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Research Article

Evaluating a Sustainable Intelligent Logistic System (ILS) Utilizing O-S Data and Holistic Managerial Models

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The intelligent logistic system (ILS) has benefited Industry 4.0. ILS assures clean, on-time manufacturing. Due to its unique architectures, qualities, and sensory aspects, the robot logistic system (RLS) is sought after as an ILS in Industry 4.0. In case of COVID-19, multiple nations routinely used RLS as ILS to cleanse areas, check patients, and monitor crowds on highways. Research documents (RDs) show that prior researchers attempted to build the static robot logistic system (RLS) performance mapping index; however, most indexes measured only anatomy performance of static RLS. Thus, few RDs are edited previously in the context of MRLS. It is sensed that few RDs examined MRLS-linked performance mapping indexes, including only regular subjective (S) or objective (O) designs, excluding mixed S-O architectures. Most RDs constantly execute the linguistic variables related to fuzzy, grey, rough, ambiguous, and intuitionistic sets/scales to tackle the uncertainty connected with MRLS designs. The authors prioritize those as RGs. The authors proposed (1) an MRLS performance mapping index with respect to technical, cost, and value O-S architectures for recruiting MRLS, (2) linear information to assign ratings in a range of min-max values choosing from 1 to 100% without executing the linguistic scale, and (3) Holistic Managerial Models (HMM-1 and HMM-2) to handle subjective ratings and significance, assigned by Ex against evaluated O-S architectures under linear scale (1–100%). To prove the concept, RLS performance mapping is shown. Only MRLS recruitment and selection are covered. The effort helps CIM, FMS, and WCMS create sustainable, cleaner operations and achieve future goals.

1. Introduction

RLS (robot logistic system) is ascertained as an auxiliary unit of production systems such as flexible manufacturing, world class, and computer-integrated manufacturing (CIM) systems, which favors the customized production with agility. It is found that mobile RLS is executed more than static RLS due to mobility around space. The MRLS is employed to perform the rapid logistics operations and positioning the components at accurate location under controlling of soft and hardwire software. MRLS is defined as a movable engine of IoTs such as cyber physical system, gadgets, and sensors, which lead ILS to perform the various critical and hazardous tasks such as right positioning and changing the operations and tools, navigation control, and performing the various toxic practices by programming. MRLS is deployed in serious circumstances to perform the tasks, where humans fail to perform. Therefore, MRLS is described as ILS by various authors under various features such as degree of automation, flexibility, mobility, mechanism, and transportation. MRLS is found as an electric power actuator operated vehicle system, which is manipulated over the several industrial sectors by programming and nonprogramming path for shaping the various complicated and hazardous tasks. In accordance with [1, 2], MRLS is an automatic mechanical-electronic vehicle system, which is capable to navigate around the unstructured route under danger environment. MRLS is able to perform the locomotion and need not be appended with persons as it can control its functions automatically by PLC (Programming Logic Circuit). The authors of [3, 4] argued that MRLS is an autonomous vehicle, which is capable of performing the movement in any surroundings and it can move automatically by evaluating and selecting the direction by sensing the signal from sensor. The authors of [5, 6] described MRLS as an automatic system, which has capability to escape via wheels, tracks, legs, or a combination of them to perform the logistics operations. Later, the authors of [7–10] addressed a note about MRLS and explicated that MRLS is automated ILS, whose functions include exploration (locomotion only), transport of payloads, or to perform the more complex tasks in/onboard by manipulating arms. MRLS is capable of performing independent movement and certain actions by ILS intellectual skills. Essentially, in addition to mobility concern, MRLS is able to perform the function autonomously, without requiring human intervention. MRLS has ability to provide the service to several locations and perform the wide range of tasks for specialized or defined application. During the COVID-19 attack, MRLS was employed for disinfecting facilities and patients, assisting surveillance, and delivering stuff and goods. During COVID-19 attacks, MRLS proved itself as magnificent and intellectual mechatronics device. Apart from usage of MRLS in COVID-19, the application of MRLS has various coverage, i.e., for surgical uses, personal assistance, security, warehouse and distribution applications, and ocean and space exploration. MRLS is found as a grand fighter in case of terror prevention, disaster control, and military usage. Other application areas of MRLS include the agriculture and public road transport, including self-driving motor vehicles.

Today's production system is intelligent as well as autonomous due to the integration of IoTs (Internet of Things) with Production Queues (PQs) which is called Industry 4.0. Today, the agile manufacturing is only possible across PQs due to MRLS because it is highly automatic and reacts to compensate the customer's demand swiftly. The MRLS becomes the bone of PQs in Industry 4.0 by addressing the several challenges, i.e., to fulfill the demand of customized products under lead time, to overcome the fierce competition at market place, simulating the production under least cost, etc. It is investigated that aforesaid challenges might be fulfilled if MRLS is audited and selected in accordance with routine operations over PQs. Therefore, there is necessity to design the decision support systems and tools especially for evaluation, recruitment, and selection of the MRLS for defined routine operations to address challenges of Industry 4.0.

To respect above concerns, currently logistics and transportation scholars increased their curiosity towards the area of evaluating, recruiting-benchmarking, and selecting the economic MRLS among others under various technical, cost, and value architectures. MRLS architectures are of two types, where Subjective (S) MRLS architectures deal with subjective information of expert (Ex), while Objective (O) includes the numeric or experimental data. The recent literature and empirical surveys reflected that the Research Documents (RDs) focused on efficiency, effectiveness, and performance improvement as well as the mechanism optimizations of MRLS. Among those RDs, few RDs are linked with recruitment, evaluation, and selection of the MRLS under advanced technical, cost, and value architectures. However, all identified RDs dealt with application of grey, fuzzy, vague, rough, and intuitionistic sets corresponding to linguistic variables to tackle the Subjective (S) information of experts in same problem (for recruiting MRLSs). Aforesaid grounds emphasized the authors to consider the same as Research Gaps (RGs), which are described below.

(i) There is need to develop MRLS performance mapping and recruitment index, including advance O (Objective) mixed with S (Subjective) information corresponding to MRLS alternatives.

(ii) There is a need to develop a linear information set, which could assist the experts to assign the S-information in a range of 1–100% rating scale against S-architectures of MRLS without using linguistic variables.

(iii) There is necessity to frame holistic mathematical model, which can tackle 1–100% rating of experts in the terms of min-max for robust as well as potential evaluation of MRLS among alternatives.

Research Contributions (RCs) are addressed against above said RGs and summarized that there is need to frame the dynamic MRLS performance mapping and recruitment index (consisted of advance O-S architectures) integrated with robust mathematical model for recruiting the MRLS by using ratings and significance scale in a range of 1–100. The RCs are supposed to be confirmed by further relevant literature survey. The authors attempted to conduct the relevant literature survey in the context of MRLS evaluation and recruitment concerning MRLS evaluation S and O architectures, rating sets and scales, and optimization techniques.

This paper is organized as follows. Section 2 gives the literature review. Section 3 gives a summary of the literature survey and research objectives. Section 4 is devoted to Holistic Managerial Models (HMM-1 and HMM-2) for recruitment: planning and operations. Section 5 gives case study-demonstrated MRLS transportation-recruitment drives (planning and operations). Section 6 includes dominance theory and results and novelties, applications, limitations, and implications. Section 7 gives the conclusions.

2. Literature Review

The authors conducted the relevant literature review as discussed in Table 1.

3. Summary of the Conducted Literature Survey and Research Objectives (ROs)

3.1. Summary of the Literature Survey. The authors attempted to organize the above literature survey in the context of MRLS by executing the open-access Google research search engine. The authors found 150 RDs from leading academic journals and conferences, where 51 are observed not in the line of proposed RO. Later, out of 99, 66 RDs are considered for literature survey as cited across the research work. After in-depth literature survey, only 47 RDs were exclusively tied up with RO (evaluation and benchmarking of MRLS under O-S architecture index).

As said above, out of 47, only 23 RDs are explored to construct the MRLS performance mapping and recruitment index, wherein none of the RDs enrolled the mixed integration of Objective (O) cum Subjective (S) or both architectures; therefore, the authors extracted only crucial and significant MRLS evaluation O-S-architectures from 23 RDs, which can address the challenges of present Industry 4.0. Furthermore, 10 RDs out of 47 are determined in line of different fuzzy, grey, and vague rough rating and weight sets, wherein all 10 RDs focused on Likert and linguistic variables to assess rating and weight against MRLS S-architectures; therefore, none of the RDs dealt with thoughts to assess the rating and significance (weight) against MRLS architectures using experts' opinion in the terms of min-max value corresponding to 1–100% scale (without using linguistics scale). At last, 14 RDs out of 47 are traced and all 14 RDs enrolled individual multivariable decision-making techniques; therefore, reliability of decision making becomes the high concern for authors; thus, 12 RDs are executed to prepare the Holistic Managerial Models (HMM-1 and HMM-2) to evaluate the robust MRLS under mapping index.

3.2. Research Objectives (ROs). The summarized report of literature survey potentially confirmed the RCs of Section 1. Therefore, ROs are shaped and pointed out below, and a flowchart of research contributions is also structured as RC guide of presented research work, which is depicted in Figure 1.

(i) To construct the dynamic MRLS performance mapping, recruitment, and selection index incorporating the advanced O-S architectures, meeting the objective of the present Industry 4.0.

(ii) To invent the logic as well as idea of linear scale to facilitate the experts for assigning the ratings and significance against MRLS and S-O architectures, respectively, in the form of min-max value choosing from 1 to 100% by experts (Exs).

(iii) To build Holistic Managerial Models (HMM-1 and HMM-2); this can measure the performance of MRLS, selecting robust and reliable MRLS under application of dominance theory.

4. Holistic Managerial Models (HMM-1 and HMM-2) for Recruitment: Planning and Operations

The proposed models are composed specifically to address the optimization problems of multiple variables under assigning the S-ratings, and significance by experts in a band of max and min value is called as linear information. The concept of information representation is shown in Figures 2 and 3.

These models such as HMM-1-2 have the aptitude to undertake the individual vague or nonambiguity information (in the form of S-significance and ratings) conjunctively in a range of min-max reflected by equations (1) and (2). S-significance and rating values require the subjective assessment from experts. The experts select one low and upper number in % from linear scale (1–100%). The experts assign the S-significance assessment vs architectures and S-ratings assessment vs architectures corresponding to alternatives. In HMM-1-2, equations (3) and (4) are used to summarize and transform the summarized subjective assessment (in the form of S-significance and ratings) into crisp values (CRs), respectively. After evaluation of CRs, equations (5) and (6) are used to normalize the CRs of significance vs architectures.

Among both models, HMM-1 model is developed to aid in the alternative evaluation decision making under multiple architectures. In HMM-1, architectures, whose rating values are beneficial (B) in nature, are normalized by using equation (7), while values of nonbeneficial (C) architectures are transposed into beneficial values and normalized by using equation (8). This model facilitates the experts to assign the S-significance and rating values vs architectures and architectures corresponding to alternatives, respectively, in a range of any value (1–100% point scale). Eventually, equation (9) is executed to decide the alternative rank (max value is preferred for selection).

Next, HMM-1 model is extended to HMM-2 model. HMM-2 also facilitates the experts to assign S-significance and rating values in the range of min-max by using 1–100% point scale. But beneficial (B) as well as nonbeneficial (C) architectures are normalized collectively by using equation (7). Eventually, equation (10) is executed to decide the alternative rank (max value is preferred for selection).

The mathematical representation is formulated here. Presume that there are n possible opportunities (alternatives) $\Gamma_1, \Gamma_2, \ldots, \Gamma_n$ from which expert's panel $E_k (k = 1, 2, \ldots, K)$ is requested to choose in accordance with m architectures $\psi_1, \psi_2, \ldots, \psi_m$, both qualitative (subjective) and quantitative (objective). Suppose the subjective/qualitative information of architectures $\psi_j (j = 1, 2, \ldots, n)$ is proposed against opportunities $\Gamma_i (i = 1, 2, \ldots, m)$ by decision makers $E_k (k = 1, 2, \ldots, K)$.

Just suppose that the information is proposed as set $\{{}^{\mathrm{Min}}\mathrm{Value}^{\%} \leq {}^{\mathrm{Max}}\mathrm{Value}^{\%}\}$.

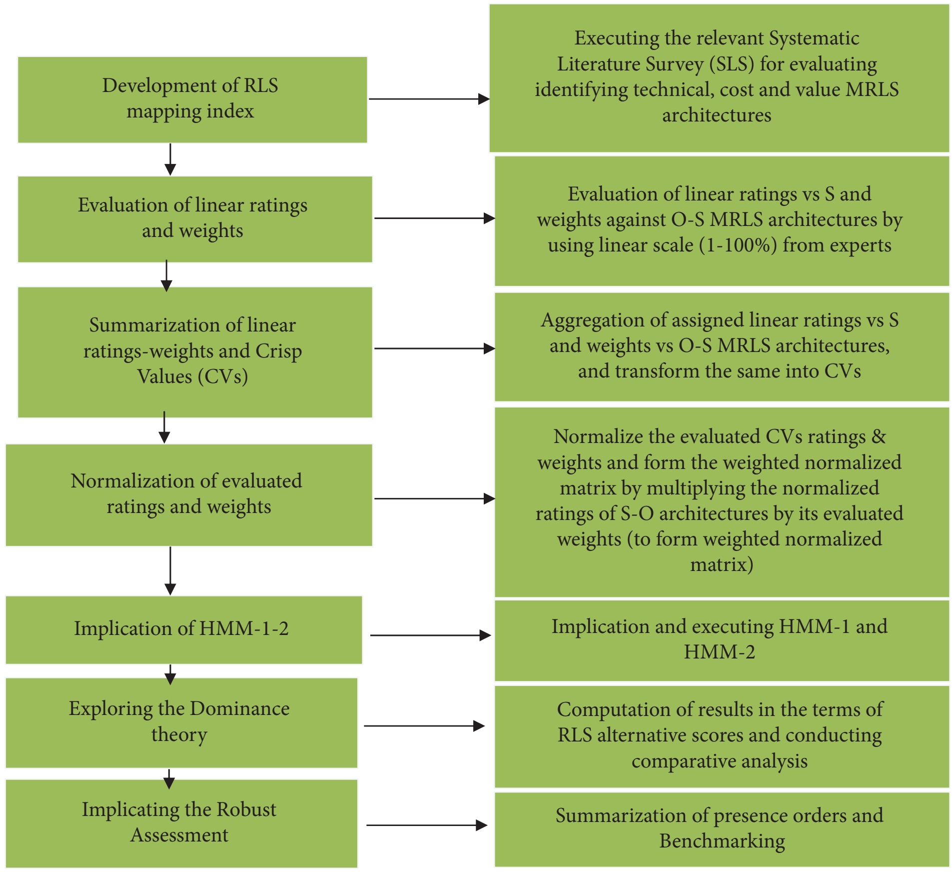

FIGURE 1: Flowchart of research contributions.

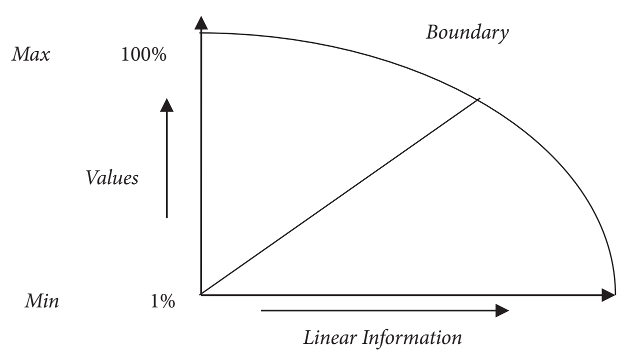

FIGURE 2: Linear information concept.

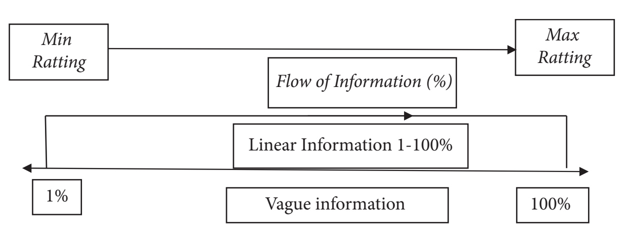

FIGURE 3: Linear rating representation.

Presume that the subjective scores against each architecture corresponding to the opportunities can be computed as follows.

Submission of assigned sets or ratings in percentage as min-max by experts:

$$\psi_{ij} = R = \frac{\left\{{}^{\text{Min}}\text{Value\%} \le {}^{\text{Max}}\text{Value\%}\right\}}{k_1} + \frac{\left\{{}^{\text{Min}}\text{Value\%} \le {}^{\text{Max}}\text{Value\%}\right\}}{k_2} \cdots \frac{\left\{{}^{\text{Min}}\text{Value\%} \le {}^{\text{Max}}\text{Value\%}\right\}}{K}$$
$$= \left[\sum_{k=1}^{K}\left\{{}^{\text{Min}}\text{Value\%}\right\}, \sum_{k=1}^{K}\left\{{}^{\text{Max}}\text{Value\%}\right\}\right]. \tag{1}$$

Evaluation of Crisp Rating (CR) on obtaining output is set by equation (1).

$$\text{CR} = \left[\sum_{k=1}^{K}\left\{{}^{\text{Min}}\text{Value\%}\right\}, \sum_{k=1}^{K}\left\{{}^{\text{Max}}\text{Value\%}\right\}\right]$$
$$= \frac{\left[\sum_{k=1}^{K}\left\{{}^{\text{Min}}\text{Value\%}\right\} + \sum_{k=1}^{K}\left\{{}^{\text{Max}}\text{Value\%}\right\}\right]}{2}. \tag{2}$$

CR1, CR2, CR3 correspond to $\psi_{ij} = \psi_{11}, \psi_{12}, \psi_{13}, \ldots \psi_{mn}$.

Similarly, submission of assigned two sets or weights in percentage as min-max by experts:

$$\psi_j = S = \frac{\left\{{}^{\text{Min}}\text{Value\%} \le {}^{\text{Max}}\text{Value\%}\right\}}{k_1} + \frac{\left\{{}^{\text{Min}}\text{Value\%} \le {}^{\text{Max}}\text{Value\%}\right\}}{k_2} \cdots \frac{\left\{{}^{\text{Min}}\text{Value\%} \le {}^{\text{Max}}\text{Value\%}\right\}}{K}$$
$$= \left[\sum_{k=1}^{K}\left\{{}^{\text{Min}}\text{Value\%}\right\}, \sum_{k=1}^{K}\left\{{}^{\text{Max}}\text{Value\%}\right\}\right]. \tag{3}$$

Evaluation of Crisp Weights (CW) on obtaining output is set by equation (3).

$$\text{CR} = \left[\sum_{k=1}^{K}\left\{{}^{\text{Min}}\text{Value\%}\right\}, \sum_{k=1}^{K}\left\{{}^{\text{Max}}\text{Value\%}\right\}\right]$$
$$= \frac{\left[\sum_{k=1}^{K}\left\{{}^{\text{Min}}\text{Value\%}\right\} + \sum_{k=1}^{K}\left\{{}^{\text{Max}}\text{Value\%}\right\}\right]}{2}. \tag{4}$$

CS1, CS2, CS3 correspond to $\psi_j = \psi_1, \psi_2, \psi_3, \ldots \psi_m$.

Hence, a multiarchitecture matrix can be expressed as follows:

$$\left(\psi_{ij}^{k}\right)_{m\times n} = \begin{array}{c} \Gamma_i \\ \psi_j \\ \psi_2 \\ \vdots \\ \psi_m \end{array} \begin{array}{c} \begin{array}{cccc} \Gamma_1 & \Gamma_2 & \cdots & \Gamma_m \end{array} \\ \begin{bmatrix} \psi_{11}^{k} & \psi_{12}^{k} & \cdots & \psi_{1n}^{K} \\ \psi_{21}^{k} & \psi_{22}^{k} & \ldots & \psi_{2n}^{K} \\ \vdots & \vdots & \vdots & \vdots \\ \psi_{m1}^{k} & \psi_{m2}^{k} & \ldots & \psi_{mn}^{K} \end{bmatrix} \end{array} \quad (k = 1, 2, \ldots, K). \tag{5}$$

Evaluation of Normalized Significance Weight (NCwv) in a range of {0-1}:

$$\text{NCwv} = \frac{\psi_j}{\sum_{j=1}^{n}\psi_j}\, j \ldots n,$$
$$\text{NCwv}\psi_{1.,}\text{NCwv}\psi_{2.,}\text{NCwv}\psi_{3.,} \ldots \sum_{j=1}^{n}\text{NCwv}\psi = 1. \tag{6}$$

Here the normalization of evaluated max CRs and transposed min-max CRs is done by exploring

$$\begin{aligned} \mathrm{NB}_{\mathrm{ij}} &= \frac{\psi_{\mathrm{ij}}}{\sum_{i=1}^{m}\psi_{\mathrm{ij}}}, \\ \psi_{\mathrm{ij}} &= \psi_{i1}, \psi_{i2}, \psi_{i3}, \psi_{i4}\psi_{i5}\ldots\psi_{\mathrm{in}}, \\ \max\psi_{\mathrm{ij}} &\Rightarrow \max\psi_{\mathrm{ij}} \\ &\Rightarrow \max\psi_{i1}, \Rightarrow \max\psi_{i2.}, \Rightarrow \max\psi_{i3}, \ldots \Rightarrow \max\psi_{\mathrm{in}}, \end{aligned} \tag{7}$$

$$\begin{aligned} \mathrm{NNB}_{\mathrm{ij}} &= \frac{\min\left(\psi_{\mathrm{ij}}\right)}{\psi_{\mathrm{ij}}}, \\ \psi_{\mathrm{ij}} &= \psi_{i1}, \psi_{i2}, \psi_{i3}, \psi_{i4}\psi_{i5}\ldots\psi_{\mathrm{in}}, \\ \min\psi_{\mathrm{ij}} &\rightarrow \max\psi_{\mathrm{ij}} \\ &\rightarrow \max\psi_{i1}, \rightarrow \max\psi_{i2}, \rightarrow \max\psi_{i3}, \ldots \rightarrow \max\psi_{\mathrm{in}}. \end{aligned} \tag{8}$$

Multiplication of evaluated NCwv with $\longrightarrow \max\psi_{\mathrm{ij.}}$ and $\Rightarrow \max\psi_{\mathrm{ij.}}$ respective opportunities Γ_i:

$$\begin{aligned} \Gamma_{\mathrm{HMM1}} &= \left(\otimes\Gamma_i\right)_m \\ &= \sum_{j=1}^{m}\left(\Rightarrow \max\psi_{\mathrm{ij.}}\right), \\ \Gamma_i &= \Gamma_1\Gamma_2\ldots\Gamma_m, \end{aligned} \tag{9}$$

$$\begin{aligned} \Gamma_{\mathrm{HMM2}} &= \left(\otimes\Gamma_i\right)_m \\ &= \prod_{j=1}^{m}\Gamma_i\left(\rightarrow \max\psi_{\mathrm{ij.}}\right)\ldots\Gamma_m, \Gamma_i = \Gamma_1, \Gamma_2\ldots\Gamma_m. \end{aligned} \tag{10}$$

5. Case Study Demonstrated MRLS Transportation-Recruitment Drives (Planning and Operations)

The recruitment drive of MRLS is demonstrated to ensure the application and validity of the proposed research work. Case study is conducted for an automobile industry to recruit and select the most economical MRLS among others. The proposed index is constructed by advance O-S MRLS architectures, gathered from literature survey, as shown in Figure 4.

The above-depicted MRLS performance mapping, recruitment, and selection index included the speeds ψ_1, degree of freedom ψ_2, unit load ψ_3, power ψ_4, purchasing cost ψ_5, maintenance cost ψ_6, depreciation ψ_7, overall efficiency ψ_8, fitness to production ψ_9, and quickness ψ_{10} architectures, where power ψ_4, purchasing cost ψ_5, maintenance cost ψ_6, and depreciation ψ_7 are accounted as nonbeneficial, while others are respected as beneficial architectures. In index, ψ_1, ψ_2, ψ_3, ψ_4, ψ_5, ψ_6, ψ_7 are prioritized as Objective (O) architectures and residue architectures are subjective (S) in nature. The MRLS selling companies are requested to send their MRLS quotations against O architectures of MRLS performance mapping index, while S data are assessed by experts of case study company, as shown in Figure 3. Table 2 depicts the index consisting of Objective (O) and S architectures corresponding to MRLS alternatives. Table 3 reflects the definitions of MRLS architectures.

First of all, a team of four experts is constituted by electing the four executives from production, maintenance, purchasing, and design departments.

Prior to overview and judging the performance, the significance against O-S architectures is assessed by team of Exs by assigning the S ratings in a range of 1–100% against all architectures, as exhibited in Table 3.

The aggregation of all assigned significance against architectures is evaluated by using equations (4) and (6). Next similar team of Exs are invited to visit alternative MRLSs of selling company and assign the S-ratings in a range of linear scale (1–100%) by taking min-max subjective perception in % against only S-architectures, as shown in Table 4.

Then, assigned S-ratings are aggregated by usage of equation (2) and next transformed into crisp value by usage of equation (3), as shown in Table 5.

After computing significance of both (S-O) architectures and ratings of S-architectures, the problem seemed to be structured problem of multivariable matrix, as shown in Table 6.

By using equation (5), a multiarchitecture matrix is formed. Later, all the O-S architectures are normalized (0-1) and mixed with their significant architectures corresponding to MRLSS to form multiarchitecture decision-making matrix by using equations (7) and (8) as shown in Table 7.

The economic value of candidate MRLS under O-S architectures is computed by using equations (9) and (10), which is depicted in Tables 8 and 9.

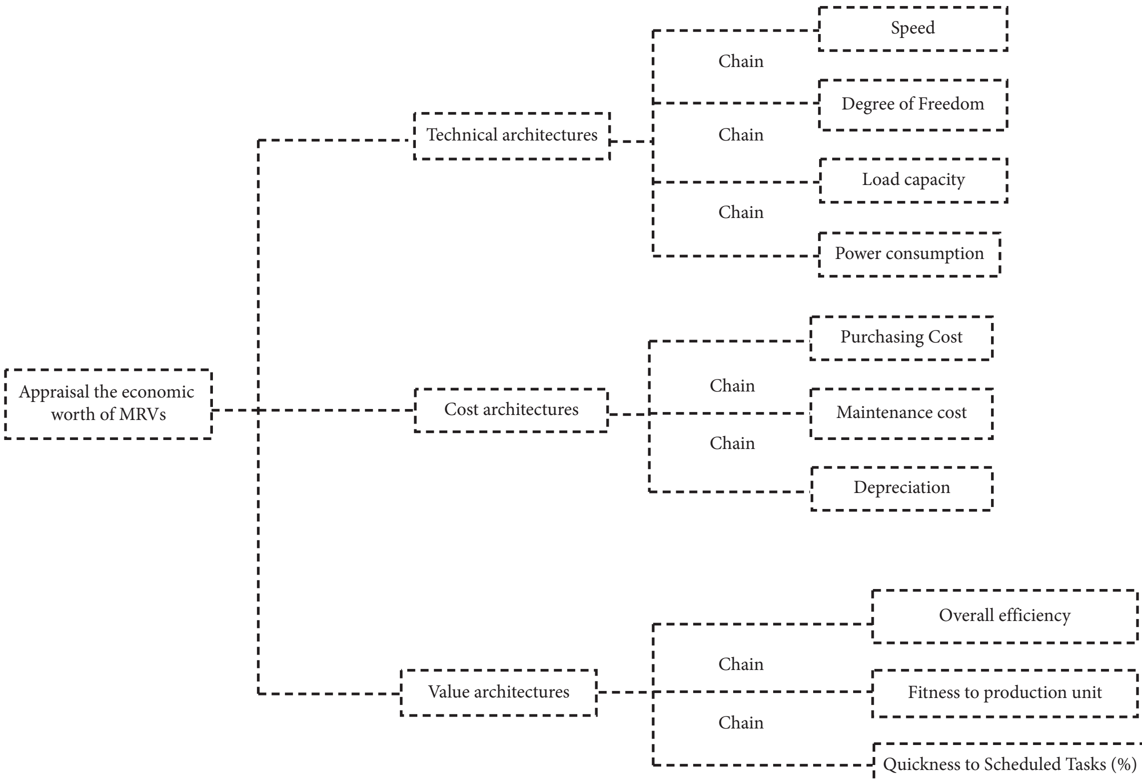

Figure 4: MRLS performance mapping, recruitment, and selection index.

Table 1: Conducted systematic literature survey.

Reference	Conducted works	Focused on
[11]	The author investigated the depreciation plan of a mechanical device in accordance with the best possible interterm portal resource allocation	Depreciation-based architectures
[12]	The author audited the gross as well as net depreciation maintenance of a company and confirmed that depreciation rate becomes double under nonunion maintenance	Depreciation- and maintenance-based architectures
[13]	The author depicted that monopolists procured uneconomically high rates of depreciation for their production of goods and uphold a high price for future	Depreciation-based architectures
[14]	The authors articulated that objective maintenance and depreciation are caused due to technological events, while economic depreciation is the part of obsolescence (replacement of nonproductive equipment by advanced technological equipment)	Depreciation and maintenance architectures
[4]	The authors identified and addressed the two issues such as assessing the degree of similarity among visual quality ratings of landscapes, provided by evaluators and the equivalence of judgments made by photographs. To solve said issues, the authors analyzed the data of various prior studies, conducted to assess the visual quality ratings of landscapes, and finally provided a few insights to professionals about how to assess and validate the reliability of their visual quality ratings of landscapes.	Rating evaluation and expert's opinions
[15]	The author formed the machine evaluation decision support model and applied it to solve the industrial decision-making problems	Machine evaluation decision-making architectures and index
[16]	The authors concluded that accelerated depreciation techniques consume larger capital investments as compared to usage of straight-line depreciation techniques	Depreciation evaluation techniques
[7]	The authors delivered an overview of the various applications of rough set theory for dealing with uncertainty associated with architectures of modern mobile robotics system	Rough rating set application towards robotics
[8]	The authors demonstrated the multicriteria decision-making (MCDM) techniques towards selecting the proficient CNC machine tool that would satisfy the needs of an organization	Machine evaluation decision-making architectures and index

Table 1: Continued.

Reference	Conducted works	Focused on
[9]	The author implicated the multiobjective optimization (ratio analysis) technique in order to resolve various decision-making troubles. In addition to this, the technique has been found as the best decision-making technique for resolving the real-time manufacturing troubles.	Optimization technique
[10]	The authors constructed a novel approach by incorporating ANP (analytical network process) with fuzzy-TOPSIS (Technique for Order Preference by Similarity to the Ideal Solution) methods to select the best supplier alternative under similar supply chain architectures	Vendor evaluation decision-making architectures and index
[17]	The author explored a degree of freedom, unit load, power consumption, fitness to production, and deprecation as significant architectures in evaluation and recruitment of MRLS	Robot evaluation decision-making architectures and index
[18]	The authors implicated the modified TOPSIS and the analytical network process (ANP) to compute the performance of machine tools	Machine evaluation decision-making architectures and optimization techniques
[19]	The authors developed a two-phase robot selection decision support system called as ROBSEL for solving real-life dilemmas	Robot evaluation decision-making architectures and index
[20]	The authors applied fuzzy DEMATEL (Decision-Making Trial and Evaluation Laboratory), ANP, and DEA methodologies to select the resilient cum green suppliers. The proposed methodology has been implemented upon an automotive interior component manufacturing company.	Vendor evaluation decision-making architectures and index and optimization techniques
[21]	The authors presented operators such as union, intersection, addition, and multiplication of intuitionistic fuzzy multiset to be used for robot evaluation	Robot evaluation decision-making architectures and index and fuzzy rating sets
[22]	The authors used interval-valued grey numbers (IVGN) to tackle subjective evaluation information of an expert team; finally, MULTI-MOORA (multiobjective optimization by ratio analysis) approach is applied to sort out RLS evaluation problem	Robot evaluation decision-making architectures, index, interval-grey rating set, and optimization techniques
[23]	The authors displayed a fuzzy group decision-making approach TOPSIS integrated with the aggregate fuzzy weight method to rank the suppliers for a manufacturing firm	Fuzzy rating weight set and optimization techniques
[24]	The authors applied the hybrid fuzzy method upon a multiindex decision-making module in order to select the best machine tool among few recommended machine tools	Machine evaluation decision-making architectures and index and optimization techniques
[25]	The authors applied the grey relational analysis (GRA) method accompanied with fuzzy set theory to measure the green supply chain performance of manufacturing firms	Green supply chain evaluation decision-making architectures, index, fuzzy rating set, and optimization techniques
[26]	The authors mapped the performance of six decision-making methods, i.e., weighted sum method (WSM), weighted product method (WPM), weighted aggregated sum product assessment (WASPAS) method, multiobjective optimization on the basis of ratio analysis and reference point approach (MOORA) method, and multiplicative form of MOORA method (MULTIMOORA), investigating the industrial robot evaluation, benchmarking, and selection problems	Robot evaluation decision-making architectures and index and optimization techniques
[27]	The author presented a Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) technique for evaluation and selection of robots in the context of type-2 fuzzy sets. Type-2 fuzzy set corresponding to linguistic scale handled the degree of risk associated with robot evaluation architectures.	Robot evaluation decision-making architectures and index, fuzzy rating sets, and optimization techniques
[28]	The authors proposed an integrated linguistic MCDM technique for robot evaluation and selection under weight (significance) set for robot evaluation	Robot evaluation decision-making architectures and index and evaluation of significance vs architectures
[26]	The authors ranked the MCDM methods for robot evaluation and selection under various robot architectures	Robot evaluation decision-making architectures and index and evaluation architectures
[29]	The authors prescribed the fuzzy knowledge towards the new learners and readers, so that fuzzy set can be applied to address the alternative evaluation problem of industries	Fuzzy rating set application to robot evaluation and optimization techniques

Table 1: Continued.

Reference	Conducted works	Focused on
[30]	The authors proposed 59 crucial beneficial and nonbeneficial architectures and found degree of freedom, unit load, power, fitness to production, and quickness as important architectures. Moreover, the authors used all 59 architectures to measure the economic worth of MRLS.	Robot evaluation of 59 critical decision-making architectures and index
[31]	The authors explored the two key issues of robot evaluation and selection. To address issues, a decision support model, which worked on cloud data and TODIM (an acronym in Portuguese of interactive and multiple criteria decision making) technique, is applied for the purpose of handling robot evaluation and selection problems with high degree of hesitant in information.	Robot evaluation decision-making index and optimization techniques
[32]	The authors implemented the VIKOR-based fuzzy extended analytic hierarchy process technique for mobile robot selection. To avoid any loss of information, the VIKOR is used for base calculation, and later the fuzzy ranking technique is employed to address the degree of possibility of information.	Robot evaluation decision model with fuzzy rating set and optimization techniques
[33]	The authors identified the robot evaluation and selection attributes under appropriate combination of different characteristics for robot industrial application	Robot evaluation architectures
[34]	The authors analyzed the error on the calculated torque in stable motion for a robot. The variation characteristics of the joint torque error during a collision are analyzed and optimized. Based on conclusion, the variation characteristics of the joint torque and ILS collisions of robot are classified into two types: hard and soft.	Robot evaluation decision-making architectures and index
[35]	The authors presented a complete relative pose error model for robot calibration power, respective to relative distance error and the relative rotation error of the robot end-effectors for improving calibration accuracy	Robot decision-making architectures and index
[36]	The authors stated that the application of robots was carried out for learning of 15 individuals. In total, 11 out of the 15 individuals completed the complex task leaning correctly by following different outputs of mobile robot's criteria.	Robot decision-making architectures and index
[37]	The authors applied evaluation based on distance from average solution (EDAS) method as MCDM for robot selection under multiple architectures such as maintenance, power, speeds, and others	Robot evaluation MCDM models and evaluation architectures
[38]	The authors tried to solve the robot evaluation and selection problem using fuzzy best-worst method and PROMETHEE technique for prioritizing the criteria and ranking the robot's alternatives	Robot evaluation decision-making architectures and index
[39]	The authors proposed a deformable two-wheel-like mobile mechanism over constrained mechanism, with the attitude of quick rolling and obstacle surmounting ILS area	Robot evaluation decision-making architectures and index and optimization techniques
[40]	The authors proposed an improved SMAA technique known as iterative-SMAA (I-SMAA) for option evaluation and selection in NPD. Finally, I-SMAA multistep decision-making process is advised to adopt as advanced SMAA option evaluation and selection technique.	Optimization techniques
[41]	The authors applied the object detection, grasp planning, and motion execution technique to justify the motion of the real robot. The selected grasping techniques were found very effective to detect the raw depth images of configuration of the gripper of mobile robot.	Robot decision-making architectures and index
[42]	The authors proposed a dynamic model of the restricted workspace to protect the motion of arm of robot from outreach. A self-protective policy decision executed tree is proposed to regulate and to protect the motion of arm of robot from outreach	Robot decision-making architectures and index
[43]	The authors applied an offline learning method to learn a basic reach model for arm and a motion of mobile robot fingers. An online dynamic adjustment technique of arm speed for active and passive grasping mode is designed and implemented to improve the motion of mobile robot fingers.	Robot decision-making architectures and index
[44]	The authors attempted to integrate the additive ratio assessment (ARAS) with TOPSIS and complex proportional assessment (COPRAS) to demonstrate the real-time robot selection problem under 12 alternative robots with five effective selection criteria such as degree of freedom, unit load, power consumption, fitness to production, and deprecation	Robot evaluation MCDM models, evaluation architectures, and optimization techniques
[45]	The authors implemented knowledge-based cluster with the grey relational analysis approach to short out the many advanced manufacturing machine tools such as robot, CNC, and FMS evaluation problems under objective-grey data	Robot decision-making architectures and index, grey rating set, and optimization techniques

Table 1: Continued.

Reference	Conducted works	Focused on
[46]	The authors proposed a deep hybrid model, which can jointly learn the latent representations of users and items from ratings and reviews collectively. The proposed model can learn the high-order textual features from reviews based on the GRU network.	Optimization techniques
[47]	The author applied the fuzzy mathematical programming to develop a multiobjective model for a reverse logistics network. The developed multiobjective model targeted the minimization of cost of facility construction, vehicle fuel, and environmental damage from polluting gases as objective functions of the model.	Optimization techniques
[48]	The authors proposed a novel ELICIT-MOORA technique for assessing the vertical farming technology. The MOORA technique is modified to solve alternative evaluation problems under linguistic variables.	Optimization techniques
[49]	The authors applied a mobile robot intelligent obstacle avoidance algorithm (consisting of the reaction, deliberation, and the supervision layers) with fuzzy neural network to assess intelligent logistics system's path adaptability. After analysis, it is summarized that sensor performance improves the model accuracy, path obstacle avoidance optimization, and obstacle avoidance simulation.	Fuzzy rating set application to robotics and optimization techniques
[50]	The authors developed a variant pick-up and delivery problem for an urban transportation system under constrained time. Both MRLS and SV features of multiple depots, partial recharging strategies, and fleet sizing of urban transportation are considered to solve the problem.	Robot decision-making architectures and index
[51]	The authors proposed a dynamic controller, which adapts and changes the behavior based on the knowledge of both: a modified personal space distribution and human user velocity of robot motion	Robot decision-making architectures and index
[3]	The authors proposed the integrated application of step-wise weight assessment ratio analysis (SWARA) and combined it with compromise solution (CoCoSo) technique to recognize the most apposite spray painting robot for an automobile industry. The seven evaluation criteria (payload, mass, speed, repeatability, reach, cost, and power consumption) are grasped to identify the best robot.	Many robot decision-making architectures and index and optimization techniques
[52]	The authors proposed a resilience-based optimization model in order to evaluate and select an optimal restoration sequence scheme, maximizing the global average efficiency of metro networks of China under the contingency of network accessibility meeting resilience requirements. Evolutionary algorithm NSGA-II is applied to solve the said model.	Many robot decision-making architectures and indexes and optimization techniques
[53]	The authors proposed the three techniques, agent-based model (ABM), product life cycle management (PLM), and discrete firefly optimization algorithm (DFOA), to investigate the vehicular ad hoc networks of local infrastructure functions after glancing the local and global functions	Many robot decision-making architectures and indexes and optimization techniques
[54]	The authors investigated the compliant leg configuration, addressed the requirements of SLIP robot model. The authors concluded that most of the mass of robot is concentrated in the hip, and the leg, must be constructed by spring, which is light in weight	Robot evaluation decision making architectures and index
[55]	The authors conducted bibliographic review on fractional-order control laws and applied fractional-order control law to design the manipulators of robot logistic system and man-robot systems. The same law is applied to tackle and control the biologically inspired robots.	Robot decision-making architectures and index
[56]	The authors found that alternative evaluation decision-making framework is used to process the alternative evaluation decision by considering the preference similarities of expert's opinions. For example, collective opinion generation framework realized the drawbacks of individual opinion decision making. Therefore, to overcome this concern, the authors proposed an expertise-structure and risk-appetite-integrated two-tiered collective opinion generation framework to respect the subgroup and later group decision making, respectively, to facilitate the reliable decision for alternative evaluation and benchmarking.	Rating evaluation and expert opinions
[57]	The author applied the multicriteria decision-making (MCDM) technique to improve the quality of the financial decision-making process and alternative evaluation	Optimization techniques
[58]	The authors used Atanassov's intuitionistic fuzzy-grey relational analysis sort (IF-GRA-sort) technique in order to strategize the reopening of the tourism industry	Optimization techniques

Table 1: Continued.

Reference	Conducted works	Focused on
[59]	The authors applied the multiobjective optimization system-based TOPSIS decision-making technique to identify the significant factors under the economic and environmental criteria in order to generate the optimum power and heating and cooling supply. The factors such as minimum payback period and maximum carbon emission reduction are chosen as important factors to generate the optimum power and heating and cooling supply.	Optimization techniques
[60]	The authors developed a novel fairness-aware large-scale collective opinion generation framework-based probability distribution function aggregation model (constituted by combining the biobjective optimization model with fairness concern among the experts of subject matter). The proposed model is used for evaluating and benchmarking the blockchain adoption barriers for a medical SC.	Rating evaluation and expert opinions
[61]	The authors established a BIM maturity model by combining the probability aggregation paradigm with a large-scale group decision-making framework for evaluating the project-based BIM performance according to an expert system. The case study of the Corning Gen 10.5 glass substrate production line workshop in Wuhan is demonstrated to show the effectiveness of the proposed model.	Rating evaluation and expert opinions
[62]	The authors conducted literature survey of various optimization techniques to select the best alternative among various alternatives such as selection of supplier, selection of best raw material, and optimization of machining parameters under various criteria	Optimization techniques
[63]	The authors proposed the new integration-based best worst method (BWM) and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE II) to rank the optimal sets under group decision making (GDM)	Optimization techniques

Table 2: The objective (O) information against RLS architectures corresponding to MRLS.

Γ_i	Speeds (m/s)	Degree of freedom	Unit load (kg)	Power (unit/hrs)	Purchasing cost ($)	Maintenance cost ($/annum)	Deprecation/year	Overall efficiency (%)	Fitness to production (%)	Quickness to tasks (%)
	ψ_1	ψ_2	ψ_3	ψ_4	ψ_5	ψ_6	ψ_7	ψ_8	ψ_9	ψ_{10}
Γ_1	0.52	6	50.5	2	10000	520	589	S^{ratings}	S^{ratings}	S^{ratings}
Γ_2	0.45	5	52.3	1.5	11000	530	545	S^{ratings}	S^{ratings}	S^{ratings}
Γ_3	0.51	6	53.5	1.6	12000	550	456	S^{ratings}	S^{ratings}	S^{ratings}
Γ_4	0.62	4	57.3	1.8	11000	510	545	S^{ratings}	S^{ratings}	S^{ratings}
Γ_5	0.58	5	57.5	1.9	11500	550	500	S^{ratings}	S^{ratings}	S^{ratings}
Γ_6	0.59	6	51.2	1.8	11000	560	556	S^{ratings}	S^{ratings}	S^{ratings}
Γ_7	0.52	6	51.5	1.9	10500	600	658	S^{ratings}	S^{ratings}	S^{ratings}
Γ_8	0.56	6	52.5	2.0	10540	650	456	S^{ratings}	S^{ratings}	S^{ratings}
Γ_9	0.57	4	59.3	2.1	11325	690	504	S^{ratings}	S^{ratings}	S^{ratings}
Γ_{10}	0.554	6	57.5	2.0	11235	520	532	S^{ratings}	S^{ratings}	S^{ratings}

6. Dominance Theory and Results and Novelties, Applications, Limitations, and Implications

Section 6 includes the dominance theory and results (Section 6.1) and novelties, applications, limitations, and implications (Section 6.3).

6.1. Dominance Theory and Results. The dominance theory is prioritized as analytical tool for confirming the most economic and feasible option among available alternative options after comparative analysis. The dominance theory was utilized to provide the benchmarking solution to one of the machine tool alternative evaluation problems in a case study. The said approach is renowned across the benchmarking scholars for evaluating the single or individual rank after comparison. Therefore, the need of holistic approach is found. In the presented work, HMM-1-2 models are implicated for appraising and evaluating the robust decision by exploring the comparative analysis under dominance theory. The computed results by different HMM-1-2 models are supposed to be demonstrated for comparative analysis according to synergy among preference orders of MRLS alternatives, obtained by HMM-1 and HMM-2, respectively. The simulated results from dominance theory to assure the consistent alternative selection by the benchmarking tool are shown in the following.

Table 3: Definitions of MRLS architectures.

Qualitative/quantitative architectures	Definitions
Speeds (m/s), ψ_1	It is the linear movement of MRLS about X-Y axis. The speed of MRLS is recorded by the computer's memory and controlled by lining up the path or PLC component of MRLS with servo-controller unit.
Degree of freedom, ψ_2	It is related to motions of robot's arms and occurs due to independent joints, which provide the freedom of movement for the MRLS manipulators, either in a linear or rotational sense. Most of the MRLS have six degrees of freedom.
Unit load (kg), ψ_3	It is the weight carrying capacity of MRLS. It is observed that MRLSs are available in a broad range such as carrying weight from 0.5 kg to as heavy as up to 1000 kg.
Power (unit/hrs), ψ_4	It refers to the electrical energy, which is supplied to operate MRLSs. One unit is generally measured in terms of KW/hr.
Purchasing cost (\$), ψ_5	It is the cost associated with buying the MRLS from vendor for producing the goods. It is reflected by \$ at global standards.
Maintenance cost (\$/annum), ψ_6	It is the expenditure incurred to avoid the sudden breakdown or failure in MRLSs. These costs might be spent for the ordinary maintenance such as repairing and oiling of MRLS.
Depreciation/year, ψ_7	It reflects the reduction in value of MRLS within a fiscal year. Each tangible asset's value, i.e., equipment, vehicles, and robots, declines with respect to time.
Overall efficiency (%), ψ_8	It is described as ratio of actual or produced output to standard/expected output. The efficiency of MRLS is about 75% to 90% (without setup time). It can be calculated, for example, MRLS is expected to produce 100 pieces per one hour and produce 80 in reality. OE is estimated to be 0.8 and 80% (with product of 100).
Fitness to production (%), ψ_9	It refers to percentage of utilization of MRLS towards addressing the various subsidiary tasks/activities of production
Quickness to tasks (%), ψ_{10}	It is the ability to react and alter the quick physical position of MRLS with motive to achieve rich production rate under least cost with high degree of quality

Table 4: The subjective information (in terms of %) assigned by expert's panel to MRLS architectures.

ψ_1/E_{K_n}	E_{K_1}	E_{K_2}	E_{K_3}	E_{K_4}
ψ_{j1}	$\{^{\text{Min}}89^{\%} \le {}^{\text{Max}}95^{\%}\}$	$\{^{\text{Min}}50^{\%} \le {}^{\text{Max}}65^{\%}\}$	$\{^{\text{Min}}80^{\%} \le {}^{\text{Max}}82^{\%}\}$	$\{^{\text{Min}}83^{\%} \le {}^{\text{Max}}87^{\%}\}$
ψ_{j2}	$\{^{\text{Min}}78^{\%} \le {}^{\text{Max}}89^{\%}\}$	$\{^{\text{Min}}73^{\%} \le {}^{\text{Max}}78^{\%}\}$	$\{^{\text{Min}}79^{\%} \le {}^{\text{Max}}85^{\%}\}$	$\{^{\text{Min}}87^{\%} \le {}^{\text{Max}}90^{\%}\}$
ψ_{j3}	$\{^{\text{Min}}90^{\%} \le {}^{\text{Max}}95^{\%}\}$	$\{^{\text{Min}}91^{\%} \le {}^{\text{Max}}96^{\%}\}$	$\{^{\text{Min}}97^{\%} \le {}^{\text{Max}}100^{\%}\}$	$\{^{\text{Min}}74^{\%} \le {}^{\text{Max}}80^{\%}\}$
ψ_{j4}	$\{^{\text{Min}}82^{\%} \le {}^{\text{Max}}89^{\%}\}$	$\{^{\text{Min}}87^{\%} \le {}^{\text{Max}}91^{\%}\}$	$\{^{\text{Min}}91^{\%} \le {}^{\text{Max}}93^{\%}\}$	$\{^{\text{Min}}78^{\%} \le {}^{\text{Max}}90^{\%}\}$
ψ_{j5}	$\{^{\text{Min}}58^{\%} \le {}^{\text{Max}}67^{\%}\}$	$\{^{\text{Min}}78^{\%} \le {}^{\text{Max}}84^{\%}\}$	$\{^{\text{Min}}77^{\%} \le {}^{\text{Max}}79^{\%}\}$	$\{^{\text{Min}}87^{\%} \le {}^{\text{Max}}95^{\%}\}$
ψ_{j6}	$\{^{\text{Min}}90^{\%} \le {}^{\text{Max}}94^{\%}\}$	$\{^{\text{Min}}95^{\%} \le {}^{\text{Max}}99^{\%}\}$	$\{^{\text{Min}}88^{\%} \le {}^{\text{Max}}89^{\%}\}$	$\{^{\text{Min}}87^{\%} \le {}^{\text{Max}}91^{\%}\}$
ψ_{j7}	$\{^{\text{Min}}75^{\%} \le {}^{\text{Max}}89^{\%}\}$	$\{^{\text{Min}}70^{\%} \le {}^{\text{Max}}80^{\%}\}$	$\{^{\text{Min}}80^{\%} \le {}^{\text{Max}}90^{\%}\}$	$\{^{\text{Min}}75^{\%} \le {}^{\text{Max}}77^{\%}\}$
ψ_{j8}	$\{^{\text{Min}}58^{\%} \le {}^{\text{Max}}67^{\%}\}$	$\{^{\text{Min}}78^{\%} \le {}^{\text{Max}}84^{\%}\}$	$\{^{\text{Min}}77^{\%} \le {}^{\text{Max}}79^{\%}\}$	$\{^{\text{Min}}87^{\%} \le {}^{\text{Max}}95^{\%}\}$
ψ_{j9}	$\{^{\text{Min}}90^{\%} \le {}^{\text{Max}}94^{\%}\}$	$\{^{\text{Min}}95^{\%} \le {}^{\text{Max}}99^{\%}\}$	$\{^{\text{Min}}88^{\%} \le {}^{\text{Max}}89^{\%}\}$	$\{^{\text{Min}}87^{\%} \le {}^{\text{Max}}91^{\%}\}$
ψ_{j10}	$\{^{\text{Min}}90^{\%} \le {}^{\text{Max}}95\%\}$	$\{^{\text{Min}}91^{\%} \le {}^{\text{Max}}96^{\%}\}$	$\{^{\text{Min}}\ 97^{\%} \le {}^{\text{Max}}100^{\%}\}$	$\{^{\text{Min}}74^{\%} \le {}^{\text{Max}}80^{\%}\}$

6.2. Results. As per HMM-1 model, Γ_3-0.4307 is ascertained as most economical and optimum in all architectures.

$$= \Gamma_3\text{-}0.4307 > \Gamma_2\text{-}0.4260 > \Gamma_4\text{-}0.4134 > \Gamma_8\text{-}0.4081 > \Gamma_6\text{-}0.4079 > \Gamma_5\text{-}0.4078 > \Gamma_{10}\text{-}0.4075 > \Gamma_1\text{-}0.4050 > \Gamma_7\text{-}0.3832 > \Gamma_9\text{-}0.3831. \quad (11)$$

As per HMM-2 model, Γ_3-0.024071 is determined as most economical and optimum in all architectures.

$$= \Gamma_3\text{-}0.024071 > \Gamma_2\text{-}0.023539 > \Gamma_4\text{-}0.020098 > \Gamma_8\text{-}0.020621 > \Gamma_5\text{-}0.020548 > \Gamma_6\text{-}0.020175 > \Gamma_{10}\text{-}0.020081 > \Gamma_1\text{-}0.018967 > \Gamma_9\text{-}0.017118 > \Gamma_7\text{-}0.015792. \quad (12)$$

Table 5: The subjective information (in terms of %) assigned by expert's panel against architectures corresponding to MRLS.

ψ_j	Γ_i	E_{k1}	E_{k2}	E_{k3}	E_{k4}
ψ_{j8}	Γ_1	$\{^{Min}90^{\%} \leq {}^{Max}93^{\%}\}$	$\{^{Min}80^{\%} \leq {}^{Max}81^{\%}\}$	$\{^{Min}94^{\%} \leq {}^{Max}98^{\%}\}$	$\{^{Min}80^{\%} \leq {}^{Max}95^{\%}\}$
	Γ_2	$\{^{Min}85^{\%} \leq {}^{Max}91^{\%}\}$	$\{^{Min}75^{\%} \leq {}^{Max}85^{\%}\}$	$\{^{Min}70^{\%} \leq {}^{Max}80^{\%}\}$	$\{^{Min}74^{\%} \leq {}^{Max}83^{\%}\}$
	Γ_3	$\{^{Min}75^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}70^{\%} \leq {}^{Max}80^{\%}\}$	$\{^{Min}80^{\%} \leq {}^{Max}90^{\%}\}$	$\{^{Min}75^{\%} \leq {}^{Max}77^{\%}\}$
	Γ_4	$\{^{Min}89^{\%} \leq {}^{Max}95^{\%}\}$	$\{^{Min}50^{\%} \leq {}^{Max}65^{\%}\}$	$\{^{Min}80^{\%} \leq {}^{Max}82^{\%}\}$	$\{^{Min}83^{\%} \leq {}^{Max}87^{\%}\}$
	Γ_5	$\{^{Min}78^{\%} \leq {}^{Max}95^{\%}\}$	$\{^{Min}91^{\%} \leq {}^{Max}96^{\%}\}$	$\{^{Min}97^{\%} \leq {}^{Max}100^{\%}\}$	$\{^{Min}74^{\%} \leq {}^{Max}80^{\%}\}$
	Γ_6	$\{^{Min}80^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}91^{\%}\}$	$\{^{Min}91^{\%} \leq {}^{Max}93^{\%}\}$	$\{^{Min}78^{\%} \leq {}^{Max}90^{\%}\}$
	Γ_7	$\{^{Min}58^{\%} \leq {}^{Max}67^{\%}\}$	$\{^{Min}78^{\%} \leq {}^{Max}84^{\%}\}$	$\{^{Min}77^{\%} \leq {}^{Max}79^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}95^{\%}\}$
	Γ_8	$\{^{Min}90^{\%} \leq {}^{Max}94^{\%}\}$	$\{^{Min}95^{\%} \leq {}^{Max}99^{\%}\}$	$\{^{Min}88^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}91^{\%}\}$
	Γ_9	$\{^{Min}90\% \leq {}^{Max}95\%\}$	$\{^{Min}91^{\%} \leq {}^{Max}96^{\%}\}$	$\{^{Min}97^{\%} \leq {}^{Max}100^{\%}\}$	$\{^{Min}74^{\%} \leq {}^{Max}80^{\%}\}$
	Γ_{10}	$\{^{Min}82^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}91^{\%}\}$	$\{^{Min}91^{\%} \leq {}^{Max}93^{\%}\}$	$\{^{Min}78^{\%} \leq {}^{Max}90^{\%}\}$
ψ_{j9}	Γ_1	$\{^{Min}89^{\%} \leq {}^{Max}95^{\%}\}$	$\{^{Min}50^{\%} \leq {}^{Max}65^{\%}\}$	$\{^{Min}80^{\%} \leq {}^{Max}82^{\%}\}$	$\{^{Min}83^{\%} \leq {}^{Max}87^{\%}\}$
	Γ_2	$\{^{Min}78^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}73^{\%} \leq {}^{Max}78^{\%}\}$	$\{^{Min}79^{\%} \leq {}^{Max}85^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}90^{\%}\}$
	Γ_3	$\{^{Min}90^{\%} \leq {}^{Max}95^{\%}\}$	$\{^{Min}91^{\%} \leq {}^{Max}96^{\%}\}$	$\{^{Min}97^{\%} \leq {}^{Max}100^{\%}\}$	$\{^{Min}74^{\%} \leq {}^{Max}80^{\%}\}$
	Γ_4	$\{^{Min}82^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}91^{\%}\}$	$\{^{Min}91^{\%} \leq {}^{Max}93^{\%}\}$	$\{^{Min}78^{\%} \leq {}^{Max}90^{\%}\}$
	Γ_5	$\{^{Min}78^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}73^{\%} \leq {}^{Max}78^{\%}\}$	$\{^{Min}79^{\%} \leq {}^{Max}85^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}90^{\%}\}$
	Γ_6	$\{^{Min}90^{\%} \leq {}^{Max}95^{\%}\}$	$\{^{Min}91^{\%} \leq {}^{Max}96^{\%}\}$	$\{^{Min}97^{\%} \leq {}^{Max}100^{\%}\}$	$\{^{Min}74^{\%} \leq {}^{Max}80^{\%}\}$
	Γ_7	$\{^{Min}75^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}70^{\%} \leq {}^{Max}80^{\%}\}$	$\{^{Min}80^{\%} \leq {}^{Max}90^{\%}\}$	$\{^{Min}75^{\%} \leq {}^{Max}77^{\%}\}$
	Γ_8	$\{^{Min}89^{\%} \leq {}^{Max}95^{\%}\}$	$\{^{Min}50\% \leq {}^{Max}65^{\%}\}$	$\{^{Min}80^{\%} \leq {}^{Max}82^{\%}\}$	$\{^{Min}83^{\%} \leq {}^{Max}87^{\%}\}$
	Γ_9	$\{^{Min}78^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}73^{\%} \leq {}^{Max}78^{\%}\}$	$\{^{Min}79^{\%} \leq {}^{Max}85^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}90^{\%}\}$
	Γ_{10}	$\{^{Min}80^{\%} \leq {}^{Max}82^{\%}\}$	$\{^{Min}80^{\%} \leq {}^{Max}88^{\%}\}$	$\{^{Min}89^{\%} \leq {}^{Max}92^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}92^{\%}\}$
ψ_{j10}	Γ_1	$\{^{Min}58^{\%} \leq {}^{Max}67^{\%}\}$	$\{^{Min}78^{\%} \leq {}^{Max}84^{\%}\}$	$\{^{Min}77^{\%} \leq {}^{Max}79^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}95$
	Γ_2	$\{^{Min}90^{\%} \leq {}^{Max}94^{\%}\}$	$\{^{Min}95^{\%} \leq {}^{Max}99^{\%}\}$	$\{^{Min}88^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}91^{\%}\}$
	Γ_3	$\{^{Min}90^{\%} \leq {}^{Max}95^{\%}\}$	$\{^{Min}91^{\%} \leq {}^{Max}96^{\%}\}$	$\{^{Min}97^{\%} \leq {}^{Max}100^{\%}\}$	$\{^{Min}74^{\%} \leq {}^{Max}80^{\%}\}$
	Γ_4	$\{^{Min}75^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}70^{\%} \leq {}^{Max}80^{\%}\}$	$\{^{Min}80^{\%} \leq {}^{Max}90^{\%}\}$	$\{^{Min}75^{\%} \leq {}^{Max}77^{\%}\}$
	Γ_5	$\{^{Min}58^{\%} \leq {}^{Max}67^{\%}\}$	$\{^{Min}78^{\%} \leq {}^{Max}84^{\%}\}$	$\{^{Min}77^{\%} \leq {}^{Max}79^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}95^{\%}\}$
	Γ_6	$\{^{Min}90^{\%} \leq {}^{Max}94^{\%}\}$	$\{^{Min}95^{\%} \leq {}^{Max}99^{\%}\}$	$\{^{Min}88^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}91^{\%}\}$
	Γ_7	$\{^{Min}75^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}70^{\%} \leq {}^{Max}80^{\%}\}$	$\{^{Min}80^{\%} \leq {}^{Max}90^{\%}\}$	$\{^{Min}75^{\%} \leq {}^{Max}77^{\%}\}$
	Γ_8	$\{^{Min}89^{\%} \leq {}^{Max}95^{\%}\}$	$\{^{Min}50^{\%} \leq {}^{Max}65^{\%}\}$	$\{^{Min}80^{\%} \leq {}^{Max}82^{\%}\}$	$\{^{Min}83^{\%} \leq {}^{Max}87^{\%}\}$
	Γ_9	$\{^{Min}78^{\%} \leq {}^{Max}95^{\%}\}$	$\{^{Min}91^{\%} \leq {}^{Max}96^{\%}\}$	$\{^{Min}97^{\%} \leq {}^{Max}100^{\%}\}$	$\{^{Min}74^{\%} \leq {}^{Max}80^{\%}\}$
	Γ_{10}	$\{^{Min}80^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}87^{\%} \leq {}^{Max}91^{\%}\}$	$\{^{Min}91^{\%} \leq {}^{Max}93^{\%}\}$	$\{^{Min}78^{\%} \leq {}^{Max}90^{\%}\}$

Table 6: The aggregated ratings vs subjective as well as objective architectures corresponding to MRLS and evaluated significance vs RLS architectures.

Γ_i	ψ_8	ψ_9	ψ_{10}	ψ_j	$\{^{Min}W^{\%} \leq {}^{Max}w^{\%}\}$ Significance	C_{wv}	NC_{wv}
Γ_1	$\{^{Min}86^{\%} \leq {}^{Max}92^{\%}\}$	$\{^{Min}76^{\%} \leq {}^{Max}82^{\%}\}$	$\{^{Min}75\% \leq {}^{Max}81^{\%}\}$	ψ_{j1}	$\{^{Min}76^{\%} \leq {}^{Max}82^{\%}\}$	79	0.093051
Γ_2	$\{^{Min}76^{\%} \leq {}^{Max}85^{\%}\}$	$\{^{Min}79^{\%} \leq {}^{Max}86^{\%}\}$	$\{^{Min}90^{\%} \leq {}^{Max}93^{\%}\}$	ψ_{j2}	$\{^{Min}79^{\%} \leq {}^{Max}86^{\%}\}$	82	0.096584
Γ_3	$\{^{Min}75^{\%} \leq {}^{Max}84^{\%}\}$	$\{^{Min}88^{\%} \leq {}^{Max}93^{\%}\}$	$\{^{Min}88^{\%} \leq {}^{Max}93^{\%}\}$	ψ_{j3}	$\{^{Min}88^{\%} \leq {}^{Max}93^{\%}\}$	90	0.106007
Γ_4	$\{^{Min}76^{\%} \leq {}^{Max}82^{\%}\}$	$\{^{Min}85^{\%} \leq {}^{Max}91^{\%}\}$	$\{^{Min}75^{\%} \leq {}^{Max}84^{\%}\}$	ψ_{j4}	$\{^{Min}85^{\%} \leq {}^{Max}91^{\%}\}$	88	0.103651
Γ_5	$\{^{Min}85^{\%} \leq {}^{Max}93^{\%}\}$	$\{^{Min}79^{\%} \leq {}^{Max}86^{\%}\}$	$\{^{Min}75^{\%} \leq {}^{Max}81^{\%}\}$	ψ_{j5}	$\{^{Min}75^{\%} \leq {}^{Max}81^{\%}\}$	80	0.094229
Γ_6	$\{^{Min}84^{\%} \leq {}^{Max}91^{\%}\}$	$\{^{Min}88^{\%} \leq {}^{Max}93^{\%}\}$	$\{^{Min}90^{\%} \leq {}^{Max}93^{\%}\}$	ψ_{j6}	$\{^{Min}90^{\%} \leq {}^{Max}93^{\%}\}$	78	0.091873
Γ_7	$\{^{Min}75^{\%} \leq {}^{Max}81^{\%}\}$	$\{^{Min}75^{\%} \leq {}^{Max}84^{\%}\}$	$\{^{Min}75^{\%} \leq {}^{Max}84^{\%}\}$	ψ_{j7}	$\{^{Min}75^{\%} \leq {}^{Max}84^{\%}\}$	92	0.108363
Γ_8	$\{^{Min}90^{\%} \leq {}^{Max}93^{\%}\}$	$\{^{Min}76^{\%} \leq {}^{Max}82^{\%}\}$	$\{^{Min}76^{\%} \leq {}^{Max}82^{\%}\}$	ψ_{j8}	$\{^{Min}75^{\%} \leq {}^{Max}81^{\%}\}$	78	0.091873
Γ_9	$\{^{Min}88^{\%} \leq {}^{Max}93^{\%}\}$	$\{^{Min}79^{\%} \leq {}^{Max}86^{\%}\}$	$\{^{Min}85^{\%} \leq {}^{Max}93^{\%}\}$	ψ_{j9}	$\{^{Min}90^{\%} \leq {}^{Max}93^{\%}\}$	92	0.108363
Γ_{10}	$\{^{Min}85^{\%} \leq {}^{Max}91^{\%}\}$	$\{^{Min}84^{\%} \leq {}^{Max}89^{\%}\}$	$\{^{Min}84^{\%} \leq {}^{Max}91^{\%}\}$	ψ_{j10}	$\{^{Min}88^{\%} \leq {}^{Max}93^{\%}\}$	90	0.106007

6.3. Novelties, Applications, Limitations, and Implications

6.3.1. Novelties of Research Work

(i) The proposed HMM-1-2 models can tackle the S-ratings of Ex against MRLS architectures in a range of 1–100% (min-max).

(ii) The proposed HMM-1-2 models can tackle the fused information i.e., Subjective (S) mixed with Objective (O) ratings or individual Subjective (S) or Objective (O) ratings provided by Exs against MRLS architectures.

(iii) The proposed HMM-1-2 models are able to compute and evaluate the significance against both S-O-architectures.

(iv) The authors proposed the linear information-based min-max value extraction from 1 to 100% rating scale in linear series, which is simple in nature to learn, understand, and teach to Exs at the time of recruitment of MRLS under multiple mixed S-O-architectures.

(v) The proposed linear information idea overcame the drawback of executing the complex fuzzy, grey,

Table 7: The mixed objective (O) and aggregated subjective (S) information scores against architectures corresponding to MRLS alternatives.

Γ_i	Speeds (m/s)	Degree of freedom	Unit load (kg)	Power (unit/hrs)	Purchasing cost ($)	Maintenance cost ($/annum)	Deprecation/year	Overall efficiency (%)	Fitness to production (%)	Quickness to tasks (%)
	ψ_1	ψ_2	ψ_3	ψ_4	ψ_5	ψ_6	ψ_7	ψ_8	ψ_9	ψ_{10}
Γ_1	0.52	6	50.5	2	10000	520	589	89	79	78
Γ_2	0.45	5	52.3	1.5	11000	530	545	80	82	92
Γ_3	0.51	6	53.5	1.6	12000	550	456	80	90	90
Γ_4	0.62	4	57.3	1.8	11000	510	545	79	88	80
Γ_5	0.58	5	57.5	1.9	11500	550	500	89	82	78
Γ_6	0.59	6	51.2	1.8	11000	560	556	87	90	92
Γ_7	0.52	6	51.5	1.9	10500	600	658	78	80	80
Γ_8	0.56	6	52.5	2.0	10540	650	456	92	79	79
Γ_9	0.57	4	59.3	2.1	11325	690	504	90	82	89
Γ_{10}	0.554	6	57.5	2.0	11235	520	532	88	86	87

Table 8: Summary of entire information in between [0, 1] against all architectures with their significant architectures corresponding to MRLS.

$\sum_{j=1}^{n} NC_{WV} = 1$	Speeds (m/s)	Degree of freedom	Unit load (kg)	Power (unit/hrs)	Cost ($)	Maintenance cost ($/annum)	Depreciation ($/annum)	Overall efficiency (%)	Fitness to production (%)	Quickness to tasks (%)
	Max	Max	Max	Min	Min	Min	Min	Max	Max	Max
	ψ_1; (w_{j1}) (0.093051)	ψ_2; (w_{j2}) (0.096584)	ψ_3; (w_{j3}) (0.106007)	ψ_4; (w_{j4}) (0.103651)	ψ_5; (w_{j5}) (0.094229)	ψ_6; (w_{j6}) (0.091873)	ψ_7; (w_{j7}) (0.108363)	ψ_8; (w_{j8}) (0.091873)	ψ_9; (w_{j9}) (0.108363)	ψ_{10}; (w_{j10}) (0.106007)
Γ_1	{0.095; 0.093051}	{0.111; 0.096584}	{0.093; 0.106007}	{0.750; 0.103651}	{1.000; 0.094229}	{0.981; 0.091873}	{0.774; 0.108363}	{0.104; 0.091873}	{0.094; 0.108363}	{0.092; 0.106007}
Γ_2	{0.082; 0.093051}	{0.093; 0.096584}	{0.096; 0.106007}	{1.000; 0.103651}	{0.909; 0.094229}	{0.962; 0.091873}	{0.837; 0.108363}	{0.094; 0.091873}	{0.098; 0.108363}	{0.109; 0.106007}
Γ_3	{0.093; 0.093051}	{0.111; 0.096584}	{0.099; 0.106007}	{0.938; 0.103651}	{0.833; 0.094229}	{0.927; 0.091873}	{1.000; 0.108363}	{0.094; 0.091873}	{0.107; 0.108363}	{0.107; 0.106007}
Γ_4	{0.113; 0.093051}	{0.074; 0.096584}	{0.106; 0.106007}	{0.833; 0.103651}	{0.909; 0.094229}	{1.000; 0.091873}	{0.837; 0.108363}	{0.093; 0.091873}	{0.105; 0.108363}	{0.095; 0.106007}
Γ_5	{0.106; 0.093051}	{0.093; 0.096584}	{0.106; 0.106007}	{0.789; 0.103651}	{0.870; 0.094229}	{0.927; 0.091873}	{0.912; 0.108363}	{0.104; 0.091873}	{0.098; 0.108363}	{0.092; 0.106007}
Γ_6	{0.108; 0.093051}	{0.111; 0.096584}	{0.094; 0.106007}	{0.833; 0.103651}	{0.909; 0.094229}	{0.911; 0.091873}	{0.820; 0.108363}	{0.102; 0.091873}	{0.107; 0.108363}	{0.109; 0.106007}
Γ_7	{0.095; 0.093051}	{0.111; 0.096584}	{0.095; 0.106007}	{0.789; 0.103651}	{0.952; 0.094229}	{0.850; 0.091873}	{0.693; 0.108363}	{0.092; 0.091873}	{0.095; 0.108363}	{0.095; 0.106007}
Γ_8	{0.102; 0.093051}	{0.111; 0.096584}	{0.097; 0.106007}	{0.750; 0.103651}	{0.949; 0.094229}	{0.785; 0.091873}	{1.000; 0.108363}	{0.108; 0.091873}	{0.094; 0.108363}	{0.093; 0.106007}
Γ_9	{0.104; 0.093051}	{0.074; 0.096584}	{0.109; 0.106007}	{0.714; 0.103651}	{0.883; 0.094229}	{0.739; 0.091873}	{0.905; 0.108363}	{0.106; 0.091873}	{0.098; 0.108363}	{0.105; 0.106007}
Γ_{10}	{0.101; 0.093051}	{0.111; 0.096584}	{0.106; 0.106007}	{0.750; 0.103651}	{0.890; 0.094229}	{0.981; 0.091873}	{0.857; 0.108363}	{0.103; 0.091873}	{0.103; 0.108363}	{0.103; 0.106007}

Table 9: Computed economic value of candidate MRLS computed by Holistic Managerial Models (HMM-1 and HMM-2).

Γ_i	Overall performance (OP) $\Gamma_{\mathrm{HMM1}_{\mathrm{gain}}}$	Preference orders of candidate robots	Overall performance (OP) $\Gamma_{\mathrm{HMM2}_{\mathrm{gain}}}$	Preference orders of candidate robots	(Dominance theory) Relative analysis among imputed preference orders of candidate robots
Γ_1	0.4050	8	0.018967	8	8
Γ_2	0.4260	2	0.023539	2	2
Γ_3	0.4307	1	0.024071	1	**1**
Γ_4	0.4134	3	0.020098	3	3
Γ_5	0.4078	6	0.020548	5	6 or 5
Γ_6	0.4079	5	0.020175	6	5 or 6
Γ_7	0.3832	9	0.015792	10	9 or 10
Γ_8	0.4081	4	0.020621	4	4
Γ_9	0.3831	10	0.017118	9	10 or 9
Γ_{10}	0.4075	7	0.020081	7	7

Bold values represent first preference.

rough, and vague sets to address the uncertainty associated with S-architectures of MRLS performance mapping and selection index.

(vi) The authors proposed the RLS recruitment and selection index incorporating the advanced and sizzling architectures in meeting sustainability pillars of Industry 4.0.

(vii) The authors introduced the dominance theory and implicated for robustly evaluating the performance of MRLS so that appropriate MRLS can be placed for future smoothing of industrial operations.

(viii) The proposed models are able to diagnose other logistics evaluation problems of Industry 4.0.

6.4. Industrial Applications of Research Work. The proposed Holistic Managerial Models (HMM-1 and HMM-2) are appropriate for materializing the economical worth of MRLS on bearing the Ex information in a range of linear scale (1–100% rating). The proposed models are also relevant to short out the other micro and medium transportation system evaluation problems such as cars, scooters, and bikes, under alerting objective cum subjective assessment. In future, in case of any disaster or circumstance, the proposed models can be simulated from the same prospectus, i.e., to recruit MRLS as per operations to be performed by them or as per crowd of area or locality. These models imply the supervisory skills to tackle real-life problems, i.e., appraise the economical worth of buses, aeroplanes, helicopters, commercial equipment, JCB, carriers, wagon autos, and trucks on alerting the architectures of MRLS or substituting MRLS recruitment problem or performance mapping index corresponding to O-S data.

6.5. Limitations of Research Work. The proposed models are limited to undertake only MRLS evaluation problems corresponding to O-S or O or S MRLS architecture corresponding proposed index. The models are not active to resolve the linear transportation problems and multi-objective as well as single parameter optimization problems.

6.6. Implications of Research Work. The proposed models discard the implication of managers and Exs or decision makers, as they can easily understand the scale for assigning the S-ratings (1–100% rating) to assign against O-S-architectures of alternative MRLSs. Furthermore, the research has economic impact at global AMSs, as it does not solicit extremely high skill operators to recruit advance transportation systems. The computations can be carried out by usage of Excel or MATLAB under feasible time. It does not require funding to buy unusual/special software.

7. Conclusions

Conclusion includes the descriptions of discussion, economic value, and future research scope.

7.1. Conclusions. The utility of ILS is broadly seen around Industry 4.0. It is learned that TPM (Transportation Performance Measurement) and decision support tools enable Industry 4.0 for acting on the suitable future planning and adapting operations under feed-forward controlling system. The research attempted to add the worth in CIM system by introducing MRLS performance mapping, recruitment, and selection index embedded with HMM-1-2 models, which can simulate the O-S architectures corresponding to alternative MRLSs. The results of the demonstrated RLS problem are shown here:

$$\begin{aligned}\Gamma_{\mathrm{HMM1}} &= \Gamma_3 - 0.4307 > \Gamma_2 - 0.4260 > \Gamma_4 - 0.4134 > \Gamma_8 - 0.4081 > \Gamma_6 - 0.4079 > \Gamma_5 - 0.4078 > \\ &\quad \cdot \Gamma_{10} - 0.4075 > \Gamma_1 - 0.4050 > \Gamma_7 - 0.3832 > \Gamma_9 - 0.3831, \\ \Gamma_{\mathrm{HMM2}} &= \Gamma_3\text{-}0.024071 > \Gamma_2\text{-}0.023539 > \Gamma_4\text{-}0.020098 > \Gamma_8\text{-}0.020621 > \\ &\quad \cdot \Gamma_5\text{-}0.020548 > \Gamma_6\text{-}0.020175 > \Gamma_{10}\text{-}0.020081 > \Gamma_1\text{-}0.018967 > \Gamma_9\text{-}0.017118 > \Gamma_7\text{-}0.015792.\end{aligned} \tag{13}$$

The authors found after quenching the dominance theory over the evaluated performance of MRLSs that Γ_3 is the best and optimum, satisfying all architectures. The AMS system is advised to plan to recruit Γ_3 for commencing the nice operations and attaining prospectus goals.

7.2. Discussion. The motive to adjoin the dominance theory with HMM-1-2 is to obtain the reliable and potential results. Therefore, synergy analysis is carried out among the evaluated performance of MRLSs by executing dominance theory. It is found that Γ_3 is the most economical and optimum in all architectures. The AMS of MRLS recruitment company is suggested to recruit only third MRLS candidate for future lovely operations.

The development of advanced RLS performance recruitment and selection index is considered as minor originality of research work. The major innovation is sparking around the development of linear scale for choosing rating value from 1 to 100% corresponding to min-max idea to assign the ratings and significance by Ex (without executing linguistic scale) against S and all O-S architectures, respectively. In continuation of that, to simulate MRLS index with 1–100% ratings as well as significance, HMM-1 and HMM-2 are proposed. The models are economical in nature and can be solved manually and by Excel sheet. The feature of research work is bright as the proposed HMM-1 and HMM-2 models can be simulated to tackle other transportation problems under same recruitment index or substitution of architectures of index. The information is formed by using min-max concept, but it can also be formed as min-medium-max if Exs perceived more degree of hesitation. The models are not applicable for resolution of the linear and single and multiobjective optimization problem, and fuzzy, grey, rough, and vague sets cannot be tackled and models are not oriented to tackle the linguistic scale.

7.3. Economic Value. The presented research forum is economic in nature as HMM-1-2 appended with MRLS index is communal to other global industries by usage of social networking sites, e-mail, etc. Microsoft Excel software can be used to compute the results. Any specific software is not required. The work does not require the high scale operator. Moderate technical skill-based operator is sought to express the essence of benchmarking decision. In terms of time, the computation is effortless and least time consuming as experimental data are not sought by MRLS index.

7.4. Future Research Scope. The research dossier has interdisciplinary value because the S-O architectures of MRLS evaluation and benchmarking index can be changed by incorporating the future challenging MRLS architectures. The depicted index can be extended vertically (expanding number of architectures at same level) and horizontally (adding subarchitectures at 2^{nd} level) according to available alternative features of architectures. In the terms of HMM-1-2 models, the model is unique in nature and can be enrolled over various MRLS indexes to provide benchmarking solution to MRLS alternative evaluation problems in future case studies. The model can also be explored for the purpose of mapping performance of individual MRLS by taking reference of benchmarking limit (standard performance) for selecting and rejecting MLRS. Therefore, the MRLS investors or industries can use the proposed work to hire the MRLS on rent/lease to transport a broad range of materials such as switch, shaft, gear, and steel socket. The scholars can utilize the research work as future research guide and direction to shape advanced MRLS indexes and models.

Data Availability

The data used to support the findings of this study are available in Tables 2–9.

Disclosure

This study is part of remote employment research.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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