Modelling of Green Human Resource Management using Pythagorean Neutrosophic Bonferroni Mean Approach

Alsadig Ahmed[1], Mamoun Badawy[1,*], Gubarah Farah Gubarah[2]

[1] Applied Management Program, Applied College at Muhyle, King Khalid University, Kingdom of Saudi Arabia
[2]Applied Management Program, Applied College at Tanumah, King Khalid University, Kingdom of Saudi Arabia
Emails: mamoustafa@kku.edu.sa; mybabkr@kku.edu.sa; gmohamed@kku.edu.sa

Abstract

Green Human Resource Management (GHRM) state a determination of the association using crossing points of employees to stimulate environment performance activity, increase the employee awareness and sustainable activities, consequently, increasing the employee awareness towards environmental challenges. The hotel industry is developing quickly in emerging nations owing to an upsurge in the tourism business; but, conversely, the hotel industry is mainly growing the problem of the environment. As a result, owing to the enormous amount of conservation problems that hotel business has faced, there is a growing potency to pay an accurate response to environmental problems and performing sustainable industry performance like the adoption of GHRM practice provides a win-win situation for its stakeholders and the organization. Accordingly, it indicates the requirement to scrutinize how GHRM performs will augment the environment in the hotel business. This manuscript models the design of GHRM using Pythagorean Neutrosophic Bonferroni Mean (GHRM-PNBM) approach. The presented GHRM-PNBM method objectives are to evaluate the limitation of hotel GRHM. Moreover, the presented technique constructs an expert system analysis technique for assessing the performance of hotel GHRM. Adaptive optimization of hotel GHRM assessment can be done using the PNBM technique, and the parameter selection method can be done using Quasi-Oppositional-Teaching-Learning-Based Optimization (QTLBO) method. The empirical analysis reports that the performance calculation of hotel GHRM has good confidence level and high accuracy

Keywords: Human Resource Management; Teaching-Learning-Based Optimization; Pythagorean Neutrosophic Bonferroni Mean; Artificial Intelligence; Fitness Function

1. Introduction

The objective of artificial intelligence (AI) in assembly Industry 4.0 standard is to transform traditional companies into advanced manufacturing technologies which boost efficacy by decreasing the essential for human labourers and generating enhanced usage of their abilities [1]. However, there are interior and exterior tasks that emerging economy corporate companies face. Where companies should familiarize themselves with the desires of Industry 4.0 by converting smart factories, also they should maintain with the developing difficulties of users and the atmosphere [2]. Green human resource management (GHRM) is highly significant as companies struggle to decrease their conservational effect, upsurge efficacy, and approve cleaner manufacturing models [3]. AI is being trusted by companies to fulfil their purposes and satisfy interior and exterior stakeholders. AI aids businesses with innovative digital tools, cloud computing (CC) data storage for generating decision, and intellectual analytical software [4]. In this research paper, we will get to understand how AI may aid GHRM enterprises. Gathering data, classifying and assessing it for usage in the services and business fields [5]. One type of AI is natural language processing (NLP) which permits individuals to interconnect with computers to finish tasks; instances contain the virtual assistant Alexa (Amazon Echo) and call centre agents.

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With gradually intense competition and ever-changing environmental situations, a hotel's capability to modify way and re-configure tactically is dangerous to its achievement in attaining performance of environmental [6]. In other words, we suggest that hotels want to hold GHRM practices [7]. Current experimental evidence supports the conflict that GHRM practices drive secure performance. It is so not amazing that GHRM practices are acquiring increasing significance in the academic and practitioner literature of management [8]. The HR function plays a very significant part in determining which conservation practices must be used in each feature of business and applied in every phase of an organization which is a constant procedure [9]. It is assumed that GHRM practices are the best tactic for environmental performance programmes and provide a central structure which permits organizations to well rule the organization's environmental impacts [10]. So, it is significant to classify the GHRM practices that quicken the influence on the performance of environment in the hotel business.

Bhuiyan et al. [11] used a quantitative method to gather information from users who used AI-aided technology in the hospital area. Data were gathered utilizing a purposive sampling model. The SmartPLS 4.0 software has been utilized to define the theories' interior constancy, validity and reliability. This research work used the partial least squares structural equation modelling (PLS-SEM) to examine the method and theories. Odugbesan et al. [12] offer evidences that green soft and hard TM have major effect on workers' innovative work performance. Likewise, transformational management and AI were established to have a major effect on workers' state-of-the-art work behavior. Siradhana and Arora [13] used the Technology–Organization–Environment (TOE) technique and integrated the trust factor to recommend an approach for examining AI acceptance in HRM. An organized questionnaire was used to survey ITeS businesses. Data analysis was executed by employing incomplete smallest squares structural calculation modelling.

Aydın and Turan [14] concentrate on the adoption of AI for employment and shortlisting as a HRM process. It is proposed to eliminate noisy data by utilizing a least depiction length method and to generate a learning technique dependent upon the SVM to select the better candidates as per the business culture and preferences. Aggarwal and Mittal [15] presented an autonomous and agile smart hotel method, DASH-Decentralized Autonomous and Smart Hotel model, functioning on a pay-per-use technique. The projected model is an incorporation of IoT, Robots, AI, and BC. This research paper used concept modeling to generate a strong structure for the DASH model, tactically incorporating autonomy, intelligence and decentralization. This model links unrealistic standards with real-world execution, modelling the prospect of hospitality over innovative technology integration. Chowdhury et al. [16] main intention is to establish the ability of Local Interpretable Model-Agnostic Explanations (LIME) model to mechanically clarify the ET forecasts produced by AI-based ML techniques for an expected employee database. From a theoretic viewpoint, the method gives to the International HRM survey by giving a theoretical analysis of AI algorithm and then deliberating its importance to endure competitive benefit by employing the values of resource-based view model.

This manuscript models the design of GHRM using Pythagorean Neutrosophic Bonferroni Mean (GHRM-PNBM) approach. The presented GHRM-PNBM method objectives are to evaluate the limitation of hotel GHRM. Moreover, the presented technique constructs an expert system analysis technique for assessing the performance of hotel green human resources. Adaptive optimization of hotel GHRM assessment can be done using the PNBM technique and the parameter selection method can be done using the Quasi-Oppositional-Teaching-Learning-Based Optimization (QTLBO) method. The empirical analysis reports that the performance calculation of hotel GHRM has good confidence level and high accuracy.

2. Proposed Methodology

In this manuscript, we focus on design and development of GHRM-PNBM approach. The presented GHRM-PNBM method objectives are to evaluate the limitation parameters of hotel GHRM. Moreover, the presented technique constructs an expert system analysis technique for assessing the performance of GHRM. Fig. 1 depicts the entire flow of GHRM-PNBM methodology.

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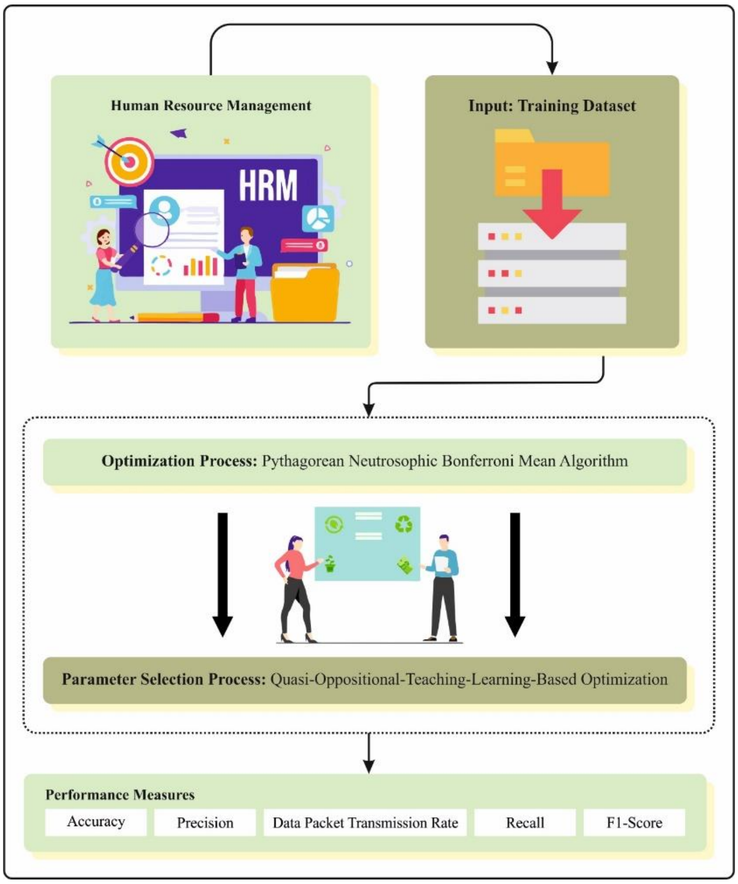

Figure 1: Overall flow of GHRM-PNBM methodology

A. Design of PNBM Model

The basic concept associated with the Pythagorean Neutrosophic set (PNS) is discussed in this section [17].

Consider X as a universe or non-empty set. The PNS with ψ and κ as reliant membership

$$A = \{\langle x, \psi_A(x), \varsigma_A(x), \kappa_A(x)\rangle | x \in X\} \tag{1}$$

In Eq. (1), ψ_A, ς_A and κ_A are the truth, indeterminacy and false memberships correspondingly.

$$0 \leq \psi^2 + \kappa^2 \leq 1 \tag{2}$$

$$0 \leq \psi^2 + \varsigma^2 + \kappa^2 \leq 2 \tag{3}$$

Consider $x_1 = (\psi_{x_1}, \varsigma_{x_1}, \kappa_{x_1})$, $x_2 = (\psi_{x_2}, \varsigma_{x_2}, \kappa_{x_2})$ and $x = (\psi_x, \varsigma_x, \kappa_x)$ are PNSs, then the operational rules are given below:

$$x_1 \oplus x_2 = \left(\sqrt{\psi_{x_1}^2 + \psi_{x_2}^2 - \psi_{x_1}^2 \psi_{x_2}^2}, \varsigma_{x_1}\varsigma_{x_2}\kappa_{x_1}\kappa_{x_2}\right) \tag{4}$$

$$x_1 \otimes x_2 = \left(\psi_{x_1}\psi_{x_2}, \varsigma_{x_1} + \varsigma_{x_2} - \varsigma_{x_1}\varsigma_{x_2}\sqrt{\kappa_{x_1}^2 + \kappa_{x_2}^2 - \kappa_{x_1}^2 \kappa_{x_2}^2}\right) \tag{5}$$

$$\mu x = \left(\sqrt{1-(1-\psi_x^2)^\mu}, \sigma_x^\mu, \kappa_x^\mu\right) where\ \mu \in \Re\ and\ \mu \geq 0 \tag{6}$$

$$x^\mu = \left(\psi_x^\mu, 1-(1-\varsigma_x)^\mu, \sqrt{1-(1-\kappa_x^2)^\mu}\right)\ where\ \mu \in \Re\ and\ \mu \geq 0. \tag{7}$$

Assume $p, q \geq 0$ with $x_i = (\psi_i(x), \varsigma_i(x), \kappa_i(x))$ where $(i = 1,2,3, \dots, n)$ is a PNS, then PNBM is given below

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$$PNBM\ (x_1, x_2, \dots, x_n)^{p,q} = \left(\frac{1}{n(n-1)} \bigoplus_{\substack{i,j=1 \\ i \neq j}}^{n} (x_i^p \otimes x_j^p) \right)^{\frac{1}{p+q}} \tag{8}$$

Step 1: Create the Direct-Relation Matrix, X^k

The matrix was made by PNS to characterize the direct relationship based on the preferences of making decisions and assesses the preference as a non-negative matrix, $X^k = [x_{ij}^k]_{n\times n}$, where $1 \leq k \leq m$. The notation of $x_{ij} = (\psi_{ij}, \varsigma_{ij}, \kappa_{ij})$ specifies the extent the decision maker feels that conditions i influence conditions j, with diagonal component being 0. The mark is measured by 7 semantic measures ranging from 'no effect' to 'high effect' according to the linguistic variable of PNS. Therefore, there are m distinct matrix $X = \{X^1, X^2, \dots, X^m\}$ corresponding to all the DMs.

Step 2: Obtain the Aggregate Direct-Relation Matrix A.

Based on Eq. (8), PN-NWBM combines the direct relationship matrix $X^k = \{X^1, X^2, \dots \dots, X^m\}$ into a combined decision matrix $A = [a_{ij}]_{n\times n}$, where $a_{ij} = (\psi_{ij}, \varsigma_{ij}, \kappa_{ij})$.

Step 3: Deneutrosophication into crisp matrix B.

The aggregated matrix $A = [a_{ij}]_{m\times n}$ into crisp matrix, B is deneutrosophicated in Eq. (9).

$$B = \frac{\psi_A(x) + \varsigma_A(x) + \kappa_A(x)}{3} \tag{9}$$

Step 4: Normalize the matrix to standardized matrix Z

Eq. (10) is used to normalize the matrix process.

$$Z = \frac{B}{s} \tag{10}$$

Where $s = \max_{l \leq i \leq n} \sum_{j=1}^{n} b_{ij}$ and each element in the matrix Z complies with $0 \leq z_{ij} < 1$.

Step 5: Construct the Total-Influence Matrix T

Construct the influence matrix using the following expression.

$$T = Z(I - Z)^{-1} \tag{11}$$

In Eq. (11), I refers to the identity matrix.

Step 6: Compute the Sum of the Rows and Columns

The vector R and C are the quantity of rows and the the overall-influence matrix T is defined in Eq. (12) and (13).

$$R = [\tilde{r}_i]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} \tag{12}$$

$$C = [\tilde{c}_i]_{1\times n} = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\times n}^{T} \tag{13}$$

Here t_{ij} refers to the component of matrix T.

$R + C$ and R-C values determine relation and importance values, correspondingly.

Step 7: Network Relationship Map (NRM), the Threshold Value

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The dataset design of the graph is $(R+C, R-C)$. $R+C$ and $R-C$ are labelled on the vertical and horizontal axis.

B. Parameter Tuning using QTLBO

Eventually, the parameter selection method can be done using QTLBO method. This study designed a novel amendment for the TLBO, which enhances the velocity and accuracy of convergence rate [18]. The fusion of SA and TLBO techniques expands the optimizer approach and avoids early convergence to local minima. The study attaches an SA method to the TLBO for enhancing the optimization technique. This study deliberates the optimizer technique that has a Pareto conception for the Best-compromise-Solution method and multi-objective approach. The original TLBO technique makes the best understanding of the suggested amendment.

Firstly, the population in each step is given below:

$$X_{k+1}^{sa} = 0.8 * X_k^{old} + rand * \left(1.2 * X_k^{old} - 0.8 * X_k^{old}\right) \rightarrow X_{k+1}^{sa} = \left[X_{k+1}^{sa,1}, X_{k+1}^{sa,2}, \dots, X_{k+1}^{sa,N}\right] \quad (14)$$

K indicates the vector constituent. The model fuses the SA with target vectors:

$$X_K^{new} = \begin{cases} X_K^{SA} \; if \; randl > rand2 \\ X_K^{v} \; otherwise \end{cases} \rightarrow X_K^{new} = \left[X_K^{new,1}, X_K^{new,2}, \dots, X_K^{new,N}\right] \quad (15)$$

$$X_{K+1}^{new} = \begin{cases} X_K^{v} \; if \; f_x(X_K^{v}) < f_x(X_K^{new}) \\ X_K^{new} \quad otherwise \end{cases} \quad (16)$$

$$X_{K+1}^{new} = \begin{cases} X_K^{v} \; if \; f_x(X_K^{v}) domjnate \; f_x(X_K^{new}) \\ X_K^{new} \; if \; f_x(X_K^{new}) \; dominate \; f_x(X_K^{v}) \end{cases} \quad (17)$$

The relationship between the sign " < " in Eq. (16) and “dominate” in Eq. (17) is shown in Appendix A. The model exploits the Max-Min approach by using the $\mu_x^f(X)$ if none $f_x(X_K^v)$ and $f_x(X_K^{new})$ dominate one another:

$$\alpha_1 = \min\left(\mu_i^1, \mu_i^2, \dots, \mu_i^L\right), \alpha_2 = \min\left(\mu_{new}^1, \mu_{new}^2, \mu_{new}^L\right), X_{k+1}^{new} = \begin{cases} X_k^{i} \; if \quad \alpha_1 > \alpha_2 \\ X_k^{new} \quad otherwise \end{cases} \quad (18)$$

QTLBO algorithm integrates the modified TLBO with quasi-opposition-based learning (QOBL). The concept of QOBL is discussed below:

The description of opposite number is given below:

$$z^* = a + b - z \quad (19)$$

Where $z e [a, b]$.

The quasi-opposite number is given below:

$$z_{qo} = rand(c, z^*) \quad (20)$$

Where $c = \frac{a+b}{2}$. assume $Z = (z_1, z_2, \dots, z_L)$ as a point in L dimensional range, where $z_1, z_2, \dots, z_L \epsilon \gamma$ and $z_l \epsilon [a_l, b_l] l \epsilon 1,2, \dots, L$. The opposite point $Z^* = (z_1^*, z_2^*, \dots, z_L^*)$ is given below:

$$Z_d^* = a_l + b_l - z_l \quad (21)$$

The quasi-opposite point is defined by:

$$z_d^{qo} = rand(C_d, z_d^{o}) \quad (22)$$

Where $C_d = \frac{a_d + b_d}{2}$, and $z_d \in [a_d, b_d D = \{1,2, \dots, d\}$. Fig. 2 represents the flowchart of QTLBO.

The fitness selection is the primary factor which influences the outcomes of QTLBO model. The hyperparameter selection model has the solution encoding process for evaluating the effectiveness of the solution candidate. Here, the QTLBO approach is used to consider accuracy as the prime condition to develop the FF.

$$Fitness = \max(P) \quad (23)$$

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$$P = \frac{TP}{TP + FP} \tag{24}$$

Here, TP and FP are the true and the false positive values.

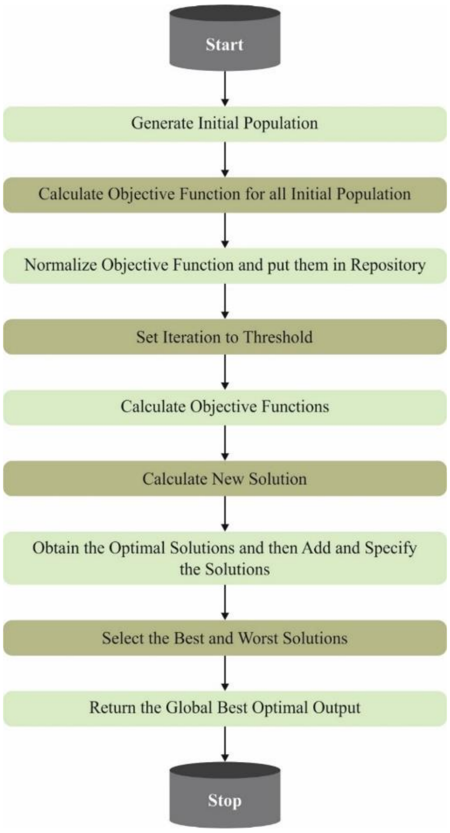

Figure 2. Flowchart of QTLBO

3. Result Analysis and Discussion

The performance evaluation of the GHRM-PNBM technique is tested under several experiments. Table 1 represents a detailed results examination of the GHRM-PNBM technique under several experiments [19].

Table 1: Comparative analysis of GHRM-PNBM technique with recent models

Accuracy (%)					
Number of Experiments	GHRM-PNBM	HGHR-ITFT	DL-EANMFFSM	HRPE-CIACRCSLA	HRA-FDMA
100	94.38	89.81	82.09	82.44	72.26
200	97.53	93.32	88.41	85.25	77.53
300	99.40	98.64	88.76	89.46	78.93
400	99.10	97.94	91.22	89.81	83.14
Precision (%)					
100	93.99	90.34	90.82	90.04	91.89
200	96.98	89.96	91.74	90.06	91.03
300	98.23	95.36	93.74	95.24	95.05

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400	98.57	92.21	95.47	93.40	95.81
Recall (%)					
100	93.00	92.99	88.31	92.20	91.72
200	97.42	89.64	92.83	89.84	89.93
300	98.46	94.04	95.22	95.70	94.82
400	98.45	95.01	94.36	95.70	93.33
F1-Score (%)					
100	92.31	88.84	90.92	90.17	89.61
200	96.55	88.98	90.26	90.09	91.09
300	97.11	96.73	96.10	92.06	92.44
400	97.86	92.94	94.62	94.62	93.48

Fig. 3 exhibits a comparison study of the GHRM-PNBM technique with recent models in terms of $accu_y$. The outcomes highlighted that the GHRM-PNBM method reaches enhanced results. With 100 experiments, the GHRM-PNBM technique offers higher $accu_y$ of 94.38% whereas the HGHR-ITFT, DL-EANMFFSM, HRPE-CIACRCSLA, and HRA-FDMA models gain reduced $accu_y$ of 89.81%, 82.09%, 82.44%, and 72.26%, respectively. Also, with 400 experiments, the GHRM-PNBM method obtains maximum $accu_y$ of 99.10% while the HGHR-ITFT, DL-EANMFFSM, HRPE-CIACRCSLA, and HRA-FDMA models gain minimum $accu_y$ of 97.94%, 91.22%, 89.81%, and 83.14%, correspondingly.

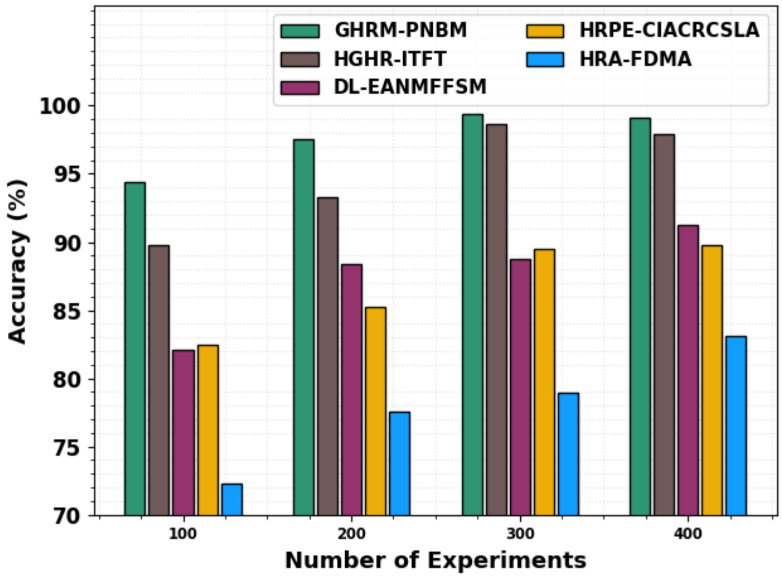

Figure 3: $Accu_y$ analysis of GHRM-PNBM method with existing models

Fig. 4 exhibits a comprehensive review of the GHRM-PNBM method with existing models in terms of $prec_n$. The outcomes emphasized that the GHRM-PNBM method gains better outcomes. With 100 experiments, the GHRM-PNBM method obtains maximum $prec_n$ of 93.99% while the HGHR-ITFT, DL-EANMFFSM, HRPE-CIACRCSLA, and HRA-FDMA approaches obtain decreased $prec_n$ of 90.34%, 90.82%, 90.04%, and 91.89%, correspondingly. Also, with 400 experiments, the GHRM-PNBM method provides maximum $prec_n$ of 98.57% while the HGHR-ITFT, DL-EANMFFSM, HRPE-CIACRCSLA, and HRA-FDMA methods obtain minimum $prec_n$ of 92.21%, 95.47%, 93.40%, and 95.81%, correspondingly.

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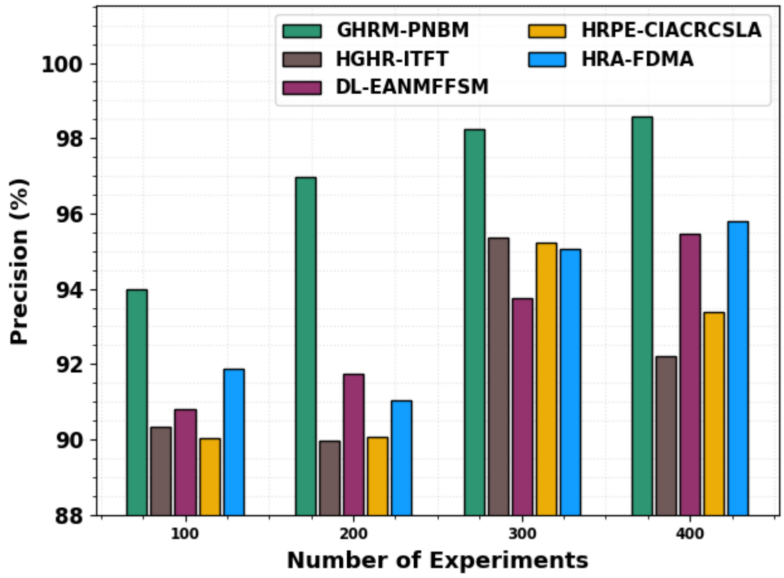

Figure 4: $Prec_n$ analysis of GHRM-PNBM method with existing models

Fig. 5 exhibits a comprehensive review of the GHRM-PNBM method with existing models in terms of $reca_l$. The outcomes emphasized that the GHRM-PNBM method gains better outcomes. With 100 experiments, the GHRM-PNBM method obtains maximum $reca_l$ of 93.00% while the HGHR-ITFT, DL-EANMFFSM, HRPE-CIACRCSLA, and HRA-FDMA approaches obtain decreased $reca_l$ of 92.99%, 88.31%, 92.20%, and 91.72%, correspondingly. Also, with 400 experiments, the GHRM-PNBM method provides maximum $reca_l$ of 98.45% while the HGHR-ITFT, DL-EANMFFSM, HRPE-CIACRCSLA, and HRA-FDMA methods obtain minimum $prec_n$ of 95.01%, 94.36%, 95.70%, and 93.33%, correspondingly.

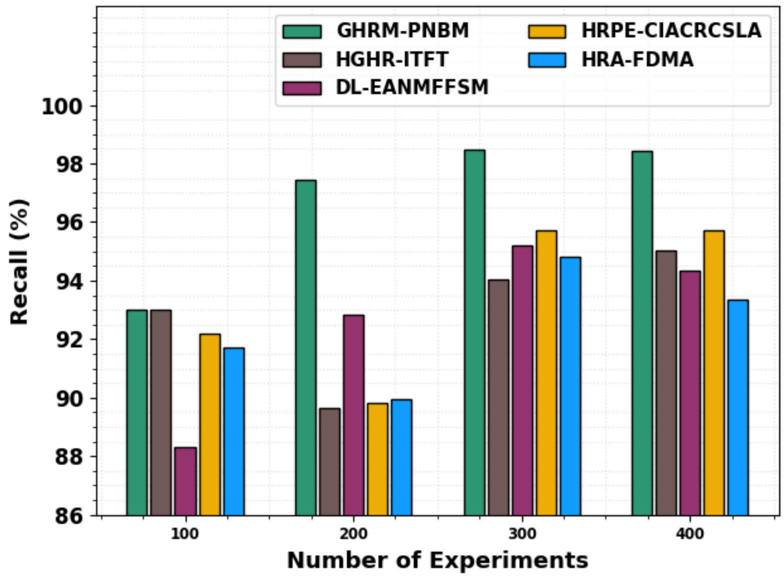

Figure 5: $Reca_l$ analysis of GHRM-PNBM method with existing models

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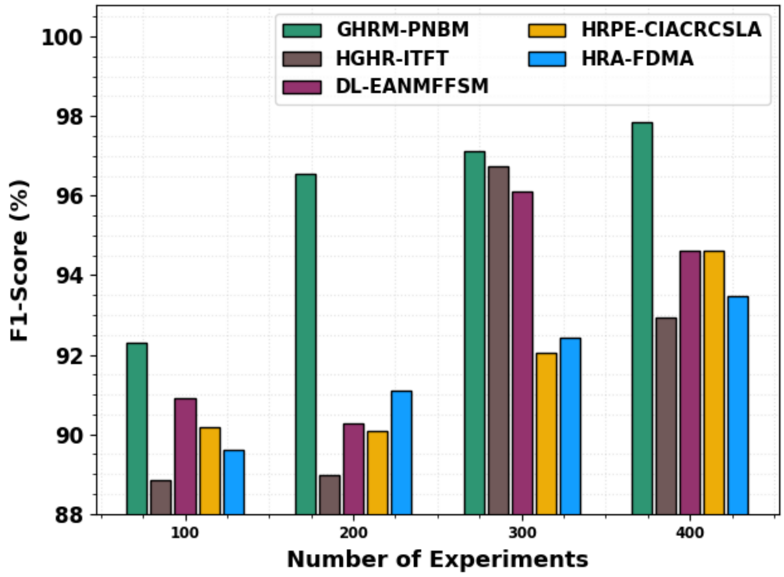

Figure 6: $F1_{score}$ analysis of GHRM-PNBM technique with recent models

Fig. 6 exhibits a comprehensive review of the GHRM-PNBM method with existing models in terms of $F1_{score}$. The outcomes emphasized that the GHRM-PNBM method gains better outcomes. With 100 experiments, the GHRM-PNBM method obtains maximum $F1_{score}$ of 92.31% while the HGHR-ITFT, DL-EANMFFSM, HRPE-CIACRCSLA, and HRA-FDMA approaches obtain decreased $F1_{score}$ of 88.84%, 90.92%, 90.17%, and 89.61%,correspondingly. Also, with 400 experiments, the GHRM-PNBM method provides maximum $F1_{score}$ of 97.86% while the HGHR-ITFT, DL-EANMFFSM, HRPE-CIACRCSLA, and HRA-FDMA methods obtain minimum $F1_{score}$ of 92.94%, 94.62%, 84.62%, and 93.48%,correspondingly.

4. Conclusion

In this manuscript, we focus on design and development of GHRM-PNBM approach. The presented GHRM-PNBM method objectives are to evaluate the limitations of hotel GHRM. Moreover, the presented technique constructs an expert system analysis technique for assessing the performance of hotel GHRM. Adaptive optimization of hotel GHRM assessment can be done using the PNBM technique and the parameter selection method can be done using QTLBO method. The empirical analysis reports that the performance calculation of hotel GHRM has good confidence level and high accuracy

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