Technological Innovation Capability Evaluation of High-Tech Firms Using Conjunctive and Disjunctive Belief Rule-Based Expert System: A Comparative Study

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Abstract

Technological Innovation Capability (TIC) is an intricate concept which defines the essence of a firm's influence in the long run. It is associated with multiple quantitative and qualitative criteria, and various types of uncertainty can be seen while measuring these criteria. Therefore, to address this issue, a Belief Rule-Based Expert System (BRBES) can be employed with the capability of handling multiple criteria and their associated uncertainties in an integrated framework. In this article, two web-based BRBESs, namely conjunctive BRBES, and disjunctive BRBES, have been developed which are capable of reading data and producing web-based output by taking uncertainties into consideration. Then a comparison has been performed between them to determine the reliability of TIC evaluation. The results show that the performance of conjunctive BRBES is promising than disjunctive BRBES for technological innovation capability evaluation. In addition, a new learning mechanism, namely Belief Rule-Based Adaptive Particle Swarm Optimization (BRBAPSO), has been developed to support learning in BRBES and a comparison between trained conjunctive and trained disjunctive BRBES has also been carried out to evaluate TIC, where trained conjunctive BRBES is found effective than trained disjunctive BRBES.

Keywords: Technological Innovation Capability, Belief Rule Base, Expert System, Learning

1 Introduction

Since firms are confronting expeditious diverting surroundings, they need ceaseless technological innovation and managerial acknowledgment to preserve their competitiveness persistently. Organizational assets need to be overhauled, and competitiveness should be escalated by a firm to acquire an adequate degree of coordination to the exterior surroundings. A firm's response to improve and refine it's technological management activities has been accelerated significantly due to globalization of markets and shortening of product life cycles [1]. Therefore, efficient management of technological resources can be achieved by identifying and evaluating technologies from various sources. As a result, technological innovation and organizational assets need to be integrated to ensure competitive advantage and survival of corporate.

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The predominant basis of market competition lies in technological innovation capabilities. Various definitions of Technological Innovation Capabilities (TICs) exist which have been debated and emphasized different technological capability aspects including the origin of innovation, innovation features and dimensions, innovation processes, and so on [2], [3]. TICs play a crucial part to initiate firms' competency, and it is the principal assurance for the sustainable development of an enterprise. Effective development of technical innovation activities depends on increasing technical innovation capability. So, it is necessary to assess technological innovation capability. TICs should be monitored recurrently, and weak capabilities need to be strengthened continuously by a firm to facilitate a competitive advantage.

Numerous organizational tasks, resource combination among several departments and multi-criteria difficulties exist in technological innovation capabilities [4]. These capabilities play a significant role in the continuous improvement of firms in a sustainable and competitive market. Due to high uncertainty and imprecision in technological innovation-related activities of a firm, it is troublesome to assess innovation processes accurately [5]. During the life of technological innovation, uncertainty exists in both radical and incremental technologies. Moreover, undeveloped and rapidly developing technology creates a form of technological uncertainty that exceeds when the firm works with more advanced technologies for which knowledge is more available and stable in the general scientific community [6]. Technological, market and enterprise-based uncertainties are three types of uncertainties that exist in technological innovation [7]. From this perspective, various sources of ambiguities and uncertainties are embedded in each phase of the technological innovation process. The term 'degree of uncertainty' refers to each period of technological development trajectory, a similar concept that is defined in [8]. Furthermore, a firm's organizational management, organizational innovation decisions, and R&D capability related information are required for the degree to which technological innovation will be successful.

Due to subjectivity and imprecision in technological innovation capabilities of a firm, the process of TICs evaluation becomes more challenging and complicated. Hence, various viewpoint regarding different criteria and objectives may be noticed between evaluators. Numerous criteria including both quantitative and qualitative criteria exist in technological innovation capabilities of a firm. For example, the percentage of researchers or number of patents can be evaluated in a quantitative way, while innovativeness of R&D ideas should be expressed in a qualitative way. Therefore, various types of uncertainty, including imprecision, vagueness, ambiguity, ignorance, and incompleteness, can be observed while measuring these criteria. These uncertainties can occur due to lack of human knowledge or insufficient data. To evaluate technological innovation capabilities efficiently, a Belief Rule-Based Expert System (BRBES) can be used which is capable of handling both quantitative and qualitative data and their associated uncertainties. BRBES uses Belief Rule Base (BRB) to represent uncertain knowledge, while Evidential Reasoning (ER) acts as an inference engine to handle both uncertain and heterogeneous data [9]. In general, there are two types of BRB, namely conjunctive BRB and disjunctive BRB. In conjunctive BRB, each rule is assumed as conjunctive in nature, while in disjunctive BRB, each rule is represented using disjunctive assumption. However, due to the conjunctive nature [10] of the rule, conjunctive BRB suffers from the combinatorial explosion problem, whereas disjunctive BRB does not suffer from the similar problem and it requires less computational time to process data.

In our previous research, a RESTful API-based BRBES was developed to evaluate TIC, which was constructed under the conjunctive assumption by covering all possible combinations of referential values of all attributes, and a comparison between BRBES and various data-driven approaches had been performed to find out the reliability in evaluating TIC, where the outcome of BRBES was found better than those data-driven approaches [11]. In this research, the main focus is to perform a comparative analysis between two types of BRBES, namely conjunctive and disjunctive BRBES, and determine how conjunctive BRBES is performing compared to disjunctive BRBES for TIC evaluation. To accomplish this goal, two web-based BRBES, namely conjunctive BRBES and disjunctive BRBES, have been developed to process heterogeneous data as well as various types of uncertainties for evaluating TIC. A web-based BRBES facilitates easy development, deployment, maintenance of the application, and better user accessibility.

However, the learning parameters of the BRBES have a significant influence to achieve a better result. In general, these parameters are assigned by experts in the domain or by generating random numbers [12]. Since these parameters may not be optimal or 100% correct, different optimization techniques have been used to support learning mechanisms in BRBES to improve the accuracy. However, most of the existing optimization models of BRBES only take rule weights, attribute weights, and belief degrees into account without considering the referential values of the antecedent attributes and the utilities of the consequent attributes. Moreover, BRBES is always trained by using the Optimization Toolbox of *MATLAB* algorithm in existing studies, where the efficiency is not ideal for complex problems. Hence, a new Belief Rule-Based Adaptive Particle Swarm Optimization (BRBAPSO) is proposed, where rule weights, attribute weights, belief degrees, as well as the referential values of the antecedent attributes and the utilities of the consequent attributes, are taken into account to improve the input-output modeling ability of BRBES. Besides, it can ensure a balance between exploration and exploitation in the search space to obtain satisfactory results for a wide range of optimization problems.

In this research, the proposed BRBAPSO is utilized for training both conjunctive and disjunctive BRBES. After that, a comparison of performance evaluation between trained conjunctive and trained disjunctive BRBES has been conducted to find out the effectiveness when evaluating TIC.

The remainder of this article is structured as follows: Section 2 covers related work on technological innovation capability evaluation and optimization of BRBES, while Section 3 provides an overview of BRBES and its learning mechanism. Afterward, the proposed BRBAPSO based learning mechanism is discussed in Section 4. Section 5 describes the web-based BRBES, and Section 6 presents the results and discussion. Finally, Section 7 concludes the paper and indicates future work.

2 Related Work

Various existing methods can be found which are used previously for TIC evaluation. The related works are summarized in Table 1.

Statistical regression analysis was used in [13] to determine the TICs of Chinese firms in Beijing based on seven capabilities, namely learning, R&D, resource allocation, manufacturing, marketing, organizing, and strategic planning. Here, regression analysis determined the relationship between TICs and innovation rate, product competitiveness, and sales growth among the firms.

Analytical Hierarchy Process (AHP) together with the fuzzy approach and multi-criteria were used for TIC evaluation in [14]. Here, the TICs decision structure was made explicit based on evaluators decision structure by using their subjective judgments. The weight of all aspects and criteria of innovation performance was determined by Analytical Hierarchy Process (AHP) method, while the fuzzy set theory was applied to make evaluators subjective judgments, and a firm's innovation performance was evaluated by employing fuzzy Multiple Attribute Decision-Making (MADM) method.

A fuzzy measure and non-additive fuzzy integral method were used to assess the performance of synthetic technological innovation capabilities in hi-tech firms in [4]. Here, the principal criteria impacting TICs at hi-tech firms were identified by employing the non-additive fuzzy integral method.

A fuzzy decision-making approach was applied to evaluate technological innovation capability in [15]. Here, an Analytic Network Process (ANP) was employed to determine the weight of subjective judgments, while the best technology innovation enterprise was derived by using the fuzzy VIKOR algorithm.

Trapezoid fuzzy numbers and extension of Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) was employed to address the assessment of technological innovation capabilities in

Table 1: Summary of Related Works

Author	Method	Specification	Limitation
Yam et al. [13]	Regression analysis	TICs are determined based on seven capabilities, and the relationship between TICs and innovation rate, product competitiveness, and sales growth among the firms is investigated	No mechanism to address uncertainty
Lu et al. [14]	Analytical Hierarchy Process (AHP) with fuzzy Multiple Attribute Decision-Making (MADM) method	The weight of all aspects and criteria of innovation performance was determined by the AHP method, while the fuzzy set theory was applied to make evaluators' subjective judgments, and a firm's innovation performance was evaluated by employing fuzzy MADM method	Unable to address uncertainties due to incompleteness and ignorance
Wang et al. [4]	Non-additive fuzzy integral method	The principal criteria impacting TICs at hi-tech firms were identified by employing the non-additive fuzzy integral method	Unable to address uncertainties due to incompleteness and ignorance
Kong et al. [15]	Analytic Network Process (ANP) with fuzzy VIKOR algorithm	An ANP was employed to determine the weight of subjective judgments, while the best technology innovation enterprise was derived by using the fuzzy VIKOR algorithm	Unable to address uncertainties due to incompleteness and ignorance
Cheng et al. [16]	Trapezoid fuzzy numbers and extension of Technique for Order Performance by Similarity to Ideal Solution (TOPSIS)	This hybrid method was used to assess the TIC of a printed circuit board firm	Unable to address uncertainties due to incompleteness and ignorance
Sumrit et al. [17]	Decision Making Trial and Evaluation Laboratory (DEMATEL) method	This method was employed to examine the significance of criteria and establish a causal connection among the criteria to evaluate the TICs of enterprises	No mechanism to address uncertainty

[16]. Here, a printed circuit board firm was assessed by using this hybrid method.

Decision Making Trial and Evaluation Laboratory (DEMATEL) method was employed in [17] to examine the significance of criteria and establish a causal connection among the criteria to evaluate technological innovation capabilities of enterprises.

Various issues of technological innovation capabilities for specific scenarios are addressed by these TIC evaluation methods. However, since linear regression and DEMATEL method have no mechanism to address uncertainty, they failed to address uncertainty in data. Fuzzy-based approaches can handle uncertainties due to imprecision, vagueness, and ambiguity, but they cannot address uncertainties due to incompleteness and ignorance, which can be observed with the associated criteria of technological innovation capability evaluation.

Therefore, a suitable knowledge representation schema and reasoning mechanism should be used for addressing different types of uncertainties existing with the criteria of technological innovation capability. So, an efficient way of evaluating TIC can be the utilization of Belief Rule Base (BRB).

However, some existing methods can also be found which are used previously for learning in BRBES. An optimization model for BRBES is first proposed in [18], where a nonlinear optimization solver, named *fmincon* in the *MATLAB* optimization toolbox is used to tune the parameters of BRBES. The same optimization model is also applied for pipeline leak detection by demonstrating the usefulness of incorporation of learning in the BRBES in [19]. A recursive algorithm to train BRBES online was developed in [20], [21]. These algorithms are effective to make BRBES working better. However, when training BRBES, the referential values of the antecedent attributes and the utilities of the consequent are not treated as the model's parameters, but they are predefined by the domain expert. Besides *fmincon* is a gradient-based method which is prone to get stuck in local optima and the convergence rate is slower for a large number of variable. Therefore evolutionary algorithms can be used which are efficient in achieving the optimal or near-optimal solution for problems with nonlinear and continuous search space [22], [23]. In this paper, a Belief Rule-Based Adaptive Particle Swarm Optimization (BRBAPSO) is utilized for learning in BRBES by considering rule weights, attribute weights, belief degrees, the referential values of the antecedent attributes and the utilities of the consequent as the model's parameters.

3 Belief Rule Based Expert System (BRBES) and Its Learning

A Belief Rule-Based Expert System (BRBES) consists of two main parts, namely a knowledge base and an inference engine. In BRBES, Belief Rule Base (BRB) is used to represent uncertain knowledge and create the initial knowledge base, whereas Evidential Reasoning (ER) works as an inference engine by handling both heterogeneous and uncertain data [24]. The knowledge representation and inference mechanisms as well as the optimal learning procedure are presented in this section.

3.1 Domain Knowledge Representation in BRBES

A Belief Rule Base (BRB) is an extended version of conventional IF-THEN rule base which can express more complicated non-linear causal connections under uncertainty. A belief rule comprises two main parts, namely antecedent and consequent. Each antecedent attribute is associated with referential values, while belief degrees are embedded with the referential values of the consequent attribute. BRB contains various learning or knowledge representation parameters, including attribute weight, rule weight, and belief degrees, which are used to capture uncertainty in data [25], [26]. A belief rule can be defined as follows:

$$R_k : \begin{cases} \text{IF } (A_1 \text{ is } V_1^k) \text{ AND / OR } (A_2 \text{ is } V_2^k) \text{ AND / OR ...AND / OR } (A_{T_k} \text{ is } V_{T_k}^k) \\ \text{THEN } C \text{ is } (C_1, \beta_{1k}), (C_2, \beta_{2k}), ..., (C_N, \beta_{Nk}) \end{cases}$$

$$\text{where } \beta_{jk} \geq 0,\ \sum_{j=1}^{N} \beta_{jk} \leq 1 \text{ with rule weight } \theta_k,$$

$$\text{and attribute weights } \delta_{k1}, \delta_{k2}, ..., \delta_{kT_k},\ k \in 1, ..., L$$

In the above rule, $A_1, A_2, ..., A_{T_k}$ are the antecedent attributes of the k^{th} rule. $V_i^k (i = 1, ..., T_k, k = 1, ..., L)$ is the referential value of the i^{th} antecedent attribute, while C_j is the j^{th} referential value of the consequent attribute. $\beta_{jk} (j = 1, ...N, k = 1, ...L)$ is the degree of belief to which the consequent reference value C_j is believed to be true. T_k is the total number of antecedent attributes used in the k^{th} rule. L is the number of total belief rules and N is the number of all possible referential values of the consequent. If $\sum_{j=1}^{N} \beta_{jk} = 1$, the k^{th} rule is said to be complete. If the summation of belief degrees is less than 1, the rule is considered as incomplete, which can happen because of ignorance or incompleteness. In traditional IF-THEN rule, antecedents and the consequent attribute has a linear relationship while the relationship is non-linear in case of belief rule. Besides, data collected from interviews or surveys are naturally non-linear [27]. As a consequence, belief rules can be used in order to represent the data efficiently.

The logical connectives of the antecedent attributes in a belief rule can be either AND or OR, which represents the conjunctive or the disjunctive assumptions of the rule, respectively. Based on the logical connectivity of the Belief Rule Base, a BRBES can be named as conjunctive or disjunctive BRBES.

Under the conjunctive assumption, the total number of rules, L is calculated using the referential values, J_i of the antecedent attributes, A_i of a BRB, as shown in Eq. (1).

$$L = \prod_{i=1}^{T_k} J_i \tag{1}$$

Under the disjunctive assumption, the total number of rules,L is equal to the number of referential values of the antecedent attributes, as shown in Eq. (2). The disjunctive assumption requires that all attributes have the same number of referential values [28].

$$L = J_1 = J_2 = ... = J_i \tag{2}$$

3.2 BRB Inference Procedures

Evidential Reasoning (ER) can handle heterogeneous data as well as different types of uncertainties such as incompleteness, ignorance, imprecision, and vagueness [29], [30]. The inference procedures using the ER approach contain different steps, namely input transformation, rule activation weight calculation, belief update, and rule aggregation, which is shown in Fig. 1.

During input transformation, the input data is distributed over the referential values of the antecedent attribute of a rule, as shown in Eq. (3) [31].

$$H(v_i) = (V_{i,j}, \alpha_{i,j}), j = 1, ..., J_i, i = 1, ..., T_k \tag{3}$$

Here, the function H transforms the input value of the antecedent attribute to the belief degrees of its referential values, where V_{ij} is the j^{th} referential value of the input, and α_{ij} is the belief degree to the referential value. These transformed values of the input data are known as matching degrees. The calculation is carried out using Eqs. (4), (5), and (6).

$$\alpha_{i,j} = \frac{V_{i,j+1} - v_i}{V_{i,j+1} - V_{i,j}},\ V_{i,j} \leq v_i \leq V_{i,j+1},\ j = 1, 2, ..., J_i - 1 \tag{4}$$

$$\alpha_{i,j+1} = 1 - \alpha_{i,j},\ V_{i,j} \leq v_i \leq V_{i,j+1},\ j = 1, 2, ..., J_i - 1 \tag{5}$$

$$\alpha_{i,k} = 0,\ k = 1, 2, ..., J_i,\ k \neq j, j+1 \tag{6}$$

After assigning the matching degree, the rules are called packet antecedent, and they become active.

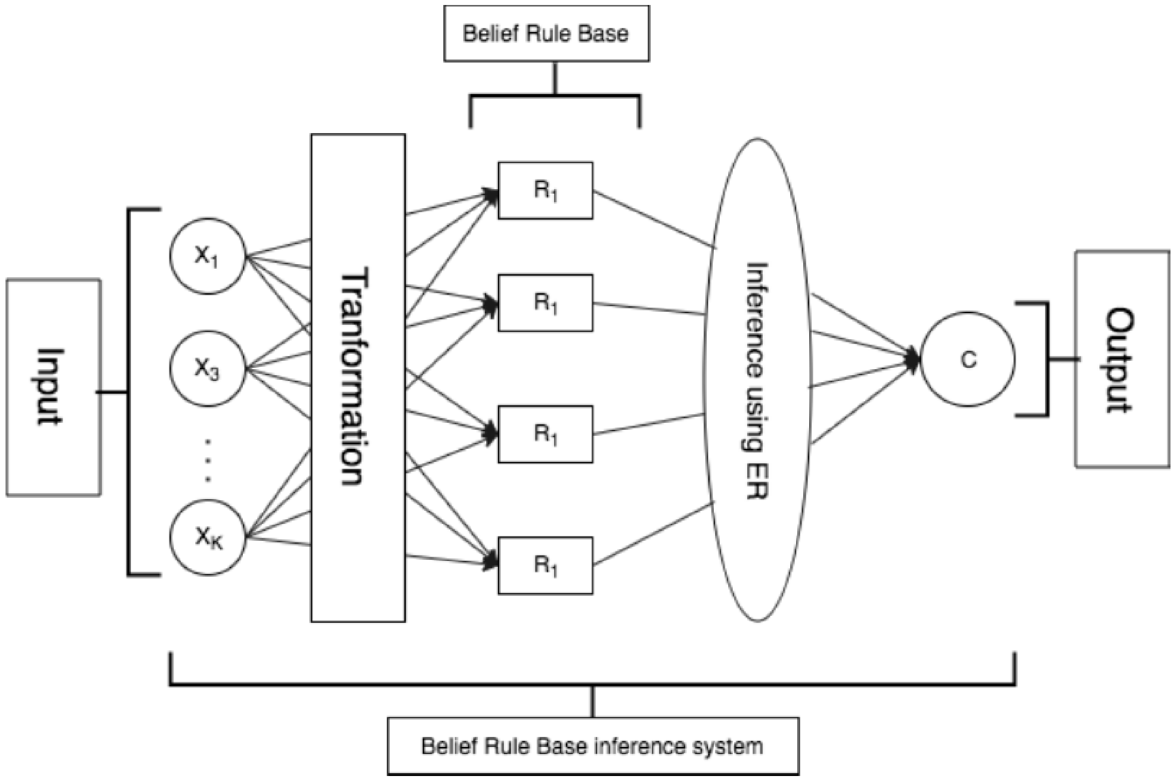


Figure 1: Sequence of BRBES Inference Procedures

In order to calculate rule activation weight, the first task is to combine the individual matching degrees of the antecedent attributes of a rule using a weighted multiplicative equation for conjunctive assumption, as shown in Eq. (7).

$$\alpha_{k_{conj}} = \prod_{i=1}^{T_k} (\alpha_i^k)^{\bar{\delta}_{ki}} \tag{7}$$

In case of disjunctive assumption, the individual matching degrees are combined using Eq. (8).

$$\alpha_{k_{disj}} = \sum_{i=1}^{T_k} (\alpha_i^k)^{\bar{\delta}_{ki}} \tag{8}$$

For both conjunctive and disjunctive assumption,

$$\bar{\delta}_{ki} = \frac{\delta_{ki}}{max_{i=1,\ldots T_k}\{\delta_{ki}\}},\ 0 \leq \bar{\delta}_{ki} \leq 1$$

Here, T_k is the total number of antecedent attributes in the k^{th} rule, δ_{ki} is the weight of each antecedent attribute V_i, and $\bar{\delta}_{ki}$ is the relative weight of V_i, which is calculated by dividing the weights of V_i by the maximum weight of all antecedent attributes.

Then, for conjunctive assumption, the combined matching degree of each rule calculated by Eq. (7) is utilized to determine the activation weight w_k for the k^{th} rule, as shown in Eq. (9) [32].

$$w_{k_{conj}} = \frac{\theta_k \alpha_{k_{conj}}}{\sum\limits_{i=1}^{L} (\theta_i \alpha_{i_{conj}})} \tag{9}$$

Similarly, for disjunctive assumption, the combined matching degree of each rule calculated by Eq. (8) is used to measure the activation weight w_k for the k^{th} rule, as shown in Eq. (10).

$$w_{k_{disj}} = \frac{\theta_k \alpha_{k_{disj}}}{\sum_{i=1}^{L} (\theta_i \alpha_{i_{disj}})} \tag{10}$$

Here, θ_k represents the rule weight, while α_k represents the combined matching degree of the k^{th} rule. The activation weight of a rule will be zero if that rule is not activated. After calculating the sum of the rule activation weight of a rule base, the result should be one [27].

In some cases, if there is an absence of data for any antecedent attributes of a rule base because of ignorance, then the initial belief degrees embedded with each rule in the rule base need to be updated to address the uncertainty due to ignorance, which is shown in Eq. (11).

$$\beta_{jk} = \bar{\beta}_{jk} \frac{\sum_{t=1}^{T_k} (\tau(t,k) \sum_{i=1}^{I_t} (\alpha_{ti}))}{\sum_{t=1}^{T_k} \tau(t,k)} \tag{11}$$

$$\text{where, } \tau(t,k) = \begin{cases} 1 & \text{if the } t^{th} \text{ attribute is used in defining rule } R_k (k = 1, ..., T_k) \\ 0 & \text{otherwise} \end{cases}$$

Here, $\bar{\beta}_{jk}$ is the original belief degree, while β_{jk} is the updated belief degree of the k^{th} rule. α_{ti} represents the degree to which the input value belongs to an attribute.

All the packet antecedents of the rules need to be aggregated to calculate the output for the input data of the antecedent attributes using the Evidential Reasoning (ER) algorithm. The aggregation of the rules can be done by using either analytical or recursive ER algorithms [33], [9]. However, the analytical approach is preferable instead of the recursive approach, since it is computationally more efficient [34]. The analytical ER computation can be performed using Eq. (12) [35].

$$\beta_j = \frac{\mu \times \left[\prod_{k=1}^{L} (w_k \beta_{jk} + 1 - w_k \sum_{j=1}^{N} \beta_{jk}) - \prod_{k=1}^{L} (1 - w_k \sum_{j=1}^{N} \beta_{jk}) \right]}{1 - \mu \times \left[\prod_{k=1}^{L} (1 - w_k) \right]} \tag{12}$$

$$\text{where, } \mu = \left[\sum_{j=1}^{N} \prod_{k=1}^{L} (w_k \beta_{jk} + 1 - w_k \sum_{j=1}^{N} \beta_{jk}) - (N-1) \times \prod_{k=1}^{L} (1 - w_k \sum_{j=1}^{N} \beta_{jk}) \right]^{-1}$$

Here, w_k represents the activation weight of the k^{th} rule, whereas β_j is the belief degree associated with one of the consequent reference values.

The uncertainty due to vagueness, imprecision, and ambiguity are addressed by Eq. (12) during the process of rule aggregation [35]. Now the calculated output value against the input data will be in a fuzzy form. So this fuzzy value can be converted into a crisp or numerical value by using the utility score associated with each referential value of the consequent attribute to obtain the final result, which is shown in Eq. (13).

$$z_i = \sum_{j=1}^{N} \mu(O_j) \beta_j \tag{13}$$

Here, z_i is the expected numerical value, while $\mu(O_j)$ is the utility score of each referential value.

3.3 Optimal Learning Procedure to Train the BRBES

The objective of optimal learning procedure is to train knowledge representation parameters to reduce errors so that the problem domain can be assessed more reliably. The optimal values of various learning parameters can be found by the optimal learning model. Rule weights, attribute weights, and belief degrees $(\theta_k, \delta_i, \beta_{jk})$ in the rule of a belief rule base and the referential values of the antecedent attributes, and the utilities of the consequent attributes $(A_{i,j}, \mu(O_j))$ are considered as learning parameters, which are assigned by experts in the domain or by generating random numbers [12]. These parameters have a significant influence on the outcome of a multi-level hierarchical BRBES with a large number of rules for achieving a better result [24]. Attribute weights and rule weights determine the importance of the corresponding antecedent attributes and rules, whereas the uncertainty of the output is represented by the belief degrees of the consequent attribute. The corresponding position of the belief rules in the input variable domain is determined by referential values of the antecedent attributes, and the value of the final output is determined by the utilities of the consequent attributes. Hence, the learning parameters are crucial for the BRB inference mechanism. However, these parameters may not be optimal or 100% correct. Therefore, the aim of optimal learning in BRBES is to obtain the optimal set of learning parameters $(\theta_k, \delta_i, \beta_{jk}, A_{i,j}, \mu(O_j))$ that will reduce the discrepancy or error $\zeta(P)$ between the output from BRBES, which is known as simulated output (z_m), and the output from the real system, known as observed output $(\bar{z}_m)$ as shown in Fig. 2.

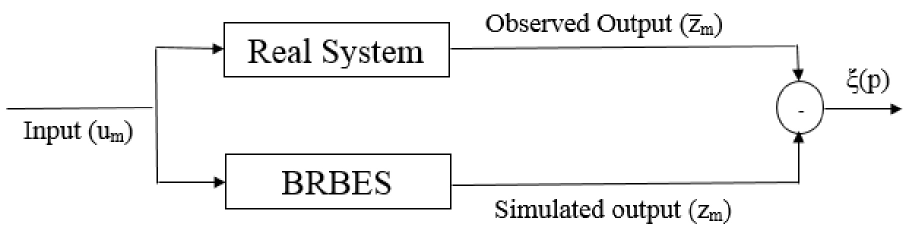


Figure 2: Optimal Learning Process of the BRB

It is presumed that there are M cases in a training sample, where input is u_m, observed output is $\bar{z}_m$, and simulated output is z_m $(m = 1, ..., M)$. The error, $\zeta(P)$ is calculated using Eq. (14).

$$\zeta(P) = \frac{1}{M} \sum_{m=1}^{M} (z_m - \bar{z}_m)^2 \tag{14}$$

To minimize the error $\zeta(P)$, the optimization of the values of the learning parameters is performed as defined in Eq. (15).

$$\min_{P} \zeta(P) \tag{15}$$

$$P = P(\theta_k, \delta_i, \beta_{jk}, A_{i,j}, \mu(O_j))$$

The optimal learning model to train the BRBES consists of three steps, namely construction of the objective function, setting constraints for the learning parameters, and optimizing the learning parameters $(\theta_k, \delta_i, \beta_{jk}, A_{i,j}, \mu(O_j))$ based on the training dataset. Eqs. (12), and (13) are used to construct the objective function for training the BRBES. Then, the constraints are set for rule weights, attribute weights, belief degrees, referential values of the antecedent attributes and utilities of the consequent attributes. The following constraints are considered for each of the learning parameters:

- Rule weights, θ_k $(k = 1, .., L)$: $0 \leq \theta_k \leq 1$;

- Antecedent attribute weights, δ_k $(k = 1,..,L)$: $0 \leq \delta_k \leq 1$;
- Consequent belief degrees for the k^{th} rule, β_{jk} $(j = 1,...,N, k = 1,...,L)$:
  $0 \leq \beta_{jk} \leq 1$;
  $\sum_{j=1}^{N} \beta_{jk} = 1$;
- Referential values of antecedent attributes, $A_{i,j}$ $(i = 1,...,T_k, j = 2,3,..,J_i - 1)$:
  $lb_i < A_{i,j} < ub_i$;
  $A_{i,1} = lb_i$;
  $A_{i,J_i} = ub_i$;
- Utilities of the consequent attributes, $\mu(O_j)$ $(j = 2,..,N-1)$:
  $l < \mu(O_j) < u$;
  $\mu(O_1) = l$;
  $\mu(O_N) = u$;

Here, lb_i and ub_i are the lower bound and the upper bound of $A_{i,j}$, while l and u are the lower bound and the upper bound of $\mu(O_j)$ respectively. Finally, the optimal values of the learning parameters are obtained by using the optimization model of BRBES based on the training dataset.

4 Belief Rule Based Adaptive Particle Swarm Optimization (BRBAPSO)

In this section, a brief description of BRBAPSO and the repair technique for handling constraint of belief degrees are discussed.

4.1 BRBAPSO

Particle Swarm Optimization (PSO) is a stochastic and population-based meta-heuristic algorithm. In PSO, a population or swarm contains a set of individuals, where each individual represents a possible solution to the problem, referred to as a particle. Three indicators, namely the position, the velocity, and the fitness value, characterize each particle. A number of particles are appointed by PSO, which move around in the search space to find the best solution. The velocity and the position is updated by using Eqs. (16) and (17).

$$v_{id} = w * v_{id} + c_1 * rand_1() * (p_{id} - x_{id}) + c_2 * rand_2() * (p_{gd} - x_{id}) \quad (16)$$

$$x_{id} = x_{id} + v_{id} \quad (17)$$

In the above equations, v_{id} and x_{id} are the velocity and the position of the d^{th} dimension of the particle $i(i = 1,2,...,SwarmSize)$. w is the inertia weight, c_1 is the cognitive factor, and c_2 is the social factor. $rand_1()$ and $rand_2()$ are two random numbers in the range $[0,1]$. $p_i = (p_{i1}, p_{i2},..., p_{id})$ is the optimal position of the i^{th} particle, and $p_g = (p_{g1}, p_{g2},..., p_{gd})$ is the global optimal position of all particles.

The velocity is restricted in the range of the velocity boundary $[V_{min},V_{max}]$ and the position is also restricted in the range of the search space $[X_{min},X_{max}]$ as shown in Eqs. (18), (19):

$$v_{id} = \begin{cases} V_{max}, & \text{if } v_{id} > V_{max} \\ V_{min}, & \text{if } v_{id} < V_{min} \end{cases} \quad (18)$$

$$x_{id} = \begin{cases} X_{max}, & \text{if } x_{id} > X_{max} \\ X_{min}, & \text{if } x_{id} < X_{min} \end{cases} \tag{19}$$

The three parameters, namely inertia weight (w), cognitive factor (c_1), and social factor(c_2) have a great impact on the performance of PSO. These parameters can be adapted dynamically to improve the performance of PSO. It is suggested that changing the values of w, c_1, and c_2 dynamically during each iteration of PSO can produce better results. Therefore, a BRBES based PSO parameter adaptation algorithm is proposed, named Belief Rule-Based Adaptive Particle Swarm Optimization (BRBAPSO), which can change the value of these parameters dynamically during each iteration of the algorithm.

In BRBAPSO, the values of w, c_1, and c_2 are initially taken as 1, 2.5, and 1.5 respectively. Then after the first iteration, normalized diversity of swarm and normalized diversity of velocity are supplied as inputs to BRBES. Afterward, based on the Belief Rule Base and using Evidential Reasoning approach, new values of w, c_1, and c_2 are produced by BRBES as outputs after the first iteration. This process continues until the current iteration number reaches the predetermined maximum iteration number.

First, the diversity of swarm is calculated as the average of the Euclidean measure of distance between each particle and the j^{th} dimension over all particles, as shown in Eq. (20).

$$\text{DiversitySwarm, } d_s = \frac{1}{N_s} \sum_{i=1}^{N_s} \sqrt{\sum_{j=1}^{N_x} (x_{ij}(t) - \bar{x}_j(t))^2} \tag{20}$$

$$\text{where, } \bar{x}_j(t) = \frac{\sum_{i=1}^{N_s} x_{ij}(t)}{N_s}$$

Then the diversity of velocity is calculated as the average of the Euclidean measure of velocity between each particle and the j^{th} dimension over all particles, as shown in Eq. (21).

$$\text{DiversityVelocity, } d_v = \frac{1}{N_s} \sum_{i=1}^{N_s} \sqrt{\sum_{j=1}^{N_x} (v_{ij}(t) - \bar{v}_j(t))^2} \tag{21}$$

$$\text{where, } \bar{v}_j(t) = \frac{\sum_{i=1}^{N_s} v_{ij}(t)}{N_s}$$

Afterward, the diversity of swarm and the diversity of velocity is normalized in the range $[0,1]$, as shown in Eqs. (22) and (23).

$$\text{Normalized Diversity of Swarm, } nd_s = \begin{cases} 0, & \text{if Min DiverSwarm = Max DiverSwarm} \\ \frac{\text{DiversitySwarm} - \text{Min DiverSwarm}}{\text{Max DiverSwarm} - \text{Min DiverSwarm}}, & \text{if Min DiverSwarm} \neq \text{Max DiverSwarm} \end{cases} \tag{22}$$

$$\text{Normalized Diversity of Velocity, } nd_v = \begin{cases} 0, & \text{if Min DiverVel = Max DiverVel} \\ \frac{\text{DiversityVelocity} - \text{Min DiverVel}}{\text{Max DiverVel} - \text{Min DiverVel}}, & \text{if Min DiverVel} \neq \text{Max DiverVel} \end{cases} \tag{23}$$

Here, Min DiverSwarm and Max DiverSwarm are the minimum and maximum diversity of swarm, while Min DiverVel and Max DiverVel are the minimum and maximum diversity of velocity respectively.

Table 2 shows the referential values and utility values of both antecedent attributes and consequent attributes, which are used in BRBES for BRBAPSO, while the Belief Rule Base used by BRBES is shown in Table 3.

Table 2: Details of BRBES for BRBAPSO

(a) Antecedent Attributes

	Antecedent Attributes					
	nd_s			nd_v		
Referential Values	High	Medium	Low	High	Medium	Low
Utility Values	1.00	0.50	0.01	1.00	0.50	0.01

(b) Consequent Attributes

	Consequent Attributes								
	w			c_1			c_2		
Referential Values	High	Medium	Low	High	Medium	Low	High	Medium	Low
Utility Values	1.0	0.7	0.4	2.5	2.0	1.5	1.5	2.0	2.5

Table 3: Belief Rule Base for BRBAPSO

Rule ID	Rule Weight	IF		THEN ($w/c_1/c_2$)		
		nd_s	nd_v	High	Medium	Low
1	1	High	High	1	0	0
1	1	High	Medium	0.5	0.5	0
1	1	High	Low	0	1	0
1	1	Medium	High	0.5	0.5	0
1	1	Medium	Medium	0	1	0
1	1	Medium	Low	0	0.5	0.5
1	1	Low	High	0	1	0
1	1	Low	Medium	0	0.5	0.5
1	1	Low	Low	0	0	1

4.2 Repair Technique for Handling Constraint of Belief Degrees

In order to deal with the constraint of belief degrees, repair technologies have been used inspired by [36], [37]. For belief degrees, they can satisfy constraints as shown in Eq. (24).

$$\beta^k = \left[\beta_{1,k}, \beta_{2,k}, \ldots, \beta_{N,k}\right] \Big/ \sum_{j=1}^{N} \beta_{j,k} \tag{24}$$

According to the above discussion, the procedure of BRBAPSO is summarized as follows:

Step 1: Generate the initial population randomly according to the characteristics of parameters in the vector P on the basis of the constraints and initialize the initial velocity for each particle as zero.

Step 2: Evaluate the objective function for each particle and set them as their own local optimal solution.

Step 3: The particle that has the minimum value for objective function is selected as the global solution.

Step 4: Initialize the values of w, c_1, and c_2 as 1.0, 2.5, and 1.5 respectively.

Step 5: If current iteration number is greater than one:

(a) Calculate normalized diversity of swarm and normalized diversity of velocity based on Eqs. (22) and (23).

(b) Calculate the parameters using BRBAPSO.

Step 6: Update the velocity based on the parameters by Eq. (16) and the position of all particles by Eq. (17), check the velocity limit using Eq. (18), handle constraint of belief degrees by Eqs. (24) and check the position limit using Eq. (19).

Step 7: Evaluate the objective function for each particle and check whether the value of the particle for the objective function is better than it's own local optimal solution. If so, update local optimal solution.

Step 8: Again, the particle that has the minimum value for objective function is selected as the global solution

Step 9: Check whether the current iteration number reaches the predetermined maximum iteration number. If satisfied, the iteration of BRBAPSO is stopped, otherwise go to step 5.

5 BRBES to Evaluate Technological Innovation Capability

This section describes the architecture of the web-based conjunctive and disjunctive BRBES for evaluating technological innovation capability.

5.1 Architecture of Web-Based BRBES

The web-based BRBES follows a three-layer architecture model which are data management layer, application layer, and interface layer. The architecture of the web-based BRBES is represented in Fig. 3.

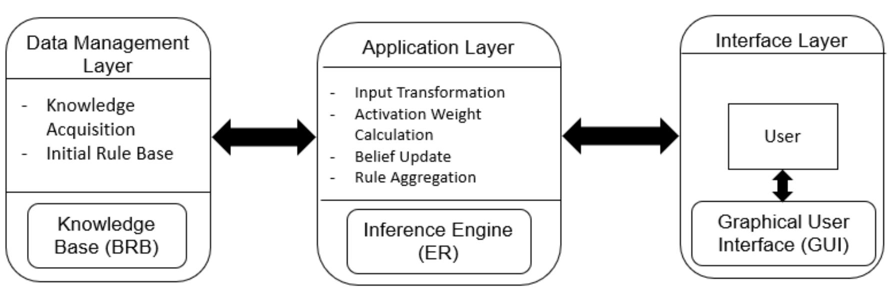


Figure 3: Architecture of the Web-Based Belief Rule-Based Expert System

5.1.1 Data Management Layer

Data management layer is accountable to create the initial rule base using the data. The initial BRB is the knowledge base of the system which is created in the data management layer. A BRB framework is created manually to construct the knowledge base by taking the criteria associated with technological innovation capability evaluation, which is shown in Fig. 4. Five aspects and their associated criteria have been considered for TIC evaluation in this framework. These aspects and criteria are defined in [4].

(a)

Meaning of the syntaxes applied in BRB

X1 = Percentage of researchers
X2 = Success rate of R&D products
X3 = Self-generated innovative products
X4 = Number of patents
X5 = R&D intensity
X6 = Innovativeness of R&D ideas
X7 = Intensity of collaboration with other firms or R&D centers
X8 = R&D knowledge sharing ability
X9 = Forecasting and evaluation of technological innovation
X10 = Entrepreneurial innovation initiatives
X11 = Market share
X12 = Intensity of new product competitiveness
X13 = Monitoring the market situation
X14 = Specialized marketing unit
X15 = Export percentage
X16 = Advanced manufacturing technology
X17 = Product quality level
X18 = Commercialization success rate
X19 = Production staff quality level
X20 = Production cycle time
X21 = Fund raising ability
X22 = Optimal capital allocation
X23 = Intensity of capital input
X24 = Return on investment
X25 = R&D capabilities
X26 = Innovation decision capabilities
X27 = Marketing capabilities
X28 = Manufacturing capabilities
X29 = Capital capabilities
X30 = Overall performance

(b)

Figure 4: BRB Framework to Evaluate Technological Innovation Capability

5.1.2 Application Layer

Application layer contains inference engine with procedures such as input transformation, rule activation weight calculation, belief update, and rule aggregation. The input of the application layer is the initial

BRB from the data management layer, and it runs the inference procedure on it. The BRB tree is multi-level, so a tree traversal algorithm is used [11] which can traverse the whole BRB tree from bottom to top and generate the result of the top node by calculating the subtrees gradually.

5.1.3 Interface Layer

The interface layer is used to display the system output in a human-readable way that can be accessed by the users via a web interface. A graphical user interface (GUI) has been built for the BRBES, which facilitates the interaction between the user and the system by giving a visual platform. The GUI of BRBES for technological innovation capability evaluation is shown in Fig. 5.

In Fig. 5, the GUI shows the data for the antecedent attributes (leaf nodes) of the BRB framework as well as the evaluation result of the top node $x30$ (Overall performance) and the result for the sub-rule base $x25$ (R&D capabilities), $x26$ (Innovation decision capabilities), $x27$ (Marketing capabilities), $x28$ (Manufacturing capabilities), and $x29$ (Capital capabilities). There are two parts of the result for each node, which are consequence values and crisp value.

6 Results and Discussion

In order to increase accuracy and decrease error for technological innovation capability evaluation, data are collected from multi-source databases. It is arduous to collect all the quantitative data from each high-tech firm because standard financial statistics of many high-tech firms do not exist, and the data is treated confidentially. Hence, each high-tech firm's annual operation report from different sources are used to collect the quantitative data. Different surveys are conducted to collect the qualitative data where the senior manager of each high-tech firm was asked to evaluate the current technological innovation performance level. Based on these sources, 100 firms data are collected. The data are considered as good enough, as sample sizes in between 30 and 500 data points are considered appropriate for most research [38]. Based on the data, technological innovation capability of each high tech firm is evaluated using both conjunctive and disjunctive BRBES. Then a comparison has been performed between conjunctive and disjunctive BRBES to determine the reliability in evaluating technological innovation capability.

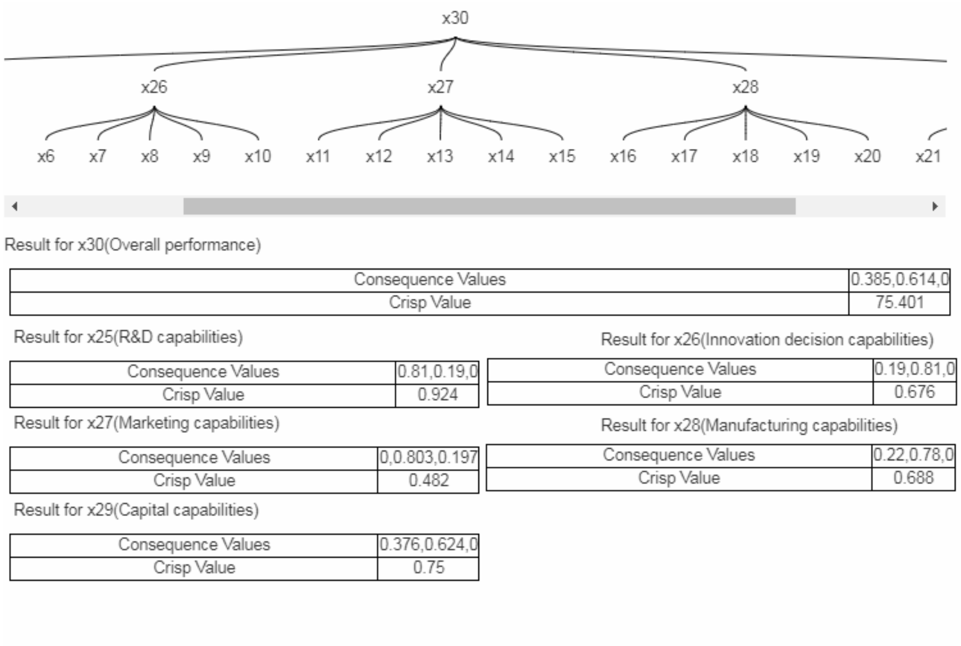
The reliability of one technique over other techniques can be acquired by evaluating, comparing, and assessing the accuracy of their results. Receiver Operating Characteristic (ROC) curves give a comprehensive and visible representation of evaluation, comparison, and assessment of various techniques [39]. Hence, it is broadly used in numerous domains, namely clinical applications, atmospheric science, and many others [40]. Therefore, ROC curves have been considered in this research to assess the accuracy and the reliability of the conjunctive BRBES in comparison to the disjunctive BRBES. The accuracy of a result is measured by utilizing the Area Under Curve (AUC) of ROC.

Fig. 6 shows ROC curves for conjunctive BRBES and disjunctive BRBES, while Table 4 shows the AUC and the confidence interval (CI) for these two BRBES.

Table 4: Comparison of AUC of Conjunctive BRBES and Disjunctive BRBES

Test Result Variable(s)	AUC	Std. Error	Asymptotic Sig.	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Conjunctive BRBES	0.955	0.021	0.000	0.913	0.996
Disjunctive BRBES	0.894	0.038	0.000	0.819	0.969

From Table 4, it can be noticed that the highest value of AUC is for conjunctive BRBES because when evaluating technological innovation capability, antecedent attributes co-influence the results in a



(a)

Antecedent Name	Node Name	Input
Percentage of researchers	x1	0.084
Entrepreneurial innovation initiatives	x10	1.0
Market share	x11	0.188
Intensity of new product competitiveness	x12	0.66
Monitoring the market situation	x13	0.33
Specialized marketing unit	x14	0.66
Export percentage	x15	0.674
Advanced manufacturing technology	x16	0.66
Product quality level	x17	1.0
Commercialization success rate	x18	0.565
Production staff quality level	x19	1.0
Success rate of R&D products	x2	0.365
Production cycle time	x20	11.0
Fund raising ability	x21	1.0
Optimal capital allocation	x22	0.66
Intensity of capital input	x23	0.66
Return on investment	x24	0.336
Self-generated innovative products	x3	9.0
Number of patents	x4	327.0
R&D intensity	x5	766.446
Innovativeness of R&D ideas	x6	0.66
Intensity of collaboration with other firms or R&D centers	x7	0.33
R&D knowledge sharing ability	x8	0.66
Forecasting and evaluation of technological innovation	x9	1.0

(b)

Figure 5: GUI of BRBES for Technological Innovation Capability Evaluation

conjunctive fashion. However, this is not the case with disjunctive BRBES as it considers the antecedent attributes separately, and they co-influence the results in a disjunctive fashion. That's why the AUC for conjunctive BRBES is greater than disjunctive BRBES. Besides, the range of confidence interval is

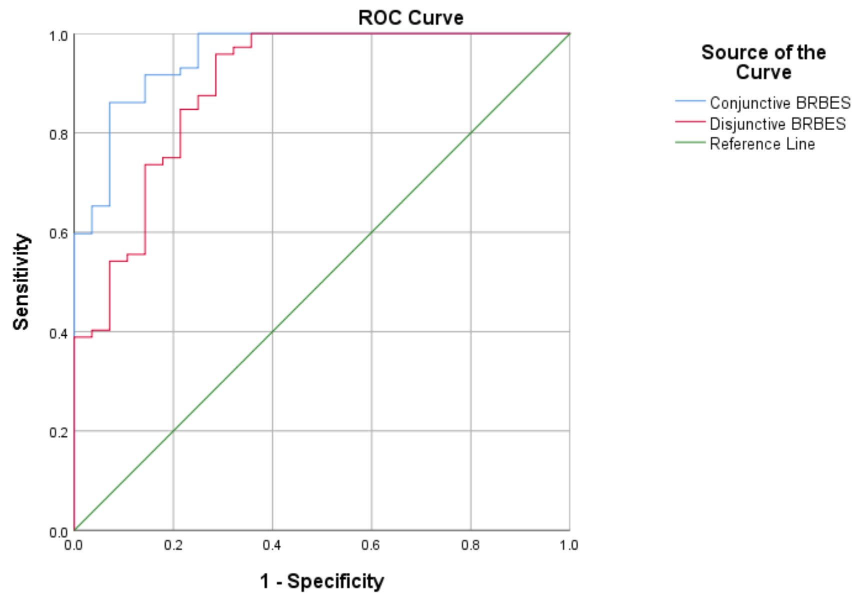


Figure 6: Comparison of Results of Conjunctive BRBES and Disjunctive BRBES Using ROC Curves

highest, and the standard error is lowest for conjunctive BRBES than disjunctive BRBES. Therefore, it can be said that conjunctive BRBES is performing better than disjunctive BRBES when evaluating technological innovation capability.

Now, to facilitate the learning for both conjunctive and disjunctive BRBES, the collected data have been separated into training data and test data. The training data is employed to train both conjunctive and disjunctive BRBES using BRBAPSO, while the test data is used to evaluate the performance of the trained conjunctive BRBES and the trained disjunctive BRBES.

Fig. 7 shows ROC curves for the trained conjunctive BRBES and the trained disjunctive BRBES, while Table 5 shows the AUC and the confidence interval (CI) for these two trained BRBES.

Table 5: Comparison of AUC of Trained Conjunctive BRBES and Trained Disjunctive BRBES

Test Result Variable(s)	AUC	Std. Error	Asymptotic Sig.	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Trained Conjunctive BRBES	0.938	0.043	0.001	0.853	1.000
Trained Disjunctive BRBES	0.894	0.084	0.002	0.731	1.000

From Table 5, it can be seen that the highest value of AUC is for trained conjunctive BRBES because of its better determination of the learning parameters based on BRBAPSO optimization. However, for trained disjunctive BRBES, the best optimal values of the learning parameters can not be determined based on BRBAPSO optimization. That's why the AUC for trained conjunctive BRBES is greater than trained disjunctive BRBES. Besides, the range of confidence interval is highest, and the standard error is lowest for trained conjunctive BRBES than trained disjunctive BRBES. Therefore, it can be said that trained conjunctive BRBES is performing better than trained disjunctive BRBES for TIC evaluation.

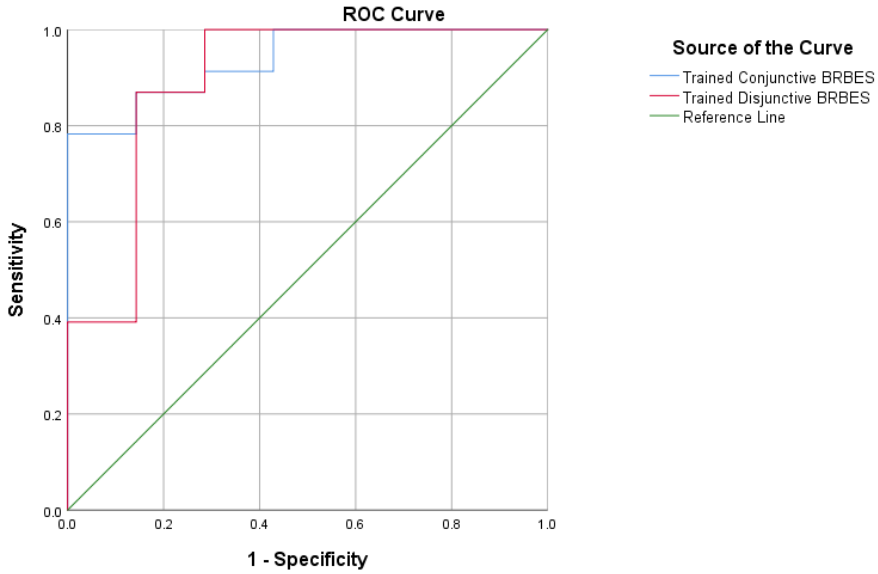


Figure 7: Comparison of Results of Trained Conjunctive BRBES and Trained Disjunctive BRBES Using ROC Curves

7 Conclusion

In this paper, two web-based BRBES, namely conjunctive BRBES, and disjunctive BRBES, have been presented for evaluating technological innovation capability. These two expert systems will facilitate a firm manager to evaluate and determine his firm's innovation capabilities, which will have a great impact to improve a firm's performance by reducing overall uncertainty associated with technological innovation. In addition, a comparison has been conducted to determine how conjunctive BRBES is performing better compared to disjunctive BRBES. Moreover, a Belief Rule-Based Adaptive Particle Swarm Optimization (BRBAPSO) is used for learning in both conjunctive and disjunctive BRBES, where trained conjunctive BRBES performs better than trained disjunctive BRBES.

However, since the dataset used in this research is not quite large, more data from other firms can be considered if accessible and more pertinent criteria can also be examined for evaluating technological innovation capability.

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