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A hybrid fuzzy rule-based multi-criteria framework for sustainable project portfolio selection

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ABSTRACT

Project selection is a complex decision making process that is influenced by multiple and often conflicting objectives. The complexity of the project selection problem is due to the high number of projects from which a subset (portfolio) has to be chosen. We present a hybrid fuzzy rule-based multi-objective framework for sustainable project portfolio selection. The multiple and conflicting objectives are considered as the input variables in a Fuzzy Rule-Based (FRB) system developed to estimate the overall fitness (suitability) of the potential project portfolios. A hybrid multi-objective framework integrates and synthesizes the results from a data mining model with the results from a Data Envelope Analysis (DEA) model and an Evolutionary Algorithm (EA) to design the structure of the proposed FRB system. The proposed framework simultaneously considers the accuracy maximization and the complexity minimization objectives. A Genetic Based Machine Learning (GBML) method is utilized to design an alternative FRB system for comparison purposes. The proposed framework and the GBML method are used to assess the alternative project portfolios in a real-world financial services institution. The statistical analysis shows the performance dominance of the proposed hybrid framework over the GBML method based on selected accuracy and interoperability measures.

1. Introduction

Project selection is a complex decision making process that is influenced by multiple and often conflicting objectives. The complexity of the project selection problem is due to the high number of projects from which a subset (portfolio) has to be chosen. In general, project selection research can be categorized into the following five semi-dependent areas: development of conceptual framework, development of Decision Support System (DSS), development of criteria/index/measurement, development of methodological frameworks, and organizational applications. Table 1 presents some recent meta-heuristic approaches for Project Selection Problems (PSPs).

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Table 1
Project selection problems-main themes and methodological approaches (meta-heuristics).

Researcher(s)	Description: theme(s)/considered factor(s)/ methodology/ application
Iniestra and Gutiérrez [42]	MODM/ benefit/cost ratio, contribution OF Project, relative importance, level of congestion in Region, social impact/ Multi-objective 0–1 knapsack, NSGA-II, ELECTRE III/ Transportation project
Ghorbani and Rabbani [37]	MODM, Meta-Heuristics/Resource, Financial, Benefit, Cost/NSGA-II/Random Instances
Lin and Liu [58]	Portfolio Selection Problem/Return, Regret/Fuzzy Sets, Markowitz Model, Genetic Algorithm, Goal Programming/ Taiwanese mutual fund data from the year 1997 to 2000
Cura [25]	Portfolio optimization/Risk, Return/ Particle Swarm Optimization, Genetic Algorithm, Simulated Annealing, Tabu Search/ Simulated Instance
Chang et al. [14]	Portfolio optimization problem/Return, Risk/Genetic Algorithm/ Simulated Instance
Branke et al. [11]	Portfolio optimization/Return, Risk/Multi-Objective Evolutionary Algorithm/Simulated Instance
Freitas et el. [30]	Portfolio optimization model/Return, Risk/ mean–variance mode, Artificial Neural Network/Simulated Instances
Carazo et al. [12]	MODM, Meta-Heuristic, Project Selection & Scheduling/Resource Constraint, Project Interdependency, strategic, political, cash-flow, sales, risk/ Nonlinear binary models, Evolutionary Algorithm, SPEA2, Scatter Search/ 760 Random Instances
Chen et al. [17]	Evolutionary Computation, Genetic Network Programming/Financial/Genetic Algorithm, Adaptive Learning/Japanese stock market
Anagnostopoulos and Mamanis [4]	MODM, Meta-Heuristics/Risk, Return, Number of Asset/NSGA-II, SPEA 2, PESA/ OR Library
Gutjahr et al. [39]	MODM, project portfolio selection, Meta-Heuristic/ Mathematical Modeling/Genetic Algorithm, NSGA-II, Pareto Ant Colony Optimization/Electronic Commerce Competence Center (EC3) Austria
Chen and Zhang [19]	Portfolio selection problem, Meta-Heuristic/ Risk, Return, transaction costs/particle swarm optimization/ benchmark Instance

As is shown in Table 1, hybrid methodologies such as Multi-criteria Decision Making (MCDM) combined with different procedures and paradigms including fuzzy systems and nature-inspired meta-heuristics are widely used to solve real-world PSPs. Different applications of fuzzy systems, including Fuzzy Rule-Based (FRB) systems, are commonly applied to engineering problems in the literature [71,88]. A FRB system is characterized by a set of fuzzy IF–THEN rules as follows:

$$\text{IF } x_{lj} \text{ is } A_{1j} \text{ and } \ldots \text{ and } x_{mj} \text{ is } A_{mj}, \text{ THEN } y_j \text{ is } B_j \quad (j = 1, 2, \ldots, n), \tag{1}$$

where $\boldsymbol{A}_j = (A_{1j}, A_{2j}, \ldots, A_{ij}, \ldots, A_{mj})$, and $\boldsymbol{B}_j$, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$ are fuzzy sets in a predefined universe of discourse. $\boldsymbol{X}_j = (x_{lj}, x_{2j}, \ldots, x_{ij}, \ldots, x_{mj})$, $i = 1, 2, \ldots, m$; and y_j, $j = 1, 2, \ldots, n$ are the input and output (linguistic) variables of the fuzzy system, respectively. Let n be the number of rules in Eq. (1).

Fuzzy systems use fuzzy rules to make inference. FRB systems are generated through different methods [77,1,80,64,31]. Several authors have studied various applications of FRB systems in the literature [24,45]. The performance of a FRB system critically depends on a suitable Knowledge Base (KB) that contains a Data Base (DB) component and a Rule Base (RB) component.

A FRB is fully covered, if all universes of inputs are covered by rules. Such FRBs are also called dense or complete rule bases. In practice, it means that for all the possible observations there exists at least one firing rule, whose antecedent part overlaps the input data. If this condition is not satisfied, the rule-base is considered a sparse rule base (i.e., containing gaps) [47,66]. The classical fuzzy reasoning techniques like, *Mamdani* or *Sugeno* cannot generate an acceptable output for sparse rule bases. Fuzzy Rule-based Interpolation (FRI) techniques have been introduced to generate inference for sparse FRBs. The FRI techniques have extended the practical applications of fuzzy inference mechanisms for sparse fuzzy rule-based systems [49,50]. Basically, the FRI techniques perform interpolative approximate reasoning by taking into consideration the existing fuzzy rules for cases where there are no fuzzy rules to fire [7].

Although the FRBs are used as a flexible tool for dealing with complicated real world cases, design of a near-optimal FRB is not a straightforward task. Optimal design of FRBs concerns different attributes like the number of required rules, granularity and number of meshes for the input/output variables, the shape of the membership functions of the input/output variables, coverage and completeness of the rules, consistency of the rules, and the consequent parameters of the rules [87]. The aforementioned attributes of FRBs are referred to as the interpretability and accuracy of FRBs. Interpretability is the main advantage of fuzzy systems and should essentially be considered in fuzzy modeling [3]. Interpretability is defined through a direct relation to applications and users [3]. Different definitions and levels of interpretability were reported in the literature. There are two main interpretability levels: "low-level or fuzzy set level" and "high-level or fuzzy rule level" [87]. A model is interpretable if anyone is able to describe and explain it easily. In order to assess the simplicity of an FRB, Alonso et al. [3] show that compact KBs (i.e., KBs with high interpretability) are easier to understand. The interpretability is divided into the readability and comprehensibility with different levels and indices, respectively [3]. Gacto et al. [32] recently presented an overview and taxonomy of the interpretability measures and techniques for obtaining more interpretable linguistic FRB systems.

The optimum design of fuzzy systems through Evolutionary Computations (ECs) has been considered in recent decades. Nawa and Furuhashi [62,63] introduced the Bacterial Evolutionary Algorithm (BEA) to discover the parameters of a fuzzy system; namely, the combination of input variables of the rules, the parameters of the membership functions of the variables, and a set of relevant rules from numerical data. Kim et al. [48] proposed a hybrid Genetic Algorithms (GA) and bacterial foraging approach for global optimization.

Hybrid Bacterial evolutionary algorithms are used efficiently to identify fuzzy rules. Gál et al. [33] proposed different methods to improve the Bacterial Memetic Algorithm (BMA) used for less and more complex FRB extraction. Gál et al. [34] proposed a new version of the BMA that performed well in both less and more complex FRB, simultaneously. Botzheim et al. [9] combined the pseudo-bacterial GA and the Levenberg–Marquardt method to gain accurate FRB from experimental data. Botzheim et al. [10] also proposed a BMA to extract FRB from a training set. Their BMA was a combination of the bacterial evolutionary algorithm and a gradient-based learning technique called the Levenberg–Marquardt method.

Recently, Kundu et al. [52] extended the invasive weed optimization approach for multi-objective cases. Tripathi et al. [79] proposed an adaptive variant of the multi-objective particle swarm optimization procedure in which some parameters of the algorithm like inertia weight and acceleration coefficients changed with iterations. Lei and Ren-hou [56] proposed an immune algorithm which evolved a population of antibodies to design a fuzzy classification system. Hachicha et al. [40] proposed a differential evolution method to design a fuzzy logic controller for modeling the financial market dynamics. Chen and Tsao [18] proposed a hybrid meta-evolutionary rule mining based model to assess the numerical data pattern in the classification problems. Chen and Tsao [18] used their approach to extract the decision rules with maximum accuracy. Zhao et al. [86] proposed a methodology for automatically extracting Takagi–Sugeno fuzzy models from data using Particle Swarm Optimization (PSO). Zhao et al. [86] proposed the Cooperative Random learning Particle Swarm Optimization (CRPSO) to

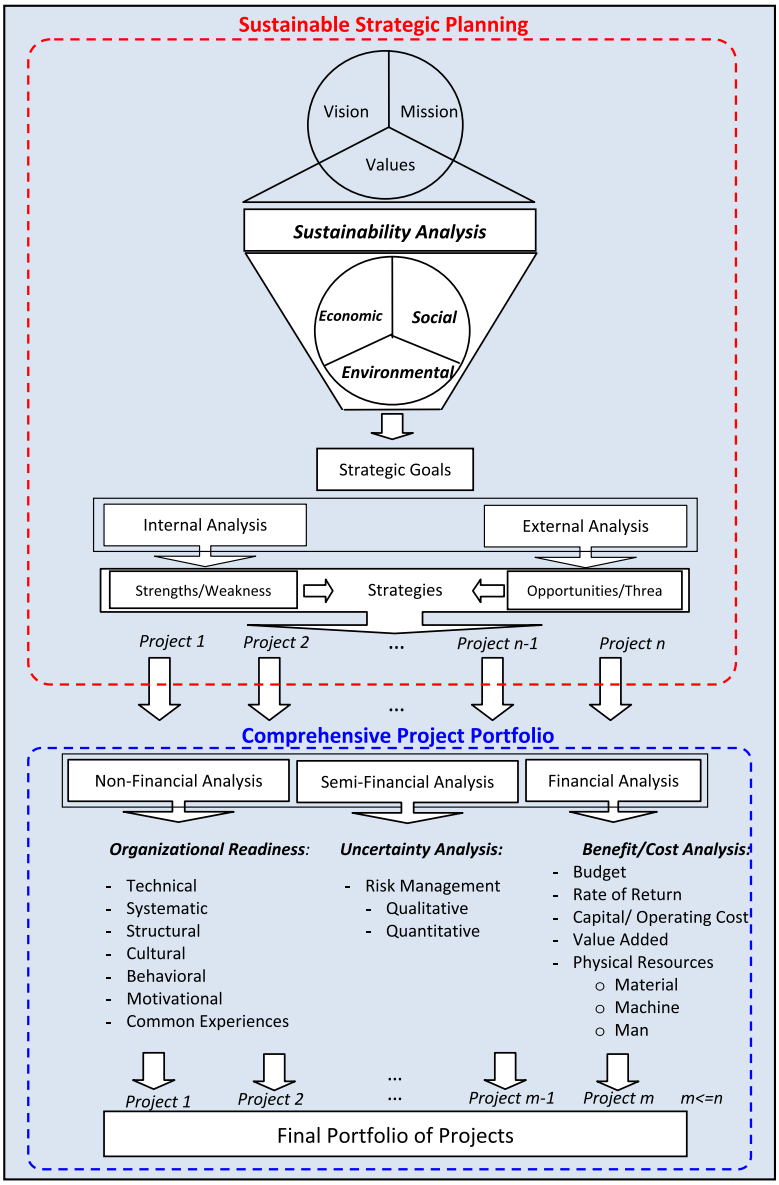


Fig. 1. Sustainable strategic framework for PSP.

enhance the performance of the PSO. They showed that CRPSO outperformed the standard PSO, the classic GA, and the Differential Evolution (DE) on some benchmark instances. Juang and Wang [46] proposed a self-generating fuzzy system with a learning ability from a combination of the Online Self-Aligning Clustering (OSAC) algorithm and Ant-Particle Swarm Cooperative Optimization (APSCO). Marinakis et al. [60] proposed a hybrid method based on ant colony optimization and PSO to solve financial classification problems.

GAs are suitable for both continuous and discrete optimization problems, and can be used to efficiently design FRB systems. The design of FRBs involves parameter tuning and structure determination [24,41]. The FRBs have two conflicting attributes including approximation ability (i.e., accuracy) and interpretability. A proper FRB is assumed to simultaneously minimize the approximation error (i.e., accuracy maximization) and maximize the interpretability (i.e., complexity minimization). Minimizing the approximation errors often results in accurate, but complicated FRBs with a low degree of interpretability. Therefore, the FRB system design is a Multi-Objective Decision Making (MODM) problem [22]. The design of FRBs, which is able to generate non-dominated frontier of aforementioned conflicting objectives (i.e., accuracy and complexity) has attracted a tremendous amount of research efforts. An impressive number of EA techniques including Multi-Objective Genetic Algorithms (MOGAs) have been developed in recent years [43–45].

Sanz et al. [74] improved the performance of FRBs using interval-valued fuzzy sets in KB. Sanz et al. [74] used a post-processing GA approach to obtain the most accurate solutions. They compared the performance of their procedure with a fuzzy hybrid genetics-based machine on a large collection of data-sets. Berlanga et al. [8] proposed a genetic programming-based method for the learning in compact and accurate FRB classification systems. Berlanga et al. [8] applied their method on high-dimensional problems. Their proposed method used a competition mechanism in favor of maintaining the diversity and compactness of fuzzy rule sets. Fernández et al. [27] improved the behavior of FRB systems within an imbalanced data-set framework using a GA as the post-processing tuning step, in which some of the data-sets had different class distributions. Roubos et al. [72] proposed an automatic optimal design procedure for designing FRB systems. They formed an initial model from the pattern data. They then applied feature selection, rule reduction procedures, and GA to compact and accurate FRB systems, respectively. Angelov and Buswell [5] proposed a GA to design the structure and optimize the parameters of FRB systems where the compactness and accuracy were concurrently met. Li and Wang [57] proposed a hybrid GA for discovering multiple rules in a single run and a local search for improving the quality of the learned rules. Wang et al. [82] proposed a method for learning fuzzy rules from samples considering initial fuzzy data sets. Wang et al. [82] presented new definitions of fuzzy lower and upper approximations by considering the similarities between the two objects.

In this paper, we propose a hybrid approach for designing an interpretable-accurate FRB system for sustainable project portfolio selection. We first propose a comprehensive conceptual framework for the project selection problem. We then form a DB from a real-world study and parameterize the RBs through linguistic terms using fuzzy membership functions. Data mining is used next to embellish the experimental patterns achieved from the real-world study. We then use Data Envelopment Analysis (DEA) to select the desirable patterns and form the initial FRB. A well-known MOGA, called NSGA-II [26], is utilized next to optimize the structure and parameters of the proposed FRB system with respect to accuracy maximization and complexity minimization. The proposed FRB system is considered to estimate the overall fitness (suitability) of the potential project portfolios. The proposed framework is applied to the Iranian Financial and credit Foundation (IFCF).

The remainder of the paper is organized as follows. In Section 2 we propose a conceptual framework for sustainable project selection. Section 3 describes the KB (i.e., DB and RB) used in the proposed procedure. The process of generating rules from the numerical data is also discussed in this section. In Section 4, the proposed framework is used to design the interpretable-accurate FRB system. The experimental results are discussed in Section 5. Finally, we end the paper with conclusions and future research directions in Section 6.

2. Conceptual framework for sustainable PSP

Although economic analysis is widely used in the conventional PSP, sustainable development suggests consideration of both financial and non-financial factors. The most well-adopted and most often quoted definition of sustainability is that of the Brundtland Commission – "development that meets the needs of the present without compromising the ability of future generations to meet their needs" [61]. There are several other definitions for sustainability and sustainable development. However, most researchers agree that the concept aims at satisfying social, environmental and economic goals. These goals are also referred to as the three pillars or objectives of sustainable development [53].

Different approaches have been proposed to manage and monitor sustainable development worldwide. Sometimes these approaches appear to be contradictory or in competition. Robèrt et al. [70] developed a systems perspective to study the relationship between different approaches and organizational perspectives for advancing sustainable development. It seems that an upper stream paradigm is essential to align sustainable development with long term goals of an organization. Strategic alignment requires extra coordination in order to gain an acceptable level of performance [73]. The combination of sustainability with strategic planning yields a smooth transformation of the strategic goals into routine daily actions [83]. These routine actions can be represented with iterative short-term projects in organizations. The strategic objectives of an organization (i.e., mission, vision and values) should be considered in the development of the sustainability paradigm. The strategic considerations can be treated as an upstream theme in the PSP [2,13,65].

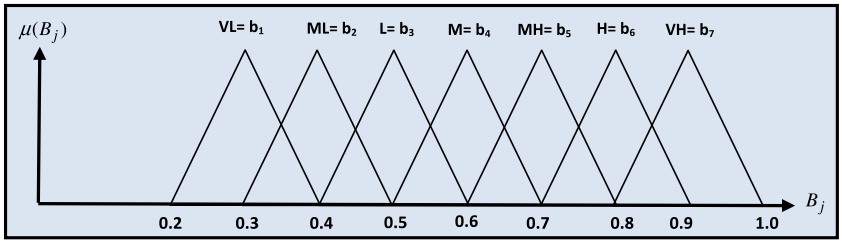


Fig. 2. Linguistic terms and their associated TFNs for the output of FRB.

A resource-based strategy requires a considerable amount of focus on available resources. Competitive strategies seek the opportunities beyond the organization boundaries [59]. A custom combination of the aforementioned strategies is necessary for coping with a turbulent marketplace [35,69]. Many approaches are reported in the PSP literature to measure and assess the risk of investment [20,84,51,54,68]. The cultural and structural perspectives as well as different active/potential capabilities are key factors in the PSP [55,67].

Considering the aforementioned factors, a sustainable project selection framework is needed to handle both the financial/non-financial and the internal/external factors. An upstream strategic framework which can operationalize the strategic objectives into operational tasks in the context of sustainability is represented in Fig. 1. The details and the number of factors can easily be tuned according to the desired methodology and the application of the PSP. The factors represented in Table 2 are used as inputs and outputs in the proposed FRB.

3. Knowledge base in the proposed hybrid framework

As discussed earlier, a fuzzy system contains both an RB structure and a DB structure. In this section, we first present the base structure of the proposed FRB and then supply the associated DB.

3.1. Fuzzy rule-based structure

The general form of a fuzzy IF–THEN rule for the sustainable PSP can be expressed as:

$$\boldsymbol{R}_j: \ \textbf{IF } x_{1j} = SA_j \text{ is } A_{1j} \text{ and } x_{2j} = \mathrm{EF}_j \text{ is } A_{2j} \text{ and } x_{3j} = SE_j \text{ is } A_{3j} \text{ and } x_{4j} = EnE_j \text{ is } A_{4j} \text{ and } x_{5j} = R_j \text{ is } A_{5j} \text{ and } x_{6j} = OR_j \text{ is } \mathrm{A}_{6j} \text{ and } x_{7j} = FA_j \text{ is } A_{7j} \textbf{ THEN } FI_j \text{ is } \boldsymbol{B}_j \ (j = 1, \ldots, n), \tag{2}$$

where $\boldsymbol{A}_j = (A_{1j}, A_{2j}, A_{3j}, A_{4j}, A_{5j}, A_{6j}, A_{7j})$ and $\boldsymbol{B}_j$ ($j = 1, \ldots, n$) are fuzzy sets. $\boldsymbol{A}_j$ and $\boldsymbol{B}_j$ are called the antecedent and consequent of rule j, respectively. The consequent part of (2) is associated with seven fuzzy classes found in Fig. 2 (i.e., $b_1, b_2, b_3, b_4, b_5, b_6, b_7$). The linguistic terms are utilized to parameterize $\boldsymbol{A}_j$ and $\boldsymbol{B}_j$.

$\boldsymbol{X}_p = (x_{lp}, x_{2p}, \ldots, x_{mp})$, where $p = 1, \ldots, s$ is reserved for s experimental pattern vectors and $m = 1, \ldots, 7$ is allocated to dimensions, respectively. A set of n rules as shown by Eq. (2) forms an FRB. For an arbitrary input vector, the FRB estimates the overall fitness of the portfolio using a fuzzy inference system (FIS) and a predefined defuzzification method.

3.1.1. Linguistic terms, membership functions, and fuzzy inference systems

The input and output factors presented in Table 2 are measured with commensurable linguistic terms parameterized with Triangular Fuzzy Numbers (TFNs). The seven linguistic terms presented in Fig. 2 are used to represent the uncertainties in the output factors. The imprecision in the input factors is represented with the linguistic terms shown in Table 3.

Table 2
Inputs/outputs for the sustainable PSP.

Variable	Factor	Description
Inputs	Strategic Alliance (SA)	The alignment of a portfolio of projects with organizational mission, vision, and values
	Economic Effect (EF)	Macro-economic effect of a portfolio of project in a long term period
	Social Effect (SE)	Direct social effect of a portfolio of project in a long term period
	Environmental Effect (EnE)	Direct environmental effect of a portfolio of project in a long term period
	Risk of investment (R)	The risk of investment on a portfolio of project
	Organizational Readiness (OR)	Previous and common experiences of the organization in a portfolio of project
	Financial Analysis (FA)	Micro-financial analysis of a project
Output	Fitness of Investment (FI)	Total fitness score of an investment on a project considering strategic alliance, sustainability (economic, social, environmental), risk, and organizational readiness

Table 3
Linguistic terms and their associated TFNs for the FRB inputs.

Linguistic terms	TFNs
Low (L)	(0, 0.2, 0.4)
Medium (M)	(0.3, 0.5, 0.7)
High (H)	(0.6, 0.8, 1)

The *"Min"* operator is used to represent *"AND"*, and the *"Max"* operator is used to represent "*OR*". The Mamdani's method is used for aggregating the rules and the centroid method is used for defuzzification in this work.

3.2. Data base formation

The knowledge and experience of the experts were used to form a practical DB. The data was collected in IFCF using a questionnaire from 2009 to 2010. The experts who provided their responses to the questionnaire had 15 years of experience on average and were expert financial project managers working for different divisions in IFCF. All managers were familiarized with the framework proposed in Fig. 1 in group meetings. Thirty managers were selected and a set of semi-randomized input vectors was generated considering seven input factors. This set contained 1500 distinct random vector of inputs. Then, each manager was asked to associate an output value for a sub-set of 50 independent investment opportunities. The collected data, reflecting the experts' opinions on 1500 independent investment scenarios, was used to form the initial DB.

Given seven inputs in the antecedent part and three optimal fuzzy numbers for each input, a huge number of rules were required to form a classic complete and dense FRB in which at least there was one fuzzy IF–THEN rule for a probable input vector. Clearly, our DB could not form a classic complete FRB. In addition, gathering a large volume of data involves duplication, inconsistencies and noises. Besides, the computation of FRB becomes unreasonably expensive. The vast number of rules in the FRB cannot guaranty a complete coverage of all probable situations. It is possible to come across an input vector which has no associated rule in the FRB. This also reduces the interpretability of the FRB. To overcome the accuracy and interpretability concerns, we design an interpretable-accurate FRB using a customized procedure, such as data mining, DEA and NSGA-II.

4. Proposed hybrid procedure for designing an interpretable-accurate FRB

Interpretability is the main advantage of FRBs in comparison with other black-box procedures. In addition, a compact FRB with a desirable interpretability degree and accuracy held in a predefined level can be challenging and interesting. We consider a procedure to propose several non-dominated fuzzy rule sets since the case results in a multi-objective problem. In the first step of the proposed procedure, the numerical data from the experimental patterns are transformed into fuzzy rules. Then, a data mining approach proposed by Ishibuchi and Yamamoto [39] is customized to select a set of candidate fuzzy IF–THEN rules. The initial data are pre-screened using the confidence and support metrics which are well-known in data mining. Ishibuchi and Yamamoto [44] demonstrated that such a pre-screening procedure improves the efficiency of the fuzzy rule selection process. In the second step, a DEA model is utilized to select the most efficient fuzzy rules for further manipulation. In the third step, the logic of NSGA-II [26] is customized to find the non-dominated fuzzy rule sets. Similar combinations of data mining and the Multi-Objective Evolutionary Algorithm (MOEA) are proposed to analyze the interpretability-accuracy trade-off in fuzzy systems [45]. This helps us to focus on the customization of the procedure for the IFCF. The overall procedure of this research is presented in Fig. 3.

4.1. Rule formation from the experimental DB

In order to form the associated fuzzy linguistic rules from the experimental patterns, the antecedent and consequent parts of each rule should be determined considering the DB. More formally, the experimental DB contains s members as $\boldsymbol{X}_p = (x_{1p}, x_{2p}, \ldots, x_{mp}; y_p)$, where $p = 1, \ldots, s$ and $m = 1, \ldots, 7$. $\boldsymbol{X}_p$ is reserved for a completed experimental pattern by the managers, and y_p in $\boldsymbol{X}_p$ is reserved for experts' responses to the associated investment scenarios.

Assume that $\boldsymbol{X}_p$ is associated with the structure of the antecedent and consequent part of n linguistic fuzzy rules (i.e.,$\boldsymbol{A}_j = (A_{1j}, A_{2j}, \ldots, A_{ij}, \ldots, A_{mj})$, and $\boldsymbol{B}_j$, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$). Each antecedent part in a linguistic fuzzy rule (i.e., A_{ij}) is parameterized through k linguistic terms, where k is equal to three as represented in Table 3 (i.e.,$k = 3, \forall j, \forall m$). The consequent part in a linguistic fuzzy rule (i.e., B_j) is parameterized through $o$linguistic terms, where o is equal to seven as represented in Fig. 2 (i.e.,$o = 7, \forall j$).

For a given entry x_{ip}, $i = 1, 2, \ldots, 7$ the experimental pattern, $\boldsymbol{X}_p = (x_{1p}, x_{2p}, \ldots, x_{7p})$, where $p = 1, \ldots, s$, is achieved from the managers' judgments, and the associated linguistic term of A_{mj} is in the antecedent part of the fuzzy rule. $\boldsymbol{X}_p$ is calculated by:

$$LT_{mp} = Max\ (\mu_{A_{mjk}}(x_{mp})), \quad k = 1, 2, 3, \tag{3}$$

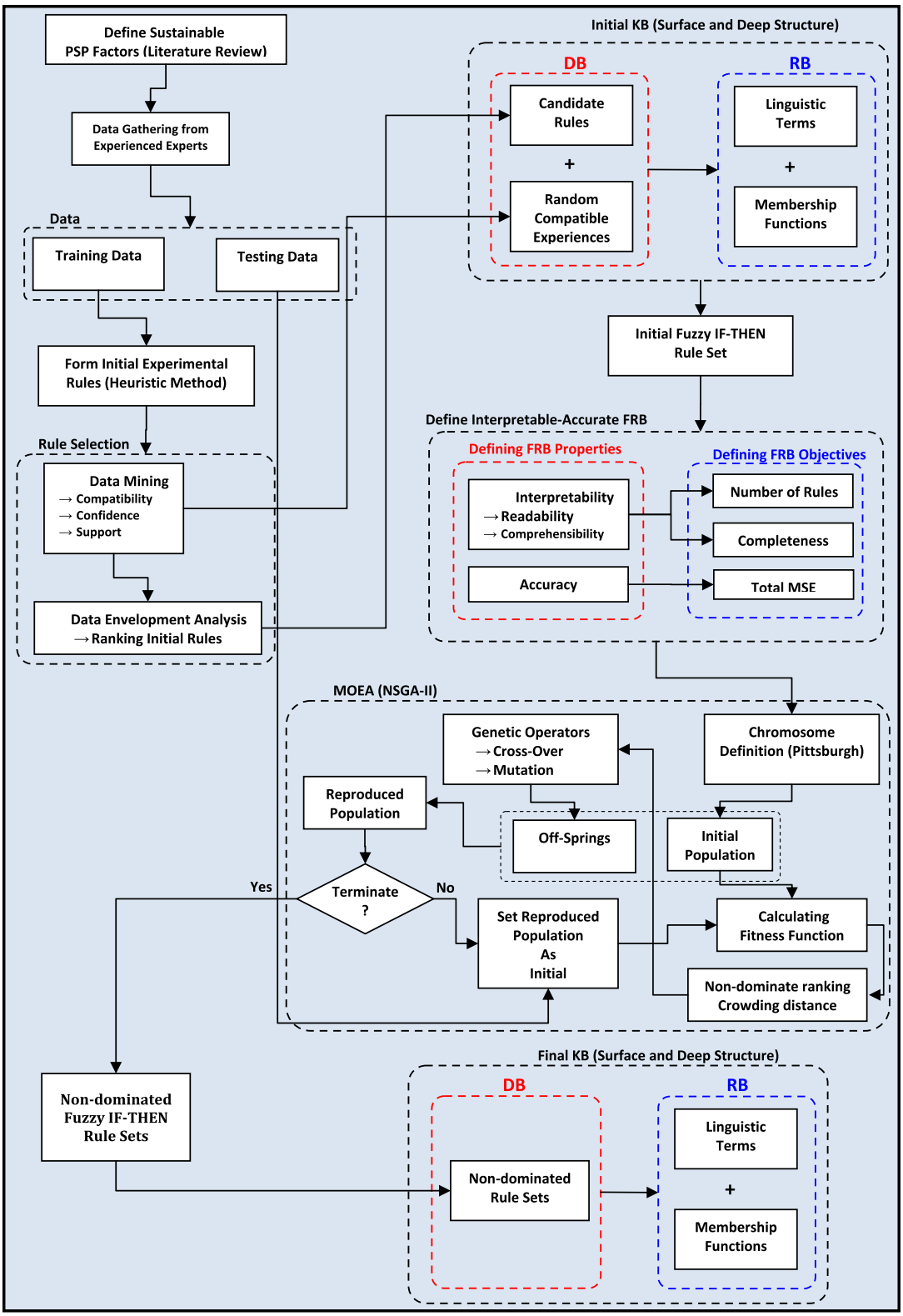


Fig. 3. Overall framework of the proposed interpretable-accurate fuzzy rule based design for the sustainable PSP.

where $\mu_{A_{mjk}}(\cdot)$ is the membership value of the kth linguistic term (LT) that describes the A_{mj} entry in the antecedent part ($\boldsymbol{A}_j$) of a fuzzy rule ($\boldsymbol{R}_j$). LT_{mp} is the selected linguistic term for the A_{mj} entry in $\boldsymbol{A}_j$ of $\boldsymbol{R}_j$. Through the aforementioned procedure, the fuzzy rules are formed from the initial experimental DB.

4.2. Pre-screening of the initial fuzzy rules using data mining

The associated fuzzy IF–THEN rules of the experimental DB were generated using the procedure described in the previous section. These rules were the initial version and needed to be manipulated through extra measurements in order to gain a set of pruned rules for additional consideration. Therefore, a pre-screening procedure is proposed here to decrease the number of candidate fuzzy IF–THEN rules. Two well-known data mining rule evaluation metrics (i.e., *confidence* and *support*) are utilized for this purpose. The product of the *confidence* and *support* is also used as another metric [44,45]. The following definitions are used to demonstrate the *confidence* and *support* metrics:

Definition 4.1. Reconsider the fuzzy rule R_j in the form of Eq. (2). The compatibility degree of each training pattern X_p with the antecedent part A_j is defined as:

$$\mu_{A_j}(X_p) = \mu_{A_{1j}}(X_{1p}) \cdot \mu_{A_{2j}}(X_{2p}) \cdots \mu_{A_{mj}}(X_{mp}), \quad p = 1, \ldots, s, \tag{4}$$

where $\mu_{A_{mj}}(\cdot)$ is the membership function of A_{mj}.

Definition 4.2. The confidence of a given rule R_j in the form of Eq. (2) is defined as:

$$C(A_j \Rightarrow B_j) = \left[\sum_{X_p \in \ Class \ b_{ij}} \mu_{A_j}(X_p) \Big/ \sum_{p=1}^{s} \mu_{A_j}(X_p), \ i = 1, \ldots, 7 \right], \quad j = 1, 2, \ldots, n, \tag{5}$$

where $B_j = \{b_{ij}\}$, $i = 1,2,\ldots,7$; $j = 1,2,\ldots,n$ is one of the seven fuzzy classes in form of Eq. (2) which can be found in Fig. 2 (i.e. $b_{1j}, b_{2j}, \ldots, b_{7j}$). The confidence value indicates the grade of validity of $A_j \Rightarrow B_j$.That is, C percentages of training patterns that are compatible with the antecedent A_j are also compatible with the consequent B_j.

Definition 4.3. Let T be the set of training patterns $X_p = (x_{1p}, x_{2p}, \ldots, x_{mp})$, where $p = 1,\ldots,s$ and $m = 1,\ldots,7$. The support of a given rule R_j in form of Eq. (2) is defined by:

$$S(A_j \Rightarrow B_j) = \left[\sum_{X_p \in \ Class \ b_{ij}} \mu_{A_j}(X_p) \Big/ |T|, \quad i = 1, 2, \ldots, 7 \right], \quad j = 1, 2, \ldots, n, \tag{6}$$

where B_j has the same definition as in (5). $|T| = s$ is the cardinality of the training patterns set. The support value indicates the grade of the coverage of $A_j \Rightarrow B_j$. S shows the percentages of training patterns that are compatible with the association rule $A_j \Rightarrow B_j$. On the other hand, it illustrates the compatibility of all the training patterns with both the antecedent A_j and the consequent B_j. To determine the consequent class of each rule, the confidence of the rule is calculated for each class using Eq. (5) and then the consequent class of each rule is specified as the class with the maximum confidence.

4.3. Selecting the set of efficient fuzzy rules with data envelopment analysis

Data mining was used next to extract fuzzy IF–THEN from similar results and experimental patterns [44,45]. We also use DEA to select the candidate fuzzy rules. DEA is a mathematical programming approach that generalizes the single-input/single-output technical efficiency measure to the multiple-input/multiple-output case to evaluate the relative efficiency of peer units with respect to multiple performance measures [29]. The units under evaluation in DEA are called decision making units (DMUs) and their performance measures are grouped into inputs and outputs. Through the optimization for each DMU, DEA yields an efficient frontier or tradeoff curve that represents the relations among the multiple performance measures. Unlike parametric methods which require detailed knowledge of the process, DEA is non-parametric and does not require an explicit functional form relating inputs and outputs.

The basic starting point in DEA is the idea by Farrell [29]. Charnes et al. [15] followed up with Farrell's idea and introduced the *CCR* model for efficiency measurement. Furthermore, Banker et al. [6] developed the BCC model. Cook and Seiford [23] provided a nice sketch for some of the major research thrusts in the DEA over the three decades since the appearance of the seminal work of Charnes et al. [15].

Each fuzzy rule is considered as a DMU with three outputs (i.e., compatibility, confidence and support). A single input of 1 is considered for all DMUs and the following model known as the additive model proposed by Charnes et al. [16] is used to check whether a DMU is efficient or not. Assuming that there are n DMUs (DMU_j, $j = 1,\ldots,n$) consuming m inputs (x_{ij}, $i = 1,\ldots,m$) to produce s outputs (y_{rj}, $r = 1,\ldots,s$), the additive model can be expressed as:

$$
\begin{aligned}
\max \quad & \sum_{i=1}^{m} S_{ip}^{-} + \sum_{r=1}^{s} S_{rp}^{+}, \\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} + S_{ip}^{-} = x_{ip}, \quad i = 1, 2, \ldots, m, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} - S_{rp}^{+} = y_{rp}, \quad r = 1, 2, \ldots, s, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j, \quad S_{ip}^{-}, \quad S_{rp}^{+} \geqslant 0, \; j = 1, 2, \ldots, n, \; i = 1, 2, \ldots, m, \; r = 1, 2, \ldots, s,
\end{aligned}
\tag{7}
$$

where S_{ip}^{-} and S_{rp}^{+} are the slack variables for the inputs and outputs, respectively. DMU_p (i.e., the pth fuzzy rule) is efficient under the additive model (7) if and only if the optimal value of its objective function is zero.

4.4. Interpretable-accurate FRB design

The interpretability is the most important property of an FRB and has different levels. In this research, we choose the "*number of rules*" in a rule set as the first objective. This objective belongs to the high level interpretability metrics and concerns readability of the FRB. The *"completeness of a rule set"* is selected as the second objective. This objective concerns the comprehensibility of the FRB. The "*Mean Square Error* (*MSE*)"of the output of the FRB is selected as third objective. This objective concerns the accuracy of the FRB. Table 4 presents the metrics and the selected objectives of the interpretable-accurate FRB.

4.5. Non-dominated sorting genetic algorithm II (NSGA-II)

The optimum value of all objectives cannot be achieved concurrently in MODM optimization. Finding a set of non-dominated solutions on the Pareto front of a MODM problem is challenging when there is no prior articulation of the preferences for the objective functions. The NSGA-II is a well-known MOEA method in evolutionary computations [26]. The elitism, fast non-dominated sorting and diversity maintenance properties of the NSGA-II have expanded its successful application in real-world problems. The NSGA-II has also been widely used to validate newly developed GA methods. Table 5 presents some recent applications of NSGA-II.

4.6. NSGA-II for FRB optimization

The NSGA-II is used to generate non-dominated sets of the fuzzy rules since the problem of interpretable-accurate fuzzy rule-based design concerns the optimization of three conflicting objectives. A brief description of the customized NSGA-II for FRB design is provided here.

The Pittsburgh approach, in which each chromosome encodes a whole RB, is utilized in this research. Each rule set of the initial fuzzy rule sets is sorted based on non-domination into each front. The first front contains only non-dominant rule sets among all rule sets; the rule sets in the second front are dominated by the rule sets in the first front as this pattern is repeated. Each rule set in each front is assigned a ranking value in accordance to the front where it belongs. Rule sets in the first front are given a fitness score of 1, the rule sets in the second front are given a fitness score of 2, and so forth.

A measure, called crowding distance, is calculated for each individual in the NSGA-II population. The crowding distance is a measure of how close an individual is to its neighbors. The large average crowding distance will result in a better diversity in the population. Parents are selected from the population by using a binary tournament selection procedure based on their rank and crowding distance. The fitness score of an individual, which belongs to a given rank, is less than others in the same rank with a greater crowding distance. The selected population (fuzzy rule sets) generates offspring through crossover and

Table 4
Selected objectives and measurements of the interpretable-accurate FRB for the sustainable PSP.

Properties	Sub-properties	Level	Selected measurement (objective)	Description
Interpretability	Readability	High-RB	Number of rules in rule set (f_1)	A rule set with less rules is preferred
		High-RB	Rule length (f_2)	Total number of premises
	Comprehensibility	–	Completeness of a rule set (for testing the results)	At least, one rule should be fired for any input vector
Accuracy	–	Rule set	Total MSE ((f_3)	Less MSE of output of a rule set and experimental patterns is preferred
	–	Single rule	–	–

Table 5
Recent applications of the NSGA-II.

Researcher(s)	Application/modification	Description and findings of research
Xu et al. [85]	Multi-project investment	The NSGA-II outperformed different procedures on a fuzzy Multi-Objective chance constraint model
Chica et al. [21]	Assembly line balancing	The NSGA-II has been used as a validated comparison reference to evaluate ant colony optimization and random greedy search algorithm on time and space assembly line balancing problem
Shi et al. [75]	Improvement of NSGA-II	Convergence and diversity of a Dominance Tree (DT) NSGA-II, SPEA2, NSGA-II, and a DT-based MOEA have been compared
Fernández et al. [28]	Improvement of NSGA-II	Improvement of NSGA-II in the sense of choosing the best compromise solution
Grosan and Abraham [38]	Multi-objective optimization/ validating using NSGA-II	The NSGA-II has been used as a validated comparison method for an aggregation line search procedure
Wang and Yang [81]	Multi-objective optimization/ validating using NSGA-II	The NSGA-II has been used as a validated comparison method for a multi-objective particle swarm optimization (MOPSO)
Tavakkoli-Moghaddam et al. [78]	Bi-objective flow-shop scheduling//validating using NSGA-II	The NSGA-II has been utilized to validate the performance of a hybrid multi-objective immune algorithm (HMOIA) for a no-wait flow shop scheduling problem

mutation operators. All individuals (fuzzy rule sets), including current population and the off-springs, are sorted again based on non-domination. Only the best N individuals are selected, in which N is the population size. The selection is based on the rank and crowding distance on the last front. It is worth noting that the inputs of NSGA-II (i.e., the initial fuzzy IF–THEN rule sets) are a combination of the rules selected by the DEA method (50%) and a random rule generation procedure (50%). The details of the NSGA-II and the modified NSGA-II for the fuzzy classifier design can be found in Deb et al. [26] and Ishibuchi and Nojima [45], respectively.

4.6.1. Pittsburgh approach for presenting fuzzy rule set

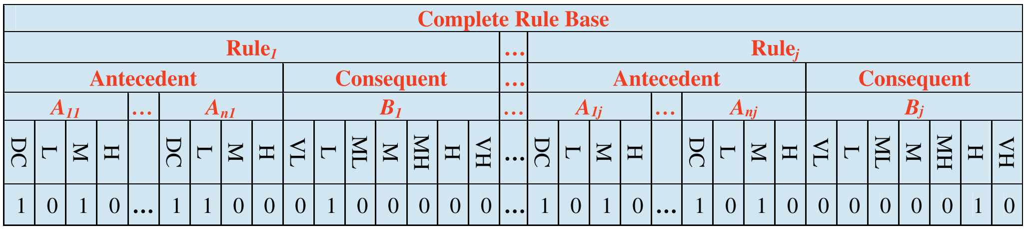
We use the Pittsburgh approach to encode the chromosomes. In this approach, each chromosome represents a complete RB, including all fuzzy rules [76]. A population of individuals (i.e., chromosomes) represents several FRBs. Fig. 4 presents the binary structure of a chromosome in the Pittsburgh approach.

Each chromosome consists of a number of fuzzy rules. Each rule in a given chromosome consists of antecedent and consequent parts. The antecedent part of a given rule consists of several inputs. Each input consists of four binary values. The first left allele of each input is assigned to the "*do not care (DC)*" category. The associated input will not be considered if this allele takes 1. The remaining alleles are assigned to represent the predefined linguistic terms as described in Table 3 (i.e., L, M and H). The consequent part of a given rule consists of a unique output. The output consists of seven alleles filling through binary values associated with the predefined linguistic terms of Fig. 2. It is worth noting that just one allele for each input/output can take 1 value (except for the DC in input alleles).

4.6.2. Genetic operators (cross over and mutation)

The chromosome length in the Pittsburgh approach is variable because the number of required rules to describe the system is unknown. Therefore, the usual genetic operators cannot be used for such chromosome and position-independent genomes.

4.6.2.1. Crossover. The crossover operator is the backbone of the GAs. This operator provides a new combination of rule sets. A customized crossover operator is applied in this study. Two binary chromosomes in the Pittsburgh format are selected as parents (i.e., P_1 and P_2). These rule sets are selected according to a predefined cross probability, called P_c. Then, a one-point crossover is implemented using these parents. Assume that P_1 and P_2 have R_1 and R_2 rules, respectively. Then N_1 and N_2 rules are selected from each parent, respectively. N_1 and N_2 are randomly determined in the intervals $[1, |R_1|]$ and $[1, |R_2|]$, respectively, where $|R_1|$ and $|R_2|$ are the cardinality of P_1 and P_2, respectively. Afterwards, these selected rules are combined and



Complete Rule Base																																
Rule$_1$																…	Rule$_j$															
Antecedent									Consequent							…	Antecedent									Consequent						
A_{11}				…	A_{n1}				B_1							…	A_{1j}				…	A_{nj}				B_j						
DC	L	M	H		DC	L	M	H	VL	L	ML	M	MH	H	VH	…	DC	L	M	H		DC	L	M	H	VL	L	ML	M	MH	H	VH
1	0	1	0	…	1	1	0	0	0	1	0	0	0	0	0	…	1	0	1	0	…	1	0	1	0	0	0	0	0	0	1	0

Fig. 4. Binary coded chromosome structure in the Pittsburgh approach.

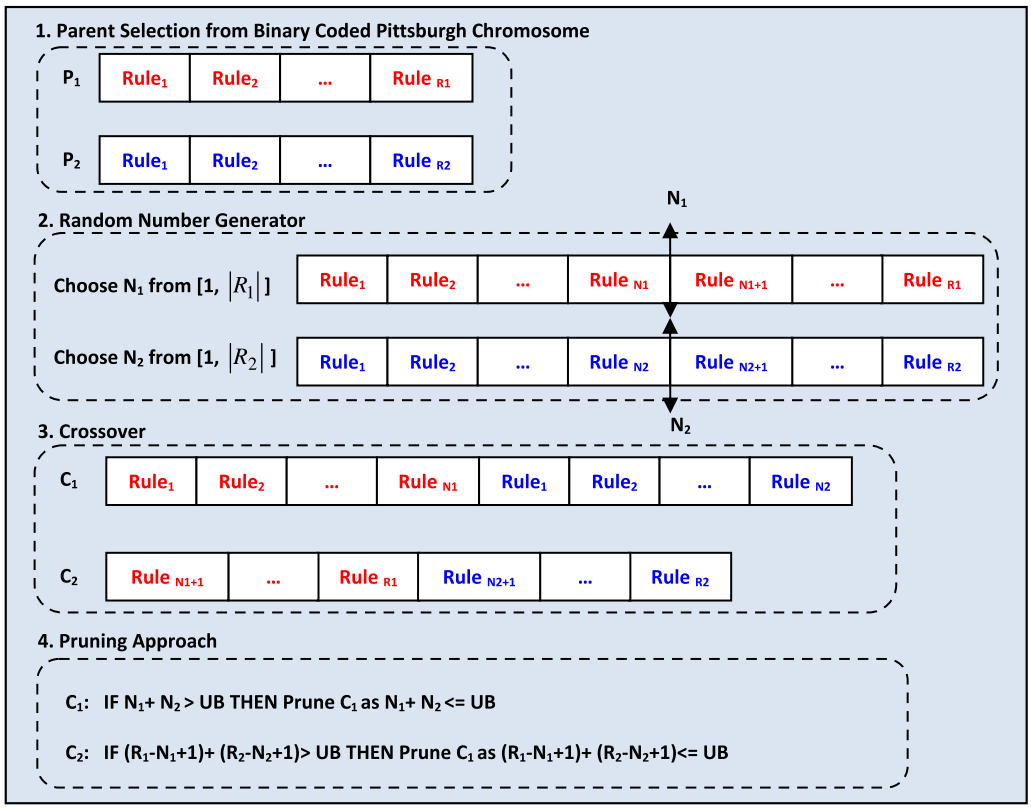


Fig. 5. Crossover operator and pruning approach for the binary coded Pittsburgh chromosome.

form two off-springs (i.e., children C_1 and C_2) with $N_1 + N_2$ and $(R_1 - N_1 + 1) + (R_2 - N_2 + 1)$ rules, respectively. $N_1 + N_2$ and $(R_1 - N_1 + 1) + (R_2 - N_2 + 1)$, which are the number of rules in the new born rule sets, can extensively be increased. So a pruning approach should be applied to avoid the extensive growth of the rule set. An upper bound (UB) is considered for the number of rules in an off-spring. On the other hand, if the number of rules in the new born rule sets exceeds the predefined UB, the pruning approach activates and decreases the number of rules. Fig. 5 presents the schematic view of the proposed crossover operator and the pruning approach.

4.6.2.2. Mutation. The mutation operator is accomplished according to a predefined mutate probability, called P_m. When one of the off-springs is selected for mutation, each antecedent part of fuzzy rules in the rule set is randomly replaced with antecedent parts of other fuzzy rules in the same rule set. Fig. 6 presents the schematic view of the proposed mutation operator.

4.6.3. Fitness function evaluation

The fitness function evaluates the population according to the number of rules, length of rules, the accuracy of prediction, and the crowding distance measure based on the NSGA-II mechanism. The non-dominant rank of each chromosome in a given population is calculated considering the above objectives, and a ranking value is assigned to all individuals in the population. This is accomplished by making different non-dominated fronts in the population. Let us provide the following working definitions for the measurements used here:

Definition 4.4. The length of a rule in the rule set is calculated as the number of zeros in all of the associated "do not care" situations.

Definition 4.5. The number of rules in the rule set is an integer value counting the rules with positive rule length in the rule set.

Definition 4.6. The accuracy of the prediction is the mean square error of all outputs for all rules in the rule set and all experimental pattern data.

1. Selected Rules in the chromosome for mutation

$Rule_1$																…	$Rule_j$															
Antecedent									Consequent							…	Antecedent								Consequent							
A_{11}				…	A_{n1}				B_1							…	A_{1j}				…	A_{nj}				B_j						
1	0	1	0	…	1	1	0	0	0	1	0	0	0	0	0	…	1	1	0	0	…	1	0	0	1	0	0	0	0	0	1	0

2. Mutated chromosome

$Rule_1$																…	$Rule_j$															
Antecedent									Consequent							…	Antecedent								Consequent							
A_{1j}				…	A_{nj}				B_1							…	A_{11}				…	A_{n1}				B_j						
1	1	0	0	…	1	0	0	1	0	1	0	0	0	0	0	…	1	0	1	0	…	1	1	0	0	0	0	0	0	0	1	0

Fig. 6. Mutation operator for the binary coded Pittsburgh chromosome.

Definition 4.7. The average rule length in the rule set is the number of zeros in all of the associated "do not care" situations for all rules in the rule set divided by the number of rules in the same rule set.

Definition 4.8. The sum of the rule lengths in the rule set is the number of zeros in all of the associated "do not care" situations for all rules in the rule set.

Definition 4.9. The average of the rule lengths in a rule set is the number of zeros in all of the associated "do not care" situations for all rules in the rule set divided by the number of rules in that rule set.

Definition 4.10. The average of the rule lengths in all rule sets is the number of zeros in all of the associated "do not care" situations for all rules in all rule sets divided by the number of rules in all rule sets.

The number of rules in a rule set refers to the interpretability of a rule. The number of rules in the Pittsburgh approach indirectly represents the length of a chromosome. If two chromosomes provide the same accuracy level, the chromosome with the smaller number of rules is preferred. Thus, NSGA-II seeks the rule sets with minimum number of rules. The length of a rule should be less than or equal to a predefined upper bound. The average length of rules in a rule set is another objective considered in this research. The sum of the lengths of the rules in the Pittsburgh approach also refers to the chromosome length and a chromosome with a smaller rule length is preferred. The accuracy of a given rule set is selected as the last objective in this research. The MSE is calculated for all individuals in a given population using the test data. The rule set with a smaller MSE is the most preferred one.

The non-dominated individuals are selected based on Pareto dominance and are given the first rank. Then, these individuals are omitted from the population and the non-dominated ranking approach will go on through selecting individuals in the second rank. The procedure continues until there are no individuals without an assigned ranking in the population. The crowding distance is calculated for all individuals in the same rank. The crowding distance presents the distribution of individuals in certain frontier. A larger crowding distance represents more diversity and is preferred to a smaller crowding distance. The final selection is accomplished based on a tournament. Off-springs are generated through genetic operators. The iteration continues until the maximum number of iterations is reached or no improvement is reported in the predefined number of iterations.

5. Experimental results

In this section, we present the experimental parameters and results of the proposed hybrid approach.

5.1. Parameters of the proposed hybrid approach

Table 6 presents an overview of the proposed hybrid approach and the parameter setting in each step. During a single run of the proposed NSGA-II algorithm, 200,000 rule sets were examined to find the non-dominated rule sets. The probabilities of the DC, crossover, and mutation are defined according to their function. These help the algorithm adapting the search process efficiently. In the first step of the NSGA-II, the mutation probability is set to 0.01. This value increases as the number of iterations continues until it reaches 0.05 in the final iteration. On the contrary, the crossover probability decreases as the number of iterations increases. This probability decreases from 0.9 in the first iteration of the NSGA-II to 0.5 in the last iteration. This dynamic parameter tuning for crossover and mutation rates improves the exploration and exploitation phases in the NSGA-II.

Table 6
Parameters of the proposed hybrid approach.

Step	Measurement	Description
Formation of antecedent part of a fuzzy rule	Eq. (3)	Degree of consistency of an input part of an experimental pattern with associated linguistic term of same input in a antecedent part of a fuzzy rule
Data mining (formation of consequent part of a fuzzy rule)	Compatibility	Definition 4.1
	Confidence	Definition 4.2
	Support	Definition 4.3
DEA	Additive model	Select all pareto-efficient fuzzy rules according to input factors (i.e. compatibility, confidence, and support)
NSGA-II	Number of fuzzy rules: each chromosome contains 15 rules Number of individuals: 50 rule sets (chromosome) Generation number: 4000 iteration DC probability: 0.5–0.0001 $\times$ I); where I is number of iterations Cross probability: (0.9–0.0001 $\times$ I); where I is number of iterations Mutation probability: min{(0.01 + 0.00001 $\times$ I), 1/n}; where I is number of iterations and n is number of rules in rule set Training data: 70% of experimental patterns; training data: 30% of experimental patterns UB: 40, maximum number of allowed fuzzy rules in a fuzzy set	

5.2. Software and hardware implementation

The data mining model and the NSGA-II algorithm are coded in the VB 6.0 programming environment. The DEA model is formulated and solved using the LINGO 12.0 software. The hybrid approach is executed on a Pentium IV PC with Core 2 duo CPU, 2 GHz, and Windows XP using 1 GB of RAM.

5.3. Interpreting the results

In the proposed FRB, the number of rules in the rule set was set to be minimized and the accuracy of the prediction was set to be maximized, concurrently. The experimental patterns were divided into the training and testing sets. The initial KB was formed using the training data. The compatibility, confidence, and support metrics were calculated for 1470 initial fuzzy rules and 45 rules were selected. This rule-reduction procedure decreased the accuracy and increased the interpretability. Model (7) was run for the 45 selected rules. Ten rules were determined as Pareto-efficient fuzzy rules. Table 7 presents the results of model (7).

Fifty fuzzy rule sets with 15 fuzzy rules were formed as follows: Ten rules were selected through the DEA approach. The remaining five rules were randomly selected among the top-ranked compatible fuzzy rules. Each of these fifty rule sets was treated as a chromosome of the Pittsburgh approach in the NSGA-II algorithm. After running the NSGA-II algorithm, different non-dominated sets of fuzzy rules were achieved. Some graphs were used to analyze the trade-off among different aspects of accuracy-interpretability for the resulting non-dominated fuzzy rule sets. Fig. 7 presents the relation between the number of rules in the rule set with the MSE value. The number of rules in the rule set illustrates high-level interpretability (certainly readability) of an FRB. The MSE is reserved for the accuracy of an FRB.

This figure demonstrates, as the number of rules in the rule set increases, the MSE value decreases. Some noises, which violate the aforementioned finding, can be identified (e.g., see number 9 in Section (a) of Fig. 7). These violations are the result of (1) the fact that a non-dominated fuzzy rule set in this study is achieved considering three objectives; and (2) the fact that the other objective is the average length of rule in the rule set. There is no evidence that a rule set with a lower number of rules also has a lower average length of rules. Therefore, although the two-dimensional graphs are suitable for representing the trade-offs between the objectives, they cannot be a suitable reference for non-dominance recognition. The second one concerns the rules that are selected from compatible random fuzzy rules in favor of a better exploration. The readability-accuracy trade-off is also depicted in Fig. 7 for both the training and the testing data. It is clear that the training data set have smaller MSE in comparison with the testing data. The exception in this case can also be contributed to the two reasons discussed earlier.

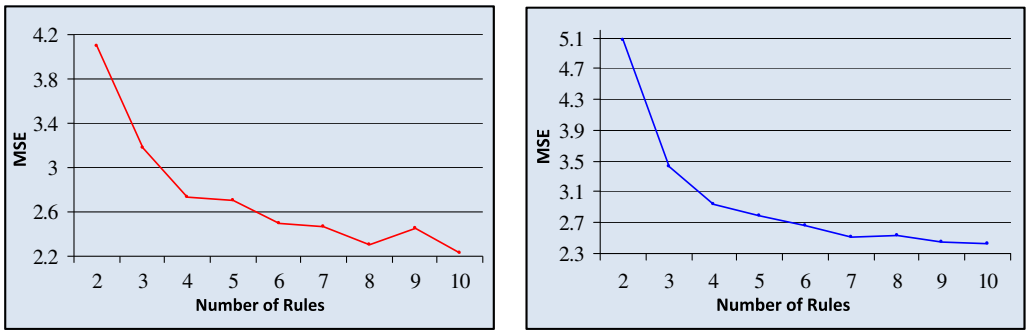
Fig. 8 plots the other indicators of readability and MSE for the training and testing data. In this figure, as the total rule set length increases, the MSE value decreases. Although exceptions can be also found in this case, the MSE measurements usually obtain smaller values for a certain total rule length in the training patterns.

Non-dominated fuzzy rule sets are studied in Fig. 9. In the resulting non-dominated fuzzy rule sets, rule sets with two rules and rule sets with five rules had the first and second highest frequency. Therefore, it can be concluded that these rules contain a large amount of knowledge concerning the Pareto front of the problem and analyzing them can reveal interesting information.

Section (a) in Fig. 9 presents the trade-off between the average rule lengths in all rule sets with two rules and the MSE value for both training and testing patterns. Section (b) in Fig. 9 presents the trade-off between the average rule lengths in the rule sets which have five rules and the MSE value for both the training and the testing patterns.

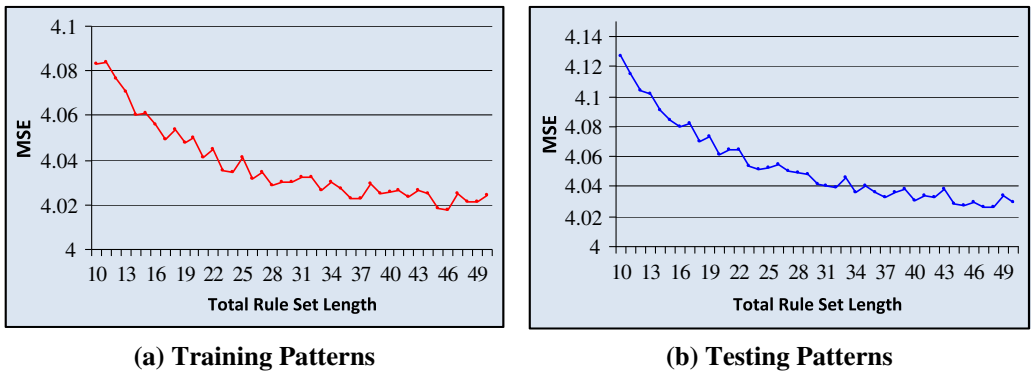
Table 7
Efficient fuzzy rules identified by additive model (7).

Fuzzy rule (DMU)	Output			Input	S^+_{rp}			S^-_{ip}	Objective value
	Confidence (%)	Support (%)	Compatibility		S^+_{1p}	S^+_{2p}	S^+_{3p}	S^-_{1p}	
DMU_1	1.78	56.93	0.004780	1	1.78	2.11	2.63	0.00	6.52
DMU_2	2.07	52.65	0.000541	1	56.93	44.01	26.91	0.00	127.85
DMU_3	2.92	39.29	0.000047	1	0.00	0.01	0.01	0.00	0.02
DMU_4	2.49	53.77	0.003898	1	2.07	2.32	2.16	0.00	6.55
DMU_5	2.21	55.83	0.003968	1	52.65	31.66	27.27	0.00	111.58
DMU_6	**2.02**	**43.04**	**0.000102**	**1**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
DMU_7	2.88	32.39	0.000226	1	2.92	2.43	2.68	0.00	8.03
DMU_8	2.37	23.57	0.027695	1	39.29	29.46	42.32	0.00	111.07
DMU_9	**2.50**	**32.04**	**0.005935**	**1**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
DMU_{10}	2.61	19.57	0.005734	1	2.49	2.82	2.99	0.00	8.30
DMU_{11}	2.99	31.39	0.000476	1	53.77	42.17	23.37	0.00	119.31
DMU_{12}	**2.34**	**45.28**	**0.000003**	**1**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
DMU_{13}	2.72	41.49	0.001639	1	2.21	2.28	2.63	0.00	7.12
DMU_{14}	2.78	24.78	0.003211	1	55.83	11.28	19.19	0.00	86.30
DMU_{15}	**2.17**	**18.72**	**0.000014**	**1**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
DMU_{16}	2.11	44.01	0.012739	1	2.02	2.66	2.50	0.00	7.18
DMU_{17}	2.32	31.66	0.000693	1	43.04	32.24	48.32	0.00	123.60
DMU_{18}	**2.43**	**29.46**	**0.000128**	**1**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
DMU_{19}	2.82	42.17	0.000430	1	2.88	2.49	2.33	0.00	7.70
DMU_{20}	2.28	11.28	0.002583	1	32.39	13.94	14.06	0.00	60.39
DMU_{21}	**2.66**	**32.24**	**0.000012**	**1**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
DMU_{22}	2.49	13.94	0.000670	1	2.37	2.04	2.70	0.00	7.11
DMU_{23}	2.04	54.28	0.000358	1	23.57	54.28	19.14	0.00	96.99
DMU_{24}	2.02	11.83	0.000227	1	0.03	0.00	0.00	0.00	0.03
DMU_{25}	2.87	53.66	0.009559	1	2.50	2.02	2.67	0.00	7.19
DMU_{26}	2.79	56.85	0.000571	1	32.04	11.83	17.14	0.00	61.01
DMU_{27}	2.91	11.23	0.000010	1	0.01	0.00	0.00	0.00	0.01
DMU_{28}	2.40	57.83	0.003062	1	2.61	2.87	2.24	0.00	7.72
DMU_{29}	2.29	57.63	0.000010	1	19.57	53.66	32.19	0.00	105.42
DMU_{30}	2.44	46.48	0.002315	1	0.01	0.01	0.00	0.00	0.02
DMU_{31}	2.63	26.91	0.000803	1	2.99	2.79	2.68	0.00	8.46
DMU_{32}	2.16	27.27	0.000005	1	31.39	56.85	22.83	0.00	111.07
DMU_{33}	2.68	42.32	0.000018	1	0.00	0.01	0.00	0.00	0.01
DMU_{34}	2.99	23.37	0.001049	1	2.34	2.91	2.85	0.00	8.10
DMU_{35}	2.63	19.19	0.001299	1	45.28	11.23	16.30	0.00	72.81
DMU_{36}	**2.50**	**48.32**	**0.000001**	**1**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
DMU_{37}	2.33	14.06	0.000275	1	2.72	2.40	2.85	0.00	7.97
DMU_{38}	2.70	19.14	0.000878	1	41.49	57.83	50.49	0.00	149.81
DMU_{39}	**2.67**	**17.14**	**0.000452**	**1**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
DMU_{40}	2.24	32.19	0.004104	1	2.78	2.29	2.73	0.00	7.80
DMU_{41}	2.68	22.83	0.000314	1	24.78	57.63	38.77	0.00	121.18
DMU_{42}	**2.85**	**16.30**	**0.000333**	**1**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
DMU_{43}	2.85	50.49	0.004378	1	2.17	2.44	2.32	0.00	6.93
DMU_{44}	2.73	38.77	0.002224	1	18.72	46.48	32.62	0.00	97.82
DMU_{45}	**2.32**	**32.62**	**0.001532**	**1**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**



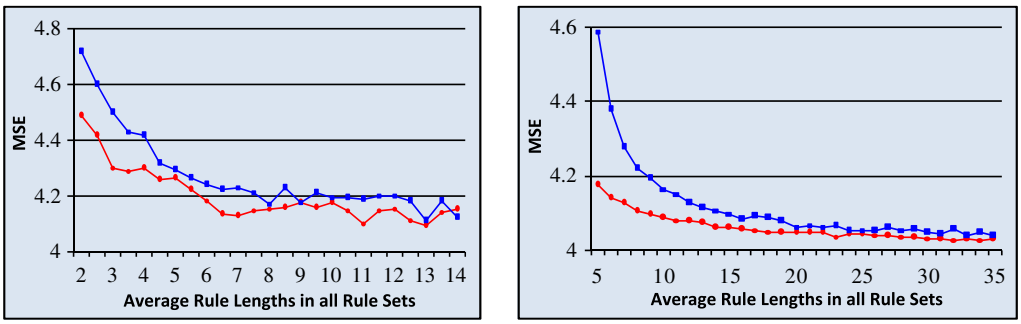
(a) Training Patterns **(b) Testing Patterns**

Fig. 7. Number of rules in the non-dominated rule sets vs. the MSE.



(a) Training Patterns **(b) Testing Patterns**

Fig. 8. Total rule set length of the non-dominated rule sets vs. the MSE.



(a) Rule sets with 2 rules **(b) Rule sets with 5 rules**

Training Patterns-Testing Patterns **Training Patterns-Testing Patterns**

Fig. 9. Average rule length in the non-dominated rule sets vs. the MSE.

As shown in Section (a) and Section (b) in Fig. 9, as the average rule lengths in all rule sets increases the MSE measurement decreases for both the training and testing patterns. The random noises and exceptions may also be seen in both sections. Although the exceptions are visible, the MSE value usually takes lower values for the training patterns in both sections of Fig. 9. It is notable that the lower and upper bounds of the MSE has generally taken smaller values in Section (b) of Fig. 9 which presents the behavior of the rule sets with five rules. Fig. 10 shows the interface for a representative non-dominated fuzzy rule set with five rules modeled with MATLAB software.

5.4. Testing the results

An additional analysis was carried out for the rule sets with five rules and the rule sets with two rules. The trade-off of the number of fired rules as an indicator of comprehensibility and the MSE value is analyzed for these rule sets. Fig. 11 presents the results from this analysis for both rule sets with two rules and rule sets with five rules. Section (a) in Fig. 11, which refers to the rule sets with two rules, presents the trade-off between the average number of the fired rules and the MSE value. As shown in this figure, when the average number of fired rules in the rule set with two rules increases, the MSE decreases for both the training and testing patterns. Negligible noise could also be observed. In general, the MSE for the training data is smaller than the MSE for the testing data. Section (b) in Fig. 11 presents the same information for the rule sets with five rules.

Although the detection of existing relations between different aspects of high-level interpretability of the FRBS requires more controlled and designed experiments, the results in this section support the following hypothesis. Generating non-dominated fuzzy rule sets based on some predefined aspects of interpretability (i.e. the number and the length of fuzzy rules in a rule set-which are indicators of the readability of the FRB) may affect other aspects of interpretability (i.e. the average number of fired rules – which is an indicator of the comprehensibility of the FRB).

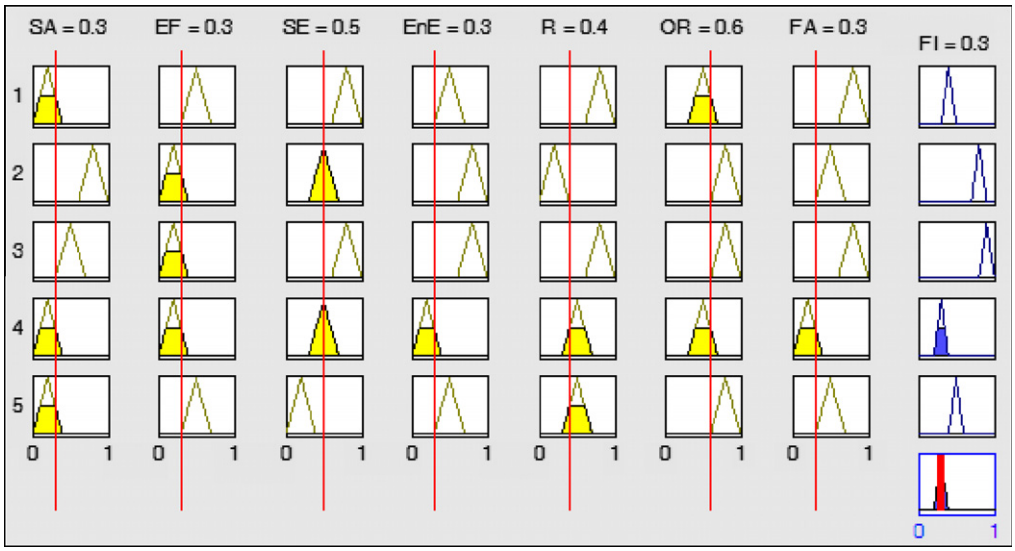
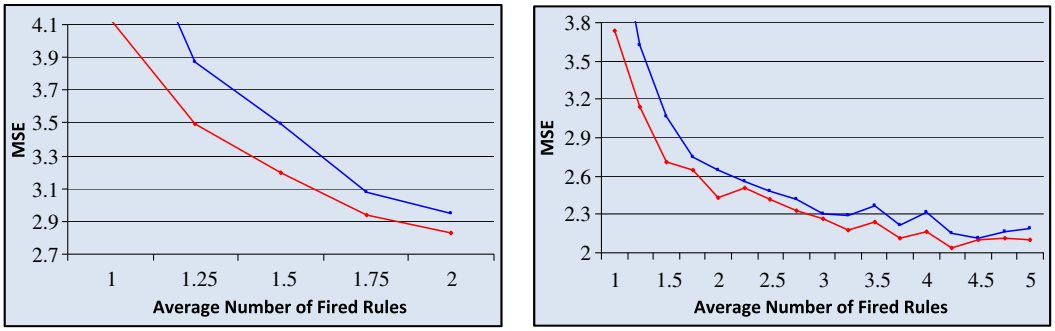


Fig. 10. Representative non-dominated fuzzy rule set with five rules.



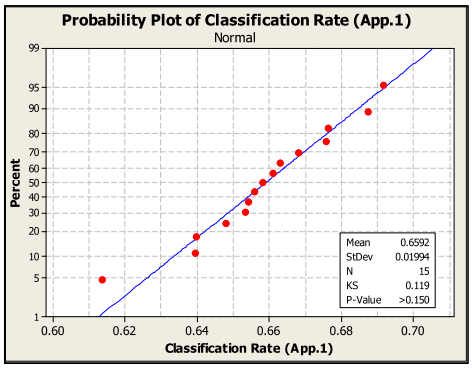
(a) Rule Sets with 2 Rules
Training Patterns-Testing Patterns

(b) Rule Sets with 5 Rules
Training Patterns-Testing Patterns

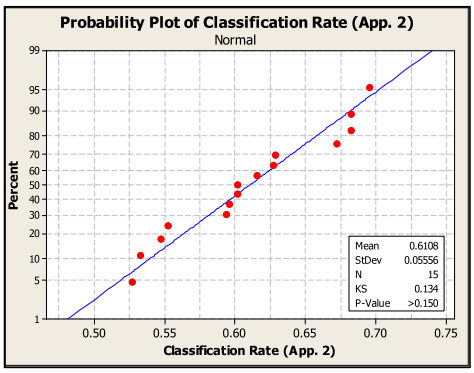
Fig. 11. Number of fired rules in the non-dominated rule sets vs. the MSE.

Table 8
Resulting measures for different approaches on the test data.

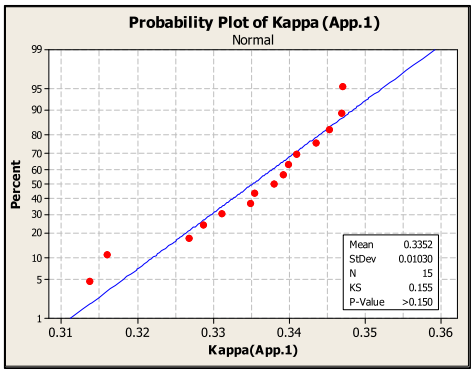
Run	Accuracy measures				Interpretability measures			
	Classification rate		Kappa		Size		ANT	
	App.1	App.2	App.1	App.2	App.1	App.2	App.1	App.2
1	0.6534	**0.6728**	**0.3399**	0.2231	**9.41**	11.75	**4.19**	6.50
2	**0.6611**	0.5525	**0.3311**	0.2622	**11.04**	11.64	**4.39**	6.45
3	**0.6631**	0.5942	**0.3355**	0.2331	**11.26**	10.11	**4.22**	6.09
4	0.6138	**0.6830**	0.3269	**0.3549**	**12.13**	12.06	**4.97**	6.02
5	**0.6759**	0.5268	0.3453	**0.3497**	**8.80**	10.38	**4.54**	6.42
6	0.6684	**0.6828**	0.3469	**0.3506**	10.71	**10.11**	**4.64**	6.82
7	**0.6766**	0.5474	**0.3160**	0.2987	**9.62**	10.44	**4.42**	6.60
8	**0.6544**	0.6293	**0.3349**	0.2545	12.74	**10.77**	**4.62**	6.51
9	**0.6398**	0.6024	**0.3393**	0.2638	**11.94**	12.56	**4.78**	6.45
10	**0.6480**	0.5333	**0.3471**	0.3101	**12.54**	11.47	**4.61**	6.71
11	**0.6582**	0.6023	**0.3410**	0.2189	**10.76**	11.51	**4.62**	6.03
12	**0.6397**	0.6157	**0.3380**	0.3074	**9.12**	10.71	**4.05**	6.63
13	0.6561	**0.6957**	**0.3138**	0.2063	12.12	**10.85**	**4.92**	6.83
14	**0.6877**	0.5962	**0.3436**	0.2336	**9.02**	10.67	**4.52**	6.75
15	**0.6917**	0.6277	**0.3287**	0.2213	**9.48**	11.45	**4.34**	6.57
Mean	0.6592	0.6108	0.3352	0.2725	10.71	11.10	4.52	6.49
SD	0.0200	0.0556	0.0103	0.0521	1.3825	0.7388	0.2599	0.2659



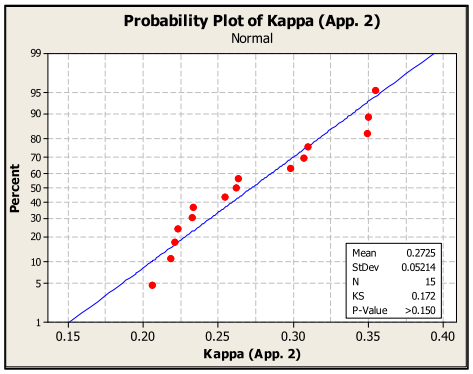
(a) Normality test for classification rate of approach 1



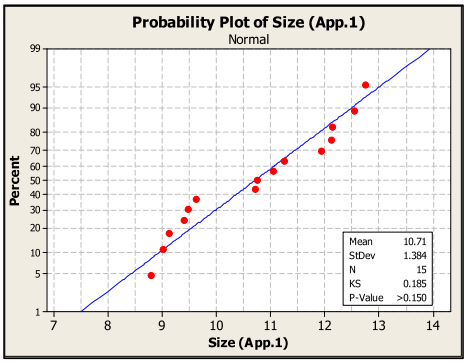
(b) Normality test for classification rate of approach 2



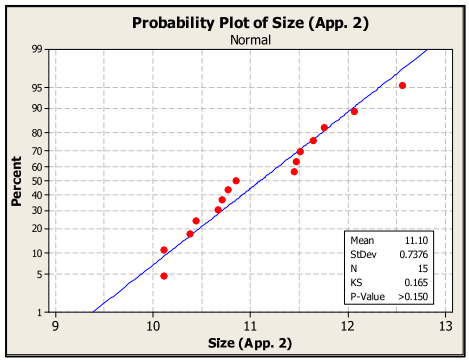
(c) Normality test for Kappa of approach 1



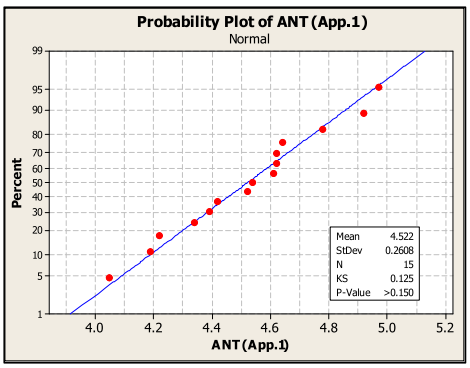
(d) Normality test for Kappa of approach 2



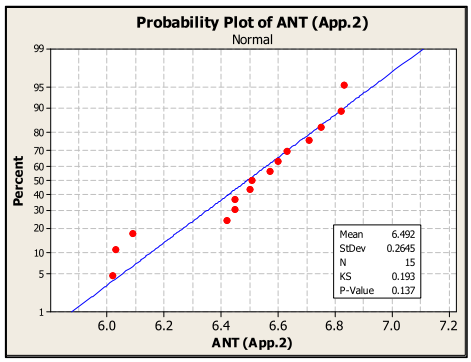
(e) Normality test for size of approach 1



(f) Normality test for size of approach 2



(g) Normality test for NT of approach 1



(h) Normality test for ANT of approach 2

Fig. 12. Normality tests for accuracy and interpretability measures.

Table 9
Analysis of variance.

Source	Degree of freedom	Sum of square	Mean square	*F*	*p*-Value
I. First measure: classification rate					
App. 1	1	0.000247	0.000247	0.73	0.400
Error	28	0.009463	0.000338		
Total	29	0.009709			
S = 0.01838 R-Sq = 2.54% R-Sq (adj) = 0.00%					
II. Second measure: kappa					
App. 1	1	0.02944	0.02944	20.85	0.000
Error	28	0.03954	0.00141		
Total	29	0.06898			
S = 0.03758 R-Sq = 42.68% R-Sq (adj) = 40.63%					
III. Third measure: size					
App. 1	1	1.12	1.12	0.91	0.349
Error	28	34.44	1.23		
Total	29	35.56			
S = 1.109 R-Sq = 3.14% R-Sq (adj) = 0.00%					
IV. Fourth measure: ANT					
App. 1	1	29.1067	29.1067	421.91	0.000
Error	28	1.9317	0.0690		
Total	29	31.0384			
S = 0.2627 R-Sq = 93.78% R-Sq (adj.) = 93.55%					

5.5. Statistical techniques for single data-set analysis

Statistical analysis is performed to compare the performance of the proposed approach with the performance of a Genetic Based Machine Learning (GBML) approach based on single data-set analysis [36]. Both approaches described below utilized the real data from the IFCF study:

- *Proposed hybrid approach (App. 1).* The proposed approach is based on fuzzy rule formation, data mining, DEA, accuracy-interpretability index, and NSGA-II algorithm.
- *GBML approach (App. 2).* The GBML approach is based on fuzzy rule formation, accuracy-interpretability index, and NSGA-II algorithm.

5.5.1. Comparative metrics

The accuracy and interpretability metrics were selected from García et al., [36]. Since the output of our approach suggests seven distinguishable levels for risk of investment, it can be assumed to be a multi-class classification machine learning procedure with the following accuracy measures [36]:

- *Classification rate:* The number of successful hits relative to the total number of classifications.
- *Cohen's kappa:* An alternative to the classification rate, a method that compensates for random hits.

The main difference between the classification rate and Cohen's kappa is the scoring of the correct classifications. Classification rate scores all the successes over all classes, whereas Cohen's kappa scores the successes independently for each class and aggregates them. The second scoring method is less sensitive to the randomness caused by different number of examples in each class [36].

In addition, the following interpretability measures were also considered [36]:

- *Size:* A measure that considers the number of rules. Reducing the size of the model increases the interpretability by the user.
- *Average number of antecedents (ANT):* The sum of the antecedents in all the rules of the rule set divided by the number of rules in the rule set.

Table 8 presents the results of these accuracy and interpretability measures over all 630 test data.

5.5.2. Analyzing the metrics

The Kolmogorov–Smirnov normality test was used to study the behavior of the metrics in Table 8. The results are shown in Fig. 12.

There is no evidence to reject the normality behavior of the metrics. Parametric statistical analysis, Analysis of Variance (ANOVA), is considered to check whether there is a significant difference between the performances of both approaches. The

confidence level of the test was set to 95%. The MINITAB 15.0 software was used to perform all the necessary calculations. ANOVA tests were performed for 15 different metrics. The results are presented in Table 9.

5.5.3. Interpreting the results of ANOVA

- *Classification Rate Measure.* According to the *p*-value for the classification rate, there is not enough evidence to reject the null hypothesis of equal classification rates for App.1 and App.2.
- *Kappa Measure.* According to the *p*-value for the Kappa, there is enough evidence to reject the null hypothesis of equal Kappa for App.1 and App.2. This can be interpreted as the compensating attribute of Kappa for random hits.
- *Size Measure.* Similar to the classification rate there is not enough evidence to reject equality of size for App.1 and App.2.
- *ANT Measure.* The *p*-value for the ANT is enough evidence to reject the equality of the ANT measures for App.1 and App.2.

Finally, we can conclude that the mean values of the metrics in App.1 represent a relative dominance in comparison with the same metrics in App.2.

6. Conclusions and future research directions

In this paper, a hybrid approach was proposed to design accurate-interpretable FRBs for sustainable project portfolio selection. The proposed approach utilized data mining, evolutionary algorithms, and DEA for optimum design of an FRB. The conceptual model proposed for the sustainable project portfolio selection contained several financial and non-financial factors. The FRB was organized using a KB equipped with a RB and a DB. The DB was formed by gathering the opinions of experts in the fields of project selection, investment, and finance. The data mining approach was used to determine the associated fuzzy rule sets from experimental patterns. An additive DEA model was utilized to select the Pareto-efficient fuzzy rules. The combination of the Pareto-efficient fuzzy rules and some compatible random fuzzy rules formed the initial FRB for further consideration.

The interpretability and accuracy of the FRB were considered. Interpretability was defined in different levels through several objectives. A well-known MOEA, called NSGA-II, was then customized and used to generate different non-dominated fuzzy rule sets considering the trade-off between interpretability and accuracy of the FRB system. The interpretability and accuracy of the resulting non-dominated fuzzy rule sets were analyzed with several metrics. The metrics represented different aspects of interpretability including readability and comprehensibility.

The interpretability and accuracy of the resulting FRB system were analyzed through a series of controlled statistical experiments. The performance of the proposed approach and a GBML approach were compared according to the aforementioned metrics. The statistical analysis revealed the performance dominance of the proposed hybrid framework over the GBML method based on selected accuracy and interoperability measures.

Future work is needed to investigate the applicability of the approach proposed in this study to other business and engineering applications. A stream of future research can extend our method by developing other hybrid approaches. We hope that the study presented here can inspire others to pursue further research in this area.

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