for the dataset on the left of the root node, and thus the algorithm is executed once more.

Cohen *et al*. [40] addressed the role of Garbage Can model for selection process. The Garbage Can model is a basic stimulation model that can be determined as far as the four streams and a lot of garbage preparing suspicions. Garbage Can model portrays a model that disengages issues, arrangements, and chiefs from one another. It sees principle segments of choice process; for example, issues, arrangements, members, decision, and circumstances are combined up in the garbage can of the association. Basic leadership by flight and oversight is a noteworthy element of the procedure as a rule. The conduct and standardizing ramifications of a choice procedure that seems to settle on decisions in vast part by flight or by oversight must be inspected. The fundamental component of the garbage can process is the halfway uncoupling of issues and decisions. But the garbage can model does not assume a feedback loop. In actuality, rather than the target models in which the substance of the response for an issue is not known definitively until the end, the garbage can indicate imagines the content of the solution, and influences the availability of resources which, in turn, affects the choice of the intervention.

Torfi *et al*. [27] proposed an evaluation framework of the selection processes using Fuzzy AHP and Fuzzy TOPSIS methodology. The main objective of this hybrid methodology is to generate the priority weights and to rank the alternatives. When the description of the criteria, observations, priority weights, and their ranking measure found to be vague and imprecise, then it is supposed to choose FAHP and FTOPSIS as preferred techniques. Sevkli *et al*. [28] presented a comparative study on two methodologies, namely Crisp TOPSIS method and Fuzzy TOPSIS method. These two approaches were applied and tested for a manufacturing company for supplier selection. The selection criteria terminologies cannot be precisely measured by using the traditional crisp TOPSIS ranking technique. In order to produce an accurate result and to make a strategic decision to be more consistent, the fuzzy TOPSIS method was appropriate one to choose.

Madi and Tap [29] discussed deeply on TOPSIS methodology involved in the selection process of investment boards for stock exchanges. The criteria terminologies involved in the decision process are market valuation, stock trading volume, and stock trading to value. Based on these criteria, the investment boards are selected by the expert practitioners. Bhutia and Phipon [30] focused on establishing a supplier selection problem, which is one of the famous MCDM problems under consideration. This paper was dealt with the evaluation of the best supplier by using AHP and TOPSIS methodology. The main intention of this paper is to generate the priority weights using AHP and to rank the alternatives (i.e., suppliers) by using the TOPSIS methodology.

The main drawback of hybridizing the traditional techniques alone leads to the following.

1) Problem in interdependency between criteria and alternatives.
2) Inconsistencies between judgment and ranking criteria.
3) Rank reversal.
4) No consideration of the correlation of attributes by the Euclidean distance.
5) Difficulty in keeping consistency of judgment.

The contribution of adding new method (TLBO) makes a difference in the following.

1) Generation of optimal weights.
2) Algorithm specific parameters (not required).
3) Number of iterations.
4) Fitness evaluation.
5) Convergence rate.

III. Proposed Method

We now consider the software selection process as an MCDM problem and it can be achieved by the following methodologies.

1) AHP is used for calculating the weights for each criterion.
2) TLBO algorithm was mainly meant to generate the optimized weights for each criterion.
3) TOPSIS is one of the best ranking techniques to solve this decision problem. The process includes the following.
   a) Dataset Collection:
      Open Source Software (OSS) package;
   b) Identify the various criteria and alternatives:
      Evaluate the data for different criteria against the alternatives;
   c) Generation of Weights:
      Weight Generation using AHP;
   d) Optimization:
      Optimize the priority weights using TLBO;
   e) Ranking:
      Rank the alternatives using TOPSIS.

A. Procedure of AHP

Now, this section explains the step-by-step algorithmic procedure of AHP, which is as follows.

Step 1: Construct a multilevel hierarchical structure by decomposing the given decision-making problem into various subproblems. Then, go to the next step.

Step 2: In this step, comparison was made between each of the criteria and also criteria with alternatives. Furthermore, we do not pay much attention on the comparison between subcriteria. Thus, pairwise comparison matrix was constructed by using 0–9 rating scale values. Go to the next step.

Step 3: Normalize the given matrix by dividing each index with its corresponding column total and move on to step 4.

Step 4: After constructing the normalized decision matrix, it is necessary to calculate the relative weights for each criteria. This can be achieved by dividing the row total of a normalized matrix with its total number of considered alternatives.

Step 5: The estimation of priority weights is generated in three different steps shown as follows.

Step 5.1: Initially, we need to calculate the geometric mean of a given decision matrix. Then, go to the step 5.2.

Step 5.2: The next step is to perform the summation of all the generated geometric mean values and go to the next step 5.3.

Step 5.3: Finally, the priority weights can be derived by dividing each of the geometric mean values of its total.

Step 6: The final decision was made by considering all these optimized priority weights.

Step 7: End.

B. Procedure of TLBO

This section explores the working of TLBO that consists of "Teacher Phase" and "Learner Phase" is explained as follows.

Step 1: Define the randomly generated Initial Population (i.e., number of learners or fellow students), design variables (i.e., number of subjects, (x_i)), benchmark functions (i.e., objective function, $f(x)$), and the termination criterion.

Step 2: Calculate the mean value for each design variables and estimate the objective function for each learners. It is desirable to set a constraint on both minimization and maximization functions. If the objective functions are said to be of minimization, then the lowest value of benchmark function is treated as the best learner. The constraint on maximization function is contrary to that of minimization function.

Step 3: Assume the random numbers (r_i) for each design variables and go to the next step.

Step 4: Calculate the difference mean (DM) values for each design variables (i.e., x_i) by using the below (1) is as follows:

$$\text{Difference\_Mean}_i = \mathrm{r}_i\left(M_{\text{new}} - T_F M_i\right) \tag{1}$$

where M_i is the mean value for each x_i, M_{new} is the new mean value and T_F is the Teaching Factor that decides the modification of mean value. The value of T_F is either 1 or 2 and it is determined randomly with equal probability shown as follows:

$$\text{Teaching\_Factor } T_F = \text{round}\left[1 + \text{rand}(0,1)\right.$$
$$\left.\{2-1\}\right]. \tag{2}$$

Step 5: The new values of x_i can be obtained by adding the DM values of its corresponding old $_i$ values. This is described as follows:

$$X_{\text{new},i} = X_{\text{old},i} + \text{Difference\_Mean}_i. \tag{3}$$

It is not necessary to calculate the DM to all the x_i values. Rather, calculate the DM for all design variables and add it to all their corresponding x_i columns.

Step 6: Calculate the objective function for new values of x_i. Thus, the "Teacher phase" of TLBO algorithm is completed.

Step 7: The objective function values generated in Steps 2 and 6 are compared and their best values of $f(x)$ are given to the learner phase.

Step 8: Update the values of the design variables and objective function based on the fitness comparison done in Step 7. Now, the learner phase starts.

Step 9: Interactions are done in a random manner (for example, i.e., Interaction between 1 and 2, 2 and 5, 3 and 1, 4 and 5, and 5 and 4). In response to that, select any two random solutions X_i and X_j and go to the next step. Furthermore, assume the random numbers for each design variable.

Step 10: If X_i is better than X_j, then utilize the following:

$$X_{\text{new}} = X_{\text{old}} + r_i\left(X_i - X_j\right) \tag{4}$$

and if X_j is better than X_i, then use

$$X_{\text{new}} = X_{\text{old}} + r_i\left(X_j - \mathrm{X}_i\right). \tag{5}$$

Step 11: Calculate the fitness function for this new values of the design variables and go to the next step.

Step 12: The objective function values generated in steps 7 and 11 are compared and their best values of *f*(*x*) are considered.

Step 13: Update the values of the design variables and objective function based on the fitness comparison done in step 12. This completes the learner phase of TLBO approach.

Step 14: Proceed until the termination criterion is satisfied.

Step 15: End.

C. Procedure of TOPSIS

This section demonstrates a well-organized algorithmic procedure for TOPSIS shown as follows.

Step 1: Establish a decision matrix for this ranking technique and its structure is described as

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix}.$$

Step 2: Normalize the given decision matrix (R) by using the Normalization method as shown

$$r_{ij} = x_{ij} / \sqrt{\sum\nolimits_{i=1}^{m} {x_{ij}}^2}. \tag{6}$$

Step 3: Calculate the weighted normalized matrix by multiplying weights with the normalized matrix using

$$v_{ij} = w_{ij} * r_{ij}, \text{where } j = 1, 2, \ldots, n$$
$$\text{and } i = 1, 2, \ldots, m. \tag{7}$$

Here, v_{ij} represents the weighted normalized matrix, $w_{ij} = \{w_1, w_2, \ldots, w_n\}$ represents associated weights, r_{ij} stands for the normalized matrix and

$$\sum_{j=1}^{m} w_j = 1. \tag{8}$$

Equation (7) can also be written as

$$V = \begin{bmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & \cdots & w_n r_{1n} \\ \vdots & \ddots & \vdots \\ w_1 r_{m1} & \cdots & w_n r_{mn} \end{bmatrix}.$$

Step 4: Estimate the PIS and NIS by setting the positive ideal alternative (A^+) and negative ideal alternative (A^-) is defined as

$$A^+ = \{((\max_i v_{ij} | j \in J), (\min_i v_{ij} | j \in J) \mid i = 1, 2, \ldots, m)\} = \{v_1{}^+, v_2{}^*, \ldots v_j{}^*, \ldots v_n{}^*\} \tag{9}$$

$$A^- = \{((\min_i v_{ij} | j \in J), (\max_i v_{ij} | j \in J) | i = 1, 2, \ldots, m)\} = \{v_1{}^-, v_2{}^-, \ldots v_j{}^-, \ldots v_n{}^-\}. \tag{10}$$

Here, *J* is the Beneficiary attribute and J^- or J^c is the cost attribute.

In case of PIS, if the attribute/criteria is treated as the beneficiary attribute, then choose the maximum value from the decision matrix. If the cost criterion is considered, then choose the minimum value from the matrix.

In case of NIS, if the criteria are said to be of beneficiary attribute, then choose the minimum value from the decision matrix. If the cost criterion is considered, then choose the maximum value from the weighted normalized matrix.

Step 5: Calculating the separation measure based on the Euclidean distance is given as follows:

$$S_{i^+} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2}, i = (1, 2, \ldots, m) \tag{11}$$

$$S_{i^-} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2}, i = (1, 2, \ldots, m). \tag{12}$$

Step 6: Determination of Closeness Coefficient (CC) is defined as follows:

$$C_{i^*} = \frac{S_{i^-}}{(S_{i^-} + S_{i^+})}, 0 < C_{i^*} < 1, \quad i = (1, 2, \ldots, m). \tag{13}$$

Step 7: Ranking the alternatives based on the abovementioned calculated CC.

D. Workflow of Proposed Method

The conceptual view of the proposed method is depicted in Fig. 1

IV. Numerical Example

In this paper, five criteria and 11 software packages are taken into consideration for better understanding of the hybrid methodologies. The considered criteria are cost, security, support, usability, and technical details. This numerical example will illustrate the working flow and a novice concept of our proposed methodology in detail. Table I shows the description of 1–9 rating scale, which is as follows.

The abovementioned decision matrix was constructed based on the importance of each criterion and the assessments of criteria are valued by using 0–9 rating scale. It is clear about the abovementioned statement that the traditional AHP methodology uses only crisp numbers to represent the strength of preferences.

Step 1: Initially, the input matrix representation of AHP is shown as follows:

$$\begin{pmatrix} 1 & 5 & 3 & 9 & 7 \\ 1/5 & 1 & 1/3 & 5 & 3 \\ 1/3 & 3 & 1 & 7 & 5 \\ 1/9 & 1/5 & 1/7 & 1 & 1/3 \\ 1/7 & 1/3 & 1/5 & 3 & 1 \end{pmatrix}.$$

Step 2: According to our hybrid methodology, AHP is mainly meant to calculate the geometric mean for all criteria. The resultant output for geometric mean generation is as follows:

$$\mathrm{GM}_1 = 3.94; \mathrm{GM}_2 = 1.0; \mathrm{GM}_3 = 2.03;$$
$$\mathrm{GM}_4 = 0.25; \mathrm{GM}_5 = 0.49.$$

These mean values of each criterion are given as an input to the TLBO algorithm. This completes the procedure of AHP algorithm.

Step 3: Now, the TLBO algorithm starts. In this step, the main intention of our new idea is to randomly generate the initial population. Here, five learners and five design variables are taken into consideration. In addition to that the teaching factor T_F is considered to be 1. The following steps explain the TLBO procedure for single iteration.

Step 4: In this step, Table II clearly explains how to generate initial population for implementing TLBO algorithm. This is explained in the following steps.

1) Get the resultant values of geometric mean from AHP and fed as an input to the first learner in TLBO approach.
2) The population of other learners is randomly generated. These two steps play a significant role in our hybrid approach.
3) This paper proposes a novice and innovative idea behind the formulation of fitness function. This concept was newly invented to show the performance and significant impact of our proposed methodology.
4) The fact behind the generation of relative weights of traditional AHP approach is used as a fitness function of TLBO technique.

D. WORKFLOW OF PROPOSED METHOD

The conceptual view of the proposed method is depicted in Fig.1

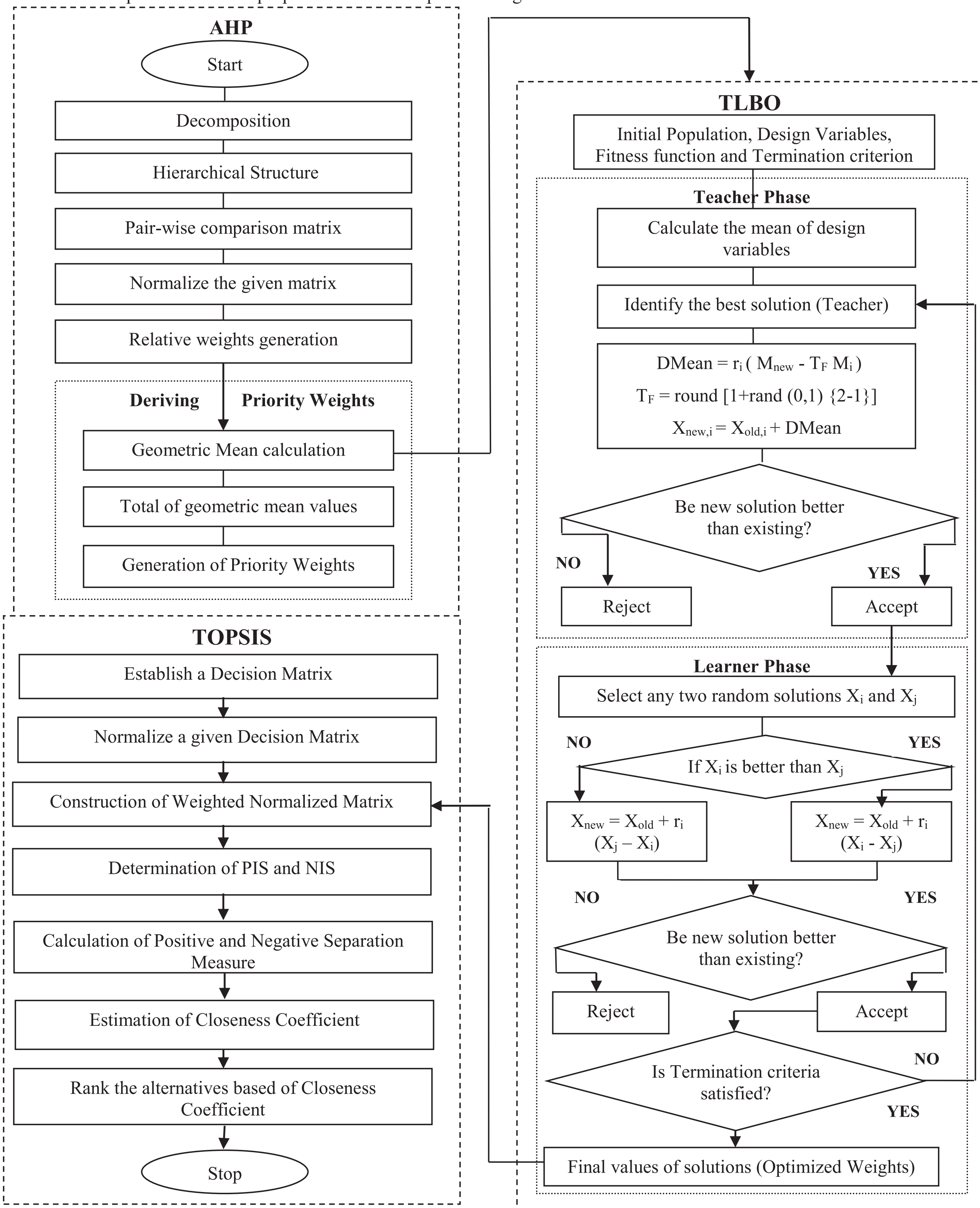

Fig. 1. Conceptual view of the proposed method.

TABLE I
1–9 RATING SCALE (ADAPTED FROM [4])

1-9 scale	Meaning
1/9	Extremely not Preferred
1/7	Very Strongly not Preferred
1/5	Strongly not Preferred
1/3	Moderately not Preferred
1	Equally Preferred
3	Moderately Preferred
5	Strongly Preferred
7	Very Strongly Preferred
9	Extremely Preferred

This is the reason that why we did not calculate relative weights in case of AHP methodology. Instead of using the relative weights as an input to the first learner, we may also use the geometric mean as an input and relative weights as a proper benchmark function.

5) The outcome of priority weights should be high. Thus, in this paper, we are setting the objective function to be maximum.
6) Calculate the mean for each design variable and determine the fitness function values.

Step 5: Generation of new values and Updated Values for Teacher phase, as shown in Table III. Furthermore, the calculated DM for each design variable is as follows: DM $(x_i) = \{1.97,\ 0.22,\ 1.06,\ -0.07,\ 0.01\}$.

Step 6: Generation of New values and Updated Values for Learner phase, as shown in Table IV. This completes the TLBO algorithm for single iteration. It is necessary to satisfy the termination criterion. In response to that, this procedure is continued until it satisfies the constraint. Table V shows the result of successive iterations for better understanding.

From Table V, it shows that the TLBO procedure is repeated for five iterations. The resultant value remains stable at the point 0.5 from the first iteration onward. Thus, it is enough to stop the procedure at the fifth iteration.

Step 7: After estimating the maximum iterations output, it is necessary to calculate the optimized priority weights. The final step of our newly introduced concept comprises three steps explained as follows.

1) Calculate the sum of each learner and determine the fitness function (i.e., $f(x)$) for calculating the optimized priority weights.
2) Estimate the max value of $f(x)$ and the corresponding collection of fitness values is chosen as the optimized priority weights.
3) Check whether the sum of determined priority weights is equal to 1.

Because, these priority weights are fed as an input to calculate the weighted normalized matrix in case of TOPSIS methodology. In general, the major constraint behind the TOPSIS approach that will greatly impact the performance of our proposed work is that the sum of weights should be equal to 1.

Step 8: The priority weights generated by AHP are further optimized by using TLBO algorithm. The resultant optimized priority weights generated at the fifth iteration is given as an input to the TOPSIS algorithm, as shown in Table IX. The generated priority weights are given as follows:

$$w_1 = 0.56; w_2 = 0.17; w_3 = 0.25; w_4 = 0.02;$$
$$w_5 = 0.01.$$

This shows that the resultant sum of w_i is equal to 1. This completes the TLBO algorithm.

Step 9: The decision matrix representation of TOPSIS is as follows:

$$\begin{pmatrix} 4 & 4 & 3 & 2 & 2 \\ 5 & 2 & 3 & 2 & 2 \\ 5 & 3 & 3 & 2 & 1 \\ 4 & 4 & 3 & 2 & 3 \\ 2 & 2 & 2 & 3 & 3 \\ 2 & 2 & 2 & 3 & 3 \\ 1 & 2 & 2 & 4 & 4 \\ 3 & 3 & 4 & 2 & 2 \\ 5 & 4 & 4 & 3 & 2 \\ 3 & 3 & 3 & 3 & 4 \\ 3 & 3 & 3 & 2 & 2 \end{pmatrix}.$$

In this step, TOPSIS algorithm starts. Here, we now consider five criteria and 11 software packages for the considered decision-making problem. TOPSIS approach is tested for a sample input matrix that was taken from [33].

Step 10: The Normalized decision matrix was constructed by the normalization method is described as follows:

$$\begin{pmatrix} 0.57 & 0.57 & 0.43 & 0.29 & 0.29 \\ 0.74 & 0.29 & 0.44 & 0.29 & 0.29 \\ 0.72 & 0.43 & 0.43 & 0.29 & 0.14 \\ 0.54 & 0.54 & 0.41 & 0.27 & 0.41 \\ 0.36 & 0.36 & 0.36 & 0.55 & 0.55 \\ 0.36 & 0.36 & 0.36 & 0.55 & 0.55 \\ 0.16 & 0.31 & 0.31 & 0.62 & 0.62 \\ 0.46 & 0.46 & 0.62 & 0.31 & 0.31 \\ 0.6 & 0.48 & 0.48 & 0.36 & 0.24 \\ 0.42 & 0.42 & 0.42 & 0.42 & 0.55 \\ 0.51 & 0.51 & 0.51 & 0.34 & 0.34 \end{pmatrix}.$$

Step 11: The optimized priority weights generated in step 10 are multiplied with the Normalized decision matrix to generate the Weighted Normalized matrix. The weights

TABLE II
INITIAL POPULATION GENERATION

Learner	x1	x2	x3	x4	x5	Sum	f(x) =xᵢ/Sum	Max [f(x)]
1	3.94	1.0	2.03	0.25	0.49	7.71	(0.511, 0.1297, 0.2633, 0.0324, 0.0636)	**0.511**
2	0.8	0.34	0.0	0.81	0.47	2.42	(0.3306, 0.1405, 0.0, 0.3347, 0.1942)	0.3347
3	0.89	0.34	0.8	0.62	0.66	3.31	(0.2689, 0.1027, 0.2417, 0.1873, 0.1994)	0.2689
4	0.78	0.51	0.72	0.39	0.64	3.04	(0.2566, 0.1678, 0.2368, 0.1283, 0.2105)	0.2566
5	0.98	0.82	0.06	0.56	0.06	2.48	(0.3952, 0.3306, 0.0242, 0.2258, 0.0242)	0.3952
Mean	1.48	0.6	0.72	0.53	0.46	-	-	-

TABLE III
TEACHER PHASE

New Values									Updated Values						
random no(xᵢ)	x1	x2	x3	x4	x5	sum	f(x)=xᵢ/Sum	Max [f(x)]	Learner	x1	x2	x3	x4	x5	Comparison F(X)
0.8	5.91	1.22	3.09	0.18	0.5	10.9	(0.54, 0.11, 0.28, 0.02, 0.05)	**0.54**	1	5.91	1.22	3.09	0.18	0.5	**0.54**
0.54	2.77	0.56	1.06	0.74	0.48	5.61	(0.49, 0.1, 0.19, 0.13, 0.09)	0.49	2	2.77	0.56	1.06	0.74	0.48	0.49
0.81	2.86	0.56	1.86	0.55	0.67	6.5	(0.44, 0.09, 0.29, 0.08, 0.1)	0.44	3	2.86	0.56	1.86	0.55	0.67	0.44
0.25	2.75	0.73	1.78	0.32	0.65	6.23	(0.44, 0.12, 0.29, 0.05, 0.1)	0.44	4	2.75	0.73	1.78	0.32	0.65	0.44
0.19	2.95	1.04	1.12	0.49	0.07	5.67	(0.52, 0.18, 0.2, 0.09, 0.01)	0.52	5	2.95	1.04	1.12	0.49	0.07	0.52

TABLE IV
LEARNER PHASE

New Values										Updated Values						
Random no(xᵢ)	x1	x2	x3	x4	x5	sum	f(x)=xᵢ/Sum	max [f(x)]	Interaction	Learners	x1	x2	x3	x4	x5	Comparison f(x)
0.15	6.39	1.66	4.08	0.00	0.51	21.12	(0.3, 0.13, 0.3, 0.13, 0.13)	0.3	1&2	1	5.91	1.22	3.09	2.78	0.5	**0.54**
0.68	2.79	0.88	2.12	0.65	0.23	6.09	(0.27, 0.15, 0.27, 0.15, 0.15)	0.27	2&5	2	2.77	0.56	1.06	0.93	0.48	0.49
0.49	6.37	1.66	3.69	0.05	0.39	12.81	(0.32, 0.17, 0.29, 0.11, 0.11)	0.32	3&1	3	2.86	0.56	1.86	1.45	0.67	0.44
0.33	2.78	0.93	1.45	0.37	0.29	1.46	(0.0, 0.45, 0.04, 0.26, 0.26)	**0.45**	4&5	4	2.75	0.73	1.78	0.37	0.65	0.45
0.61	2.78	0.93	1.45	0.37	0.29	1.73	(0.3, 0.13, 0.23, 0.17, 0.17)	0.3	5&4	5	2.95	1.04	1.12	0.29	0.07	0.52

The bold face type values of Table II, Table III, and Table IV represents the Maximum value of $f(x)$.

TABLE V
DETERMINATION OF THE OPTIMIZED PRIORITY WEIGHTS

Iteration	x1	x2	x3	x4	x5	Sum	f(x)=xᵢ/Sum (Chosen as priority Weights)	Max[f(x)]
1	5.91	1.22	3.09	2.78	0.5	13.50	(0.44, 0.09, 0.23, 0.21, 0.04)	0.54
2	3.88	1.07	1.83	0.56	0.36	7.7	(0.5, 0.14, 0.24, 0.07, 0.05)	0.50
3	6.01	2.85	2.67	0.55	0.37	12.45	(0.48, 0.23, 0.21, 0.04, 0.03)	0.55
4	9.65	3.88	4.14	0.56	0.33	18.56	(0.52, 0.21, 0.22, 0.03, 0.02)	0.52
5	6.37	1.9	2.82	0.21	0.15	11.45	**(0.56, 0.17, 0.25, 0.02, 0.01)**	0.56

The bold face type values of Table V represents the optimized priority weights chosen based on Max $f(x)$.

TABLE VI
COMPARISON ON WEIGHT GENERATION

Criteria	Weights using AHP	Optimized Weights using TLBO
C1	0.3	0.56
C2	0.14	0.17
C3	0.06	0.25
C4	0.3	0.02
C5	0.21	0.01

TABLE VII
COMPARISON ON IDEAL SOLUTION

	AHP-TOPSIS		AHP-TLBO-TOPSIS	
Alternatives	PIS	NIS	PIS	NIS
Criteria 1	0.048	0.222	0.09	0.414
Criteria 2	0.080	0.041	0.097	0.049
Criteria 3	0.037	0.019	0.155	0.077
Criteria 4	0.186	0.081	0.012	0.005
Criteria 5	0.130	0.029	0.006	0.001

are multiplied with each column (i.e., each criterion) of the normalized matrix

$$\begin{pmatrix} 0.319 & 0.097 & 0.107 & 0.006 & 0.003 \\ 0.414 & 0.049 & 0.110 & 0.006 & 0.003 \\ 0.403 & 0.073 & 0.107 & 0.006 & 0.001 \\ 0.302 & 0.092 & 0.102 & 0.005 & 0.004 \\ 0.202 & 0.061 & 0.090 & 0.011 & 0.006 \\ 0.202 & 0.061 & 0.090 & 0.011 & 0.006 \\ 0.090 & 0.053 & 0.077 & 0.012 & 0.006 \\ 0.258 & 0.078 & 0.155 & 0.006 & 0.003 \\ 0.336 & 0.082 & 0.120 & 0.007 & 0.002 \\ 0.235 & 0.071 & 0.105 & 0.008 & 0.006 \\ 0.286 & 0.087 & 0.128 & 0.007 & 0.003 \end{pmatrix}.$$

Step 12: Determination of PIS and NIS. Here, V^+ and V^- are the positive and negative alternatives, respectively. In this step, it is must to define the beneficiary and cost attributes. This influences the outcome of Ideal solutions. From the abovementioned criteria, the beneficiary attributes are Security, Support, Usability, and Technical details. Furthermore, cost belongs to the nonbeneficiary attribute (i.e., cost attributes)

$$V^+ = \{0.09, 0.097, 0.155, 0.012, 0.006\}$$
$$V^- = \{0.414, 0.049, 0.077, 0.005, 0.001\}.$$

Step 13: Calculation of positive and negative separation measures is as follows:

$$Si^+ = \{0.2356, 0.4026, 0.5112, 0.5551, 0.5716, 0.5876, 0.5944, 0.6186, 0.6686, 0.6856, 0.7149\}$$

$$Si^- = \{0.1072, 0.1114, 0.1175, 0.167, 0.2691, 0.3419, 0.4685, 0.5024, 0.5112, 0.5432, 0.5622\}$$

where Si^+ represents the positive separation measure and Si^- represents the negative separation measure.

Step 14: Estimation of the CC is described as

$$C_i^* = \{0.3127, 0.2167, 0.1869, 0.2313, 0.3201, 0.3678, 0.4408, 0.4482, 0.4333, 0.4421, 0.4402\}.$$

V. RESULTS AND DISCUSSION

In this section, Open Source Electronic Medical Record (OS-EMR) software packages are taken into consideration for better understanding of the problem. Here, we have investigated 11 software packages listed as follows: OSCAR, WorldVista, ZEPRS, Hospital OS, HOSxP, THIRRA, GNUmed, FreeMED, GNU Health, OpenEMR, and OpenMRS.

S1. OSCAR: It is a web-based EMR system for primary care clinics. It has shown its growth performance by turning it into a comprehensive EMR and billing management system used by many doctors in Canada.

S2. WorldVista: It is free and an electronic health record system used by the U.S. Department of Veterans Affairs.

S3. Zambia electronic perinatal record system (ZEPRS): ZEPRS is an EMR system used in Zambia clinics.

S4. Hospital OS: This software is supported by the Thailand Research Fund and is a research project for hospital management software. This mainly supports the small rural hospitals in Thailand.

S5. HOSxP: It is a hospital information system used around 70 hospitals in Thailand. The main motivation behind this software is to ease the healthcare workflow.

S6. THIRRA: It is freely available and a web-based electronic health record system used in rural and remote areas.

S7. GNUmed: It is available at no cost and developed by huge number of medical doctors all over the world. This is free and liberated OS-EMR software package and it has the ability to run on GNU/Linux, Windows, and Mac OS X.

S8. FreeMED: It is an open source EMR and practice management system developed in 1999.

S9. GNU Health: The main goal of GNU Health is to communicate with health professionals throughout the world. It is a free health and hospital information system and tends to improve the lives of the underprivileged people. Its main motivation is to prevent them from diseases and to optimize their health promotions.

S10. Open EMR: It is one of the best open source electronic medical record software that can run on Linux, Windows, Mac OS, etc. It is available at no cost and is medical practice management software.

S11. OpenMRS: It is an application framework that can design the medical record system. It requires the medical and systems analysis knowledge rather the programming skills.

TABLE VIII
COMPARISON ON RANK GENERATION

	AHP-TOPSIS				AHP-TLBO-TOPSIS			
Alternatives	**PSM**	**NSM**	**CC**	**RANK**	**PSM**	**NSM**	**CC**	**RANK**
S1	0.1715	0.0721	0.2960	8	0.2356	0.1072	0.3127	8
S2	0.2737	0.0794	0.2249	10	0.4026	0.1114	0.2167	10
S3	0.3526	0.0837	0.1918	11	0.5112	0.1175	0.1869	11
S4	0.3848	0.1233	0.2427	9	0.5551	0.1670	0.2313	9
S5	0.3914	0.2047	0.3434	7	0.5716	0.2691	0.3201	7
S6	0.3979	0.2619	0.3969	6	0.5876	0.3419	0.3678	6
S7	0.4004	0.3428	0.4612	**1**	0.5944	0.4685	0.4408	3
S8	0.4264	0.3555	0.4547	2	0.6186	0.5024	0.4482	**1**
S9	0.4601	0.3610	0.4397	5	0.6686	0.5112	0.4333	5
S10	0.4715	0.3879	0.4514	3	0.6856	0.5432	0.4421	2
S11	0.4924	0.3980	0.447	4	0.7149	0.5622	0.4402	4

The bold face type values of TABLE VIII represents the top ranking using AHP-TOPSIS (Existing method) and AHP-TLBO-TOPSIS (Proposed method).

TABLE IX
BEST ALTERNATIVE BASED ON RANKING STRUCTURE

Method	**Ranking Structure**	**Best Alternative**
AHP-TOPSIS	S7>S8>S10>S11>S9>S6>S5>S1>S4>S2>S3	S7
AHP-TLBO-TOPSIS	S8>S10>S7>S11>S9>S6>S5>S1>S4>S2>S3	S8

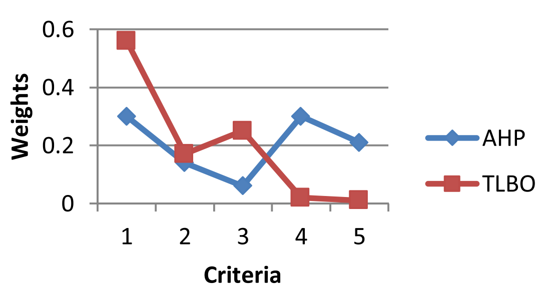

Fig. 2. Weight generation.

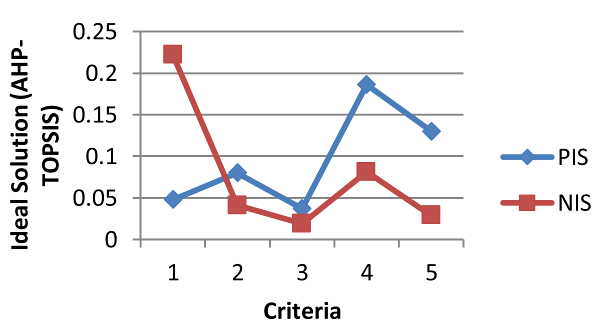

Fig. 3. Ideal Solution using AHP-TOPSIS.

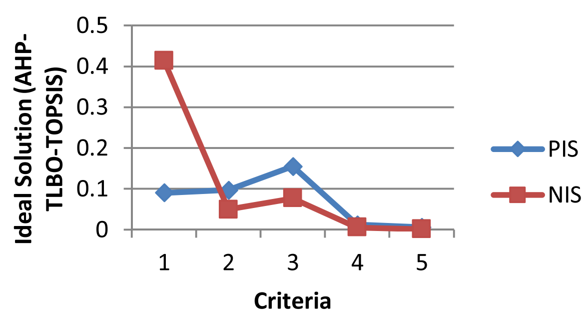

Fig. 4. Ideal Solution using AHP-TLBO-TOPSIS.

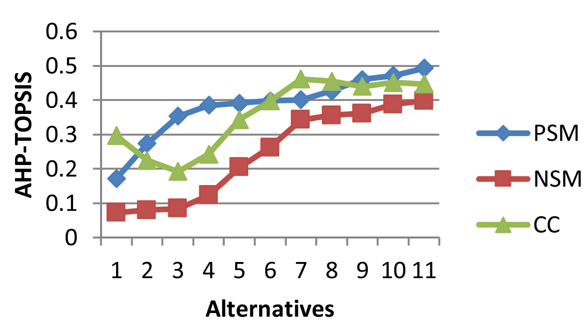

Fig. 5. Rank generation using AHP-TOPSIS.

Tables VI–IX and Figs. 2–6 show the comparison on weight generation, ideal solution, rank generation, and their corresponding ranking structure using different algorithms to estimate the best alternative.

From Table IX, it is clearly defined that GNUmed achieves greater performance using AHP-TOPSIS (existing approach) and FreeMED is the best software amidst the list of available softwares using our proposed approach. Basically, FreeMED is regarded as popular and well-known EMR software that provides openness mechanism to the public, whereas GNUmed is a liberated OS-EMR software package developed by a large number of medical doctors spread across the world. This software is considered to be the second best software among the repertoire

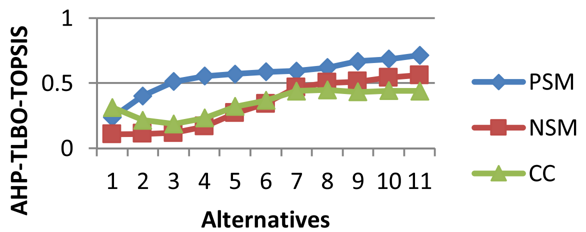

Fig. 6. Rank generation using AHP-TLBO-TOPSIS.

list. But, in the existing approach, GNUmed suits the best. In order to avoid these consequences, it is necessary to optimize the priority weights by using any of the optimization algorithms. In this paper, we have utilized TLBO as one of the best techniques to solve this problem and we have proved that FreeMED is the outstanding and superior software to choose for a particular firm. Thus, it is proven that TLBO and TOPSIS play a vital role in the decision-making environment to attain a perfect, consistent, and precise ranking structure to depict that which one will be the best for a developing firm.

VI. Conclusion

In this paper, we proposed a hybrid approach with a blend of AHP, TLBO, and TOPSIS approaches utilized for the choice of software packages for a specific firm. The software packages assume an essential part in accomplishing better execution of an association. Examination and the review of software packages accessible in the market got a handle on the consideration of the leader/master professionals. The vast majority of the analysts are investing much energy in the assessment procedure since it might bring about monetary loss of an association and yields imperfect key choices. This paper proposed a tenderfoot structure for the cross-breed techniques, which demonstrates the stream of our proposed work. TLBO approach is most suited for streamlining the need weights that are produced by any customary techniques, such as AHP, etc. Moreover, TOPSIS stands first position in the positioning procedure to help the chief in producing the rank for choosing which software package to decide for a specific association. One of the real inconveniences of TLBO is the convergence rate, and it deteriorates when managed higher measurement issues. Further works could consider expanding TLBO by adding a weighting element to the iterative procedure in this manner, making the calculation more effective. Notwithstanding that, the need weights can be produced and improved by utilizing different evolutionary algorithms with generally less parameters. Despite these strategies can be connected to different domains such as education system, healthcare, and election predictor system, which endeavors to consolidate the utilization of models or logical procedures with conventional information access and recovery capacities.

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