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A Combined Fuzzy Multi-Criteria Decision Making Framework for Evaluation of Islamic Banks: A Case of MENA Region

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A B S T R A C T

In this paper, we propose an empirical hybrid approach for measuring the performance of Islamic banks in MENA region by combination of four techniques including CAMEL, Grey Relation, fuzzy ANP, and FARAS during two three-year periods (from 2014 to 2019). Our findings that also considered as our contributions are as follows: firstly, this approach excludes indicators that overlap each other from the evaluation process (parsimony). secondly, it prevents the removal of important indicators (generosity). Thirdly, we have compared three most popular MCDM techniques and have shown which ones give us the best ranking results. Finally, we also improve the application of CAMEL model.

1. Introduction

In recent years, the analysis of Islamic banks has attracted the attention of different beneficiaries. Some reasons can be identified behind this: first, the increase in the number of banks and branches; second, the emergence of new financial products and services and the related risks; third, the increase in the number of bankrupt banks due to their bad financial situations during the recent international financial crisis. Therefore, precise and reliable assessment models can help beneficiaries evaluate the performance of banks. These causes provide us with the compelling motivation to propose an empirical synthetic approach for Islamic banks' performance evaluation. In the literature, many studies are realized by different methods to measure bank performance. While the newer methodologies are created, the more they need for such studies is growing. Many performance measurement models have been developed to evaluate bank performance. These methods can be classified into four categories: (1) traditional ratios; (2) parametric models; (3) non-parametric techniques; and (4) integrated systems for performance evaluation. The first category of performance measurement approaches has been studied by [60, 83, 35]. It is the most commonly used category to evaluate banking performance because banks that report better financial ratios tend to attract a larger share of deposits and borrowers. Lau & Sholihin [60] are critical of ratio analysis because the ratios are lagged indicators and do not provide effective

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results when dealing simultaneously with multiple criteria [35]. An alternative to these ratios is the use of parametric or econometric models. These models are intrinsically related to statistical distributions and well-known mathematical techniques that obey certain parameters to achieve optimum solutions (e.g., linear regression, correlation analysis, and factor analysis). For instance, ordinal regression analysis was proposed as a means for evaluating banking performance over multiple attributes in the presence of non-monotonic preferences in research conducted by [99]. Plenty of such methodologies exist in the performance assessment literature within different contexts (see, for instance, [79]). However, the parametric models have been criticized because they require a prior definition of a production function and seek to optimize it. Thus, they are based on pure objectivism and only seldom consider the possibility that optimum solutions may not exist. Additionally, parametric and econometric models do not always explore well the causal relations between factors, albeit such relations are increasingly important in bank branch performance evaluation [35]. For instance, [70, 46, 69] studies on Islamic banking evaluation are included in this classification. Non-parametric techniques compose the third category used to evaluate bank performance. This category of methodologies addresses some of the limitations identified in the two previous categories. One of the most popular non-parametric techniques is data envelopment analysis (DEA), introduced by [17]. It has been widely and successfully used for bank efficiency measurement (see [1, 41, 52, 19, 44, 15, 91, 92]). An interesting feature of DEA is that it can apply multiple input and output variables without requiring any specification of a cost or production function. Demir & Astarcıoglu [12, 26] considered Turkish commercial banks' performance with DEA by considering their total commercials, interest income and expenses, credits granted by them, and non-interest income and expenses. Using the DEA method, Mercan et al. [66] examined the impact of banks' ownership and growth regarding their performance with the selected financial ratios. Lin and Zhang [62] have examined the impact of ownership on bank performance through DEA. However, DEA does have its shortcomings despite its strengths and widespread use. For example, standard DEA models attribute all deviations from the frontier to inefficiency, ignoring the data's stochastic noise. Furthermore, DEA accepts the possibility of fully characterizing the production function, even knowing that some outputs are not easily measurable [35]. Integrated systems for performance evaluation compose the fourth category of methods; they result from the dissatisfaction shown towards the last three categories. For instance, [39] used the AHP method as an alternative to DEA in measuring bank performance and examined the relationship between financial and operating performance. Albayrak & Erensal [4] analyzed the financial and non-financial performance criteria for Turkish banks' performance evaluation using fuzzy AHP. Arjomandi et al. [6] investigated the efficiency and productivity growth of the Iranian Islamic banking industry between 2003 and 2008, encompassing reforms related to the period before and after 2005. This study is the first to use a complete decomposition of the Hicks-Moorsteen TFP index to analyze efficiency and productivity changes in the banking context. The balanced scorecard (BSC) [53] is perhaps the most well-known integrated system for performance evaluation. Nonetheless, the BSC has not been much explored in the banking context; in fact, it has been criticized for oversimplification and for not specifying how trade-offs among performance criteria are made explicit [35]. Some criticism has been mentioned relating to the four categories of methodologies. Jahanshahloo et al. [50, 15] argued that the method by which performance measures are often selected could lead to the omission of important criteria, resulting in a lack of transparency how weights among criteria are calculated. This paper will try to put forward a synthetic approach to make up for this inefficiency. In general, our goal in this article is to provide a synthetic model for evaluating the Islamic bank's performance. This hybrid model uses a combination of a suitable filtering method (Grey method), a comprehensive banking supervision method (CAMEL), and an appropriate ranking and decision-making method (FARAS, FVIKOR, or FTOPSIS) to evaluate the performance of a banking system. Therefore, by proposing such a combination we are going to increase the accuracy, to keep the number of criteria less (parsimonious selection), to increase the speed and the simplicity in selection and evaluation process. Islamic banking, or Sharia-compliant finance is banking or financing activity that complies with Islamic law [55]. Some of the modes of Islamic banking/finance include Wadiah (safekeeping), Musharaka (joint venture), Mudarabah (profit-sharing and loss-bearing), and Ijara (leasing), Murabahah (cost-plus). The Islamic financial system has evolved into a practical and vigorous component of the global financial system, complementing the conventional financial system. The Islamic banking system which forms the infrastructure of the Islamic financial system plays a vital role in taking deposits and financing economic sectors to facilitate growth. Islamic banking based on Sharia prohibits riba, or usury, defined as interest paid on all loans of money. Over 300 banks and 250 mutual funds around the world complying with Islamic principles, and around $2 trillion was Sharia-compliant by 2014. Islamic financial institutions represented approximately 1% of total world assets, concentrated in the Gulf Cooperation Council (GCC) countries, Pakistan, Iran, and Malaysia [85].

Over the last two decades, the Islamic banking industry has experienced many substantial changes, such as liberalization, government regulation and technological advances, universal banking, which have resulted in the extensive restructuring of the industry and financial performance.

El-Ghattis [32] suggests some factors that have together contributed to the trend towards the adoption and growth of Islamic banking. The Islamic awakening and the return of people to religion is considered the primary driver of the resurgence of Islamic banking. This factor has affected all stages of the development of Islamic banking, from its inception until now. Second factor is demographic structure. The Persian Gulf region experienced a long baby boom between the 1970s and the 1990s. As a result, 29% of the GCC's population was under the age of 15 in 2008. There is broad dissatisfaction with social and economic conditions among young, varying in intensity from one country to another, even though some GCC countries' per capita incomes are among the highest in the world. The incessant indoctrination and preaching by Islamists to the young about the necessity of adhering to and practicing Islam, and the criminalization of engagement with conventional banks, and the necessity of supporting Islamic banks, had a considerable effect on the banking habits of the people, and the young in particular. Third factor is oil and gas industry. The prices of oil and gas have continued to increase since 1980s, and have provided high income and liquidity in the MENA region. This coincided with the Islamic renaissance. In fact, a portion of these funds has gone towards the Islamic banks, encouraging them profoundly. Media transparency and globalization is also greatly beneficial for the spread of Islamic banking and finance due to the variety and availability of means of exchanging data and information. The last factor is knowledge sharing. Several forums specializing in economics, banking and Islamic finance have been established [32].

The overall number of financial institutions reporting sharia assets rose from 395 to 402, with the majority of those (284) being standalone Islamic financial institutions. The Banker's 2020 Top Islamic Financial Institutions ranking highlights the continued growth of the industry, which has doubled in size over the past decade and has experienced a compound annual growth rate (CAGR) of around 10.8% since 2006 [40]. Globally, there are now 47 financial institutions with more than $10bn in sharia-compliant assets, up one from the year before, with 27 institutions recording a pre-tax profit of more than $500m in 2019. Most of these financial institutions are located in Islamic countries, especially in the Middle East and North Africa (MENA) region, including Iran, Saudi Arabia, Bahrain, Kuwait, the United Arab Emirates, Iraq, Jordan, Qatar, Egypt, etc. For this reason, our statistical sample in this research to test the proposed hybrid model is based on the data of 19 banks from the countries of this region.

This number of changes increases the need to evaluate the performance and check the effectiveness of the mentioned financial institutions in terms of their Islamic banking performance. In fact, the more the role of these Islamic financial institutions increases, the more accurate evaluation models must be used. The measurement criteria and the models for evaluating the Islamic banks' performance are based on the criteria and models used by other financial institutions around the world. The use of the CAMEL model, BIS evaluation models, and other international regulatory bodies evident in the banking system's performance evaluation is common in the Islamic banking evaluation system. Therefore, Islamic banking evaluation and supervision system can be considered based on the other conventional international financial institutions' standards with the difference that the criteria of Islamic Sharia regarding profit and loss and income of Islamic institutions are included in their financial statements. In this regard, researchers have conducted several studies [7, 68, 81, 10]. Hassanzadeh et al. [45] determined the importance of ordering parameters, measure their impact on supply chain dynamics in terms of total cost and the bullwhip effect when these parameters change simultaneously in the supply chain and provide a model for effective supply chain management.

This paper looks for a hybrid model, which can combine some mathematical and financial models to evaluate Islamic banking performance of the banks in the region. To do that, we need a competent sample providing us with the data needed to run the model. Our statistical sample consists of 19 out 24 Islamic banks from MENA region whose assets are over 5 billion dollars in 2019.

We contribute to the Islamic banking performance evaluation literature by showing how precisely the integrated use of Grey Relation, fuzzy ANP, and FARAS techniques can support selecting evaluation criteria and deal with the trade-offs among the decision criteria CAMEL-based assessment model. This paper addresses the following research questions: How using the Grey Relation technique, will help choosing the best representative criteria from the CAMEL model so that the criteria with overlapping effects be omitted, and the highly important criteria be kept? Which one of the multi-criteria decision-making models amongst FVIKOR, FTOPSIS, and FARAS is preferable for rating Islamic bank performance? How close are the results of these three methods? What would be the results of applying our synthetic approach to the MENA region Islamic banking as a case? These results may provide some helpful information to different beneficiaries for investment and financial decision-making. For instance, bank managers could apply this approach instead of simple methods without comprehensive insight. Stakeholders may apply it to fundamentally analyze the region Islamic banks' performance (we mean the capital market's fundamental analysis) [42].

In general, the economic result of presenting this synthetic model is that First, instead of calculating a multitude of indicators, it provides an easier method for managers to make financial decisions by more important indicators and determine the parsimonious number of indices in their economic judgments about Islamic banking performance. Second, using a more efficient decision-making model, as introduced in section 2.4, banks' ranking would be more accurate, more reliable, and less based on personal judgment, which is a big challenge for Islamic financial institutions' daily affairs. Third, this paper paves the way for other researchers to provide more efficient methods by analyzing the sensitivity analysis and testing other hybrid models. Finally, the overall CAMEL rating determines whether an Islamic bank will be placed on the problem list (overall CAMEL rating of 4 or 5). The problem list receives much attention; The list is frequently referenced in the news media [16]. It is important to have a concise, accurate, and reliable model to evaluate Islamic financial institutions.

This article does not intend to evaluate the CAMEL model's effectiveness or to provide another model like it because international financial regulatory agencies empirically validate this model and many similar models. However, the purpose of combining CAMEL with a filtering model and a ranking model is to help increase the speed and the accuracy of the evaluation process, prevent using overlapping indicators, and prevent omitting the important indicators in evaluations and thus a more accurate comparative evaluation by regulators in an Islamic banking system.

In brief, this paper is organized as follows: Section 2 provides a brief theoretical background of our synthetic approach components, including some consecutive steps: rating framework selection, criteria clustering and selection, weight determination method selection, and multi-criteria decision-making method selection. In Section 3, we describe our synthetic methodology based on Section 2 selections, including the CAMEL model, Grey Relation clustering method, fuzzy ANP weight determination method, and FARAS as the latest decision-making technique. In Section 4, we will evaluate our sample consists of the 19 Islamic banks in MENA region through our proposed synthetic model and compare their ranking by FARAS, FVIKOR, and FTOPSIS methods. Finally, we discuss conclusions in Section 5.

2. Theoretical Background

a. Rating Analytical Frameworks

The classic approach to bank analysis can be greatly facilitated by placing it within a framework. Moody's rating agency has summarized using the acronym CAMEL (capital, asset quality, management quality, earnings, and liquidity). CAMEL has lately loaded up on new options, with CAMEL B-COM in the UK (for CAMEL¬ + ¬Business¬ + ¬Commercial Organization and Management Risk) and CAMELOT in the USA (CAMEL + Operating + Treasury). It may just be a matter of time before JOE CAMEL makes an appearance (Just in time Operational Equilibrium+ CAMEL). The Bank of England has already developed its new CAMEL B-COM risk framework (capital, assets, market risk, earnings, liquidity, business risk and control, organization, and management), following the Arthur Andersen Report. It reviewed its supervisory practices after the collapse of Barings in 1995. The objective is to identify and measure the main risk categories of risk (on both a quantitative and qualitative basis) and generally to set the total risk generated by a particular firm (its CAMEL B) against its control or management capability (COM). As can be observed in all the rating frameworks, the CAMEL part is the main component. Therefore, we take this part as a framework for selecting the criteria of our research. In Sub-section 3.2, we describe the CAMEL rating framework as a global standard model for assessment of Islamic banks.

b. Clustering Methods

In order to cluster and select CAMEL criteria representatives, we need a clustering method. There are different ways of clustering, and clustering algorithms may be broadly classified as the listed ones below [64]:

Table 1. Clustering methods

Hierarchical	Single linkage, Complete linkage, Group average linkage, Median linkage, Centroid linkage, Ward's method, balanced iterative reducing and clustering using, hierarchies (BIRCH), clustering using representatives (CURE), Robust clustering using links (ROCK)
Squared Error-Based (Vector Quantization)	K-means
Fuzzy	Fuzzy-means (FCM), Mountain method (MM), Possibilistic means clustering algorithm (PCM), Fuzzy shells (FCS)
Neural Networks-Based	Learning vector quantization (LVQ), Self-organizing feature map (SOFM), ART,
Kernel-Based	Kernel-means
Data visualization/High-dimensional data	Iterative self-organizing data analysis, technique (ISODATA), Genetic-means algorithm (GKA), Partitioning around medoids (PAM)

Methods including cluster analysis, discriminant analysis, factor analysis, principal component analysis, Grey Relation analysis (clustering using representatives) [27], and Kernel means [8, 56] are commonly used. Cluster analysis, factor analysis, and principal component analysis are often used in classical statistical cases such as large samples or long-term data. Although there is a set of clustering methods from old to recent (Table 1), clustering using representatives (CURE) and Kernel tools prefers to deal with a small sample or short-term data. Since most financial ratios are short-term data, classic statistical methods cannot cluster them. Therefore, we apply the Grey Relation method to cluster and select representative indicators because our sample, the Islamic banking in MENA region, is small, with 19 members. Our data consists of Islamic banks' short-term performance presented with the number sequences of the representative criteria from 2014 to 2019. This method will be described in Sub-section 3.3.

c. Weighting Criteria Method

After criteria selection based on the CAMEL model and clustering by the Grey Relation method, we should determine the criteria's weights by using a technique. In the literature, different weighting methods have been proposed to attribute weights to the criteria [74]. Attributing weights to the multi-criteria evaluation method's criteria is an important step, as final results of the multi-criteria decision-making method largely depend on such weights. Tervonen [84] stated that weight attribution to the criteria in an MCDM approach is the most difficult task. A weighting method's main purpose is to attach cardinal or ordinal values to different criteria to indicate their relative importance in a multi-criteria decision-making method. These values are then used by the MCDM method in subsequent evaluations of the alternatives. A classification of weighting methods based on internal and external types is shown in the figure below [96].

In another classification, Wang et al. [89] classified the rank-order method into three categories: subjective weighting method, objective weighting method, and combination weighting method. The subjective method determines criteria weights based on the preferences of the decision-makers. They include SMART, AHP, and ANP, SIMOS, and Delphi methods. The objective weights are obtained by mathematical methods based on the analysis of initial data. The objective weight procedure is unclear and includes the least mean square (LMS), minimax deviation, entropy, TOPSIS, and multi-objective optimization. The combination or optimal weighting methods are a hybrid of methods that include multiplication and additive synthesis. Owing to having weights attributed by 35 experts to the criteria in a pairwise comparison manner in our paper, we select the fuzzy ANP method. Moreover, this method could cover all trade-offs among criteria and possible (for more comparisons among different weighting methods, see [96]). Safari et al. [78] presented a compromise solution of interval VIKOR for evaluating and selecting the appropriate suppliers.

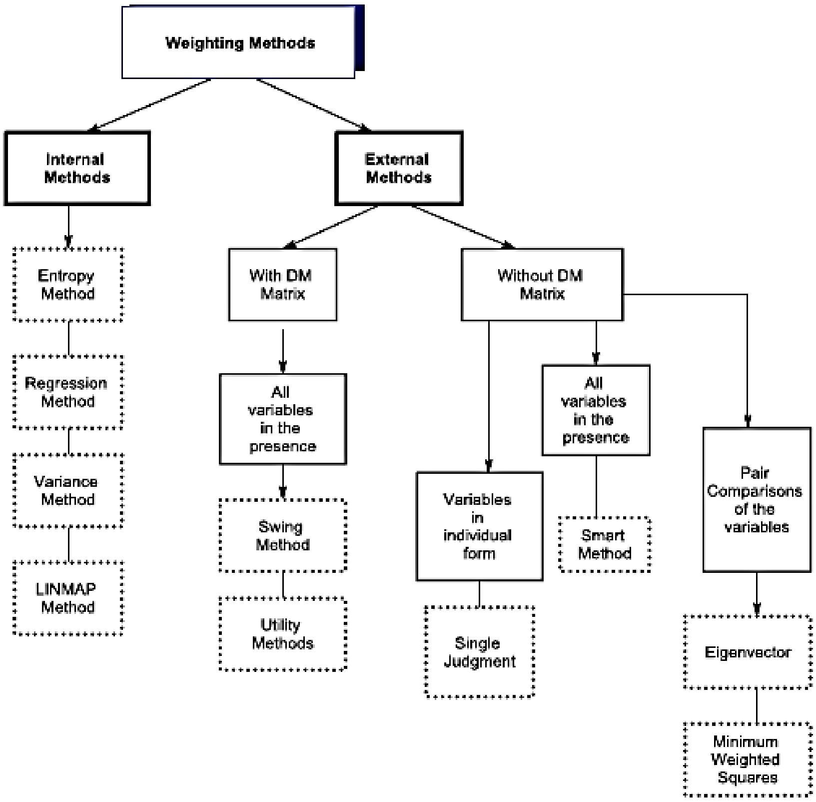

Figure 1. Schematic diagram of the weighting methods [96]

ANP considers the dependencies between elements in the same set (internal dependency) and the dependencies between elements in the different sets (external dependency). Interdependency shows that there is an interaction between the criteria within the same cluster. External dependency indicates that there is an interaction between the criteria in a different set. The fuzzy ANP method is explained more in Sub-section 3.4.

d. Multi-Criteria Decision-Making Method

We should complete our synthetic model by evaluating the Islamic banks' performance through an appropriate multi-criteria decision-making method. We apply a framework proposed by [2] to think of the methodology by choosing an appropriate MCDA method. Subsequently, we select the FARAS method among the other MCDM methods to evaluate the Islamic banks. We also compare the final results of the FARAS method with two others famous MCDM methods, FVIKOR and FTOPSIS. The FARAS method is described in Sub-section 3.5.

3. Methodology

Our methodology consists of five steps: 1) Criteria calculation based on the CAMEL rating system, 2) applying the Grey Relation technique to cluster criteria and select the representatives, 3) calculation of fuzzy weights based on experts' judgment and Fuzzy ANP technique, 4) creating the decision-making matrix, and 5) applying FARAS for the evaluation of the Islamic banks in comparison with FVIKOR and FTOPSIS methods (Figure 2).

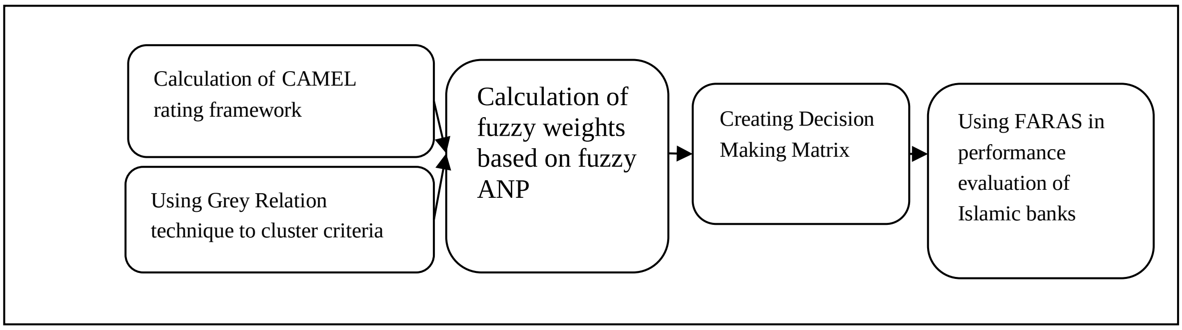

Figure 2. Methodology steps

e. Research Scope and Limitations

This study gathered some data on MENA region Islamic banks. The 24 biggest Islamic banks are shown in Table 2, and according to Cochran's sample size formula, we choose 19 out of 24 banks as our research sample. In addition, since some of the data of these banks had to be extracted from their financial statements one by one, some banks were removed from the sample and replaced with other banks due to the fact that their data was not available. We also have used the databases of Islamic Financial Services Board, World Bank, International Monetary Fund, Banker Institute, Statista website and central banks of these countries to complete our data. The data sequence in this research consists of a set of Islamic banks' performance data during three years from 2014 to 2016 for the Grey Relation technique and six years from 2014 to 2019 for comparing FARAS, FTOPSIS, and FVIKOR—which is shown based on fuzzy triangular numbers.

Table 2. The biggest Islamic banks in MENA region based on their asset amount until 2019

No.	Country	Bank	Asset bn$
1	Iran	Mellat bank	18
2		Parsian bank	7
3		Saderat bank	13
5		Tejarat bank	10
6	Saudi Arabia	Al Rajhi Bank	97
7		Alinma Bank	32
8		Bank AlBilad	19
9	UAE	Dubai Islamic Bank	60
10		Abu Dhabi Islamic Bank	34
11		Emirates Islamic Bank	15
12		Noor Bank	13
13		Sharjah Islamic Bank	12
14		Al Hilal Bank	11
15	Qatar	Qatar Islamic Bank	42
16		Masraf Al Rayan	26
17		Barwa Bank	12
18	Jordan	Jordan Islamic Bank	5
19	Kuwait	Kuwait Finance House	58
20		Boubyan Bank	15
21	Oman	Bank Nizwa	2
22	Bahrain	Al Baraka Banking Group	23
23		Ithmaar Bank	10
24	Egypt	Faisal Islamic Bank of Egypt	5

According to our model, we have selected ten criteria weighted by the fuzzy ANP model. To implement fuzzy ANP, we distributed a weighted questionnaire among 35 experts among top managers of Islamic banks and the finance and banking academics in the region. Ten out of thirty-five of them had filled out the questionnaires. The weight questionnaire comprises a table of pairwise comparisons of the selected criteria.

Like other research, this paper has some shortcomings, conditions, and influences that we cannot control, such as the variety of the weighting methods and the difficulty to select among them based on subjective characteristics. Moreover, this variety also exists in the MCDM methods that place restrictions on our methodology and conclusions. Besides, examining synthetic models in MENA region Islamic banks is troublesome because some banks don't disclose all their information in detail. The last restriction maybe refers to our research community. Since some research population members are risk managers and their jobs are too critical, the CFOs prevent us from reaching them to fill out the questionnaires.

f. CAMEL Rating System Model

To cope with the complexity and a combination of risk exposure to the banking system properly, responsibly, beneficially, and sustainably, it is absolutely important to evaluate the banks' overall performance by implementing a regulatory banking supervision framework. In 1979 the Uniform Financial Institutions Rating System (UFIRS) was implemented in US banking institutions and later globally, following a US Federal Reserve recommendation [33]. This system has become internationally known with the abbreviation CAMEL, reflecting five assessment areas: capital, asset quality, management, earnings, and liquidity ratios [5]. CAMEL rating has become a concise and indispensable tool for examiners and regulators' states [9]. This rating ensures a bank's health by reviewing the different aspects of a bank based on various information resources such as financial statements, funding sources, macroeconomic data, budget, and cash flow. The title of the method mentioned has been made out of the five components' initial letters a bank's performance is evaluated on its basis. These components are capital adequacy, asset quality, management quality, earnings, and liquidity. Each of these components has its indicators that are subject to measuring (Table 3).

Table 3. CAMEL Criteria

Categories (criteria)	Abbr.	Sub-criteria
Capital adequacy	C1	Capital Adequacy Ratio
	C2	Leverage Ratio
	C3	Net Wealth Protection
	C4	Debt Ratio
Asset quality	A1	Loans To Deposits
	A2	Loss Coverage
Management quality	M1	Cost Income Ratio
	M2	Credit To Deposit Ratio
	M3	Asset Utilization
	M4	Diversification Ratio
	M5	Income Per Capita
	M6	Cost Per Capita
	M7	Workforce Efficiency
Earning	E1	ROA
	E2	ROE
	E3	Income Margin
	E4	Operating Return
Liquidity	L1	Cash To Total Asset
	L2	Cash Equivalent To Asset
	L3	Cash To Total Deposits
	L4	Cash Equivalent To Deposits
	L5	Total Cash To Deposits
	L6	Quick Ratio
	L7	Cash Ratio

g. Grey Relation Technique (Clustering Criteria)

Ratios in different categories may overlap each other; it can lead to repetitions and simulated evaluation results. The Grey Relation (GR) method can tackle this problem. This method divides the ratios into several clusters and then finds the representative indices as evaluation criteria from each cluster. The Grey Relation analysis is one technique of the Grey Theory. The fundamental definition of greyness is information being incomplete or unknown, so that an element of the incomplete message is a grey element. The Grey Relation analysis is a method to measure the relations between the grey elements. Further, the definition and application of the Grey Relation analysis in mathematics are stated as follows [90]:

Assume that m Islamic banks are evaluated on s ratios. Let $X_i = \{x_i(k)\} \in X$ denote the sequence of the ratio i, where k=1, 2, ..., m; i=1, 2, ..., s; and X is a set comprising all ratio sequences. First, these ratios are divided into two situations to be normalized. If x_i (k) belongs to benefit items, then:

$$y_i(k) = \frac{x_i(k)}{\sqrt{\sum_{i=1}^{m}[x_i(t)]^2}} \tag{1}$$

Otherwise, x_i (k) belongs to cost items and then:

$$y_i(k) = \frac{1/x_i(k)}{\sqrt{\sum_{i=1}^{m}\left[1/x_i(t)\right]^2}} \tag{2}$$

In the above equations, $y_i(k)$ is the normalized value of the ratio i in the period k , where k=1, 2, …, m. i=1, 2, …, s.

Assume Y to be a set composed of all normalized ratio sequences. $Y_i = \{y_i(k)\} \in Y$ denotes the sequence of the normalized ratio i. Let Y be a factor set of Grey Relation, $y_0 \in Y$ represents the referential sequence, and $y_i \in Y$ represents the comparative sequence. $y_0(k)$ and $y_i(k)$ represent the ratio values of k on y_0 and y_i, respectively. If the average value $\gamma(y_0,y_i)$ of a set $\{\gamma(y_0(k),y_i(k))|k=1,2,...,m\}$ is a real number, then the Grey Relation $\gamma(y_0,y_i)$ is defined as:

$$\gamma\left(y_0,y_i\right)=\frac{1}{m}\sum_{k=1}^{m}\gamma(y_0\,(k),y_i(k))=r_{0i} \tag{3}$$

where

$$\gamma(y_0(k),y_i(k))=\frac{\min_{y_i(y\neq y_0)\in Y}\min_K|y_0(k)-y_i(k)|+\zeta\max_{y_i(\neq y_0)\in Y}\max_k|y_0(k)-y_i(k)|}{|y_0(k)-y_i(k)|+\zeta\max_{y_i(\neq y_0)\in Y}\max_k|y_0(k)-y_i(k)|} \tag{4}$$

and ζ is the distinguished coefficient $\zeta\in[0,1]$. In this article $\zeta = 0.5$. The Grey Relation analysis produces the relational matrix $R = \left(r_{ij}\right)$, where i=1, 2, …, s and j=1, 2, …, s. Furthermore, we have in our paper 19 banks and 24 criteria.

Clustering ratios according to the entries of the Grey Relation matrix are presented as follows [90]:

- If $r_{ij} \geqslant r$ and $r_{ji} \geqslant r$, then Y_i and Y_j belong to the same cluster, where r is the clustering threshold value. In this research = 0.6.

-When $r_{ij} \geqslant r$ and $r_{ji} \geqslant r$, $r_{ik} \geqslant r$ and $r_{ik} \geqslant r$, but $r_{jk} \geqslant r$ or $r_{kj} \geqslant r$, if $\min\{r_{ij},r_{ji}\}\geqslant\min\{r_{ik},r_{ki}\}$, then Y_i and Y_j belong to the same cluster.

After partitioning ratios into several clusters, the findings of representative indicators are stated as follows:

As Y_i and Y_j belong to the same cluster, the cluster's representative indicator is found by the maximum value of r_{ij} and r_{ij}. If $r_{ij} \geqslant r_{ji}$, then the representative indicator of the cluster is the ratio i.

As Y_i, Y_j and Y_k are in the same cluster, the cluster's representative indicator is decided according to the maximum value of $r_{ij} + r_{ik}$, $r_{ji} + r_{jk}$, and $r_{ki} + r_{kj}$. If $r_{ij} + r_{ik}$ is the maximum value, then the cluster's representative indicator is the ratio i. Sometimes, one cluster has more than three ratios.

As Y_i belongs to the cluster T, and the element number of T is more than 3, T's representative indicator is the ratio i if $\sum_{j(\neq i)\in T} r_{ij} \geqslant \sum_{j(\neq k)\in T} r_{kj}$, $\forall$ k∈T, but k≠i.

h. Determining the Fuzzy Weight of the Criteria by Using Fuzzy ANP

In this step, to determine the weights of the criteria, weight questionnaires were delivered to 35 Islamic banking experts and finance and banking academics; they were asked to determine each criterion's significance compared to other criteria. 10 0ut of 35 experts made this comparison completely. After preparing pairwise comparison matrices, each criterion's weight is obtained for each expert using Fuzzy ANP. The crisp ANP method was presented by [75]. He stated that the feedback approach, a generalization of a hierarchy, is used to derive priorities in a system with interdependent influences. He also mentioned that the following three steps implement the ANP model. All the interactions among the elements should be evaluated by pairwise comparisons to construct the problem's framework. A supermatrix—a matrix of the elements' influences—should be obtained based on these priority vectors. The supermatrix is derived from the limiting powers of the priorities to calculate the overall priorities. Thus, each element's cumulative influence on every other element with which it interacts is obtained [75]. The generalized supermatrix of a hierarchy with levels, as shown in the following:

$$W = \begin{array}{c} \\ c_1 \\ c_2 \\ c_3 \end{array} \begin{array}{c} \begin{array}{ccc} c_1 & c_2 & c_3 \end{array} \\ \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix} \end{array}$$

where W is a partitioned matrix, and its entries are composed of the vectors obtained from the pairwise comparisons. Since W is a stochastic column matrix, its limiting priorities depend on that matrix's reducibility and cyclist. If the matrix is irreducible and primitive, the limiting value is obtained by raising W to the powers, such as in (Eq.5), to obtain the global priority vectors [75].

Finally, after the supermatrix is assured of being column stochastic, it is raised to a sufficiently large power until convergence occurs [75]. In other words, the supermatrix is then raised to limiting powers to become W^{2K+1}, where k is an arbitrarily large number to capture all the interactions and to obtain a steady-state outcome.

After determining each expert's criteria weights based on the fuzzy ANP method, the Fuzzy group weight is determined, and then synthesizing of ratio judgments is done.

Assume that $\widetilde{W}=[\overline{\widetilde{w}_1,\widetilde{w}_n}]=[\widetilde{w}_j]$ is the fuzzy group weight for n criteria and $\widetilde{w}_j$ is the fuzzy triangular number:

$$\widetilde{w}_j=\left(w_{jl},w_{jm},w_{ju}\right) \tag{5}$$

where $w_{jl}=\min_k y_{jk}$, $j=\overline{1,n}, k=\overline{1,p}$ is the minimum possible value; $w_{jm}=\left(\prod_{k=1}^{p} y_{jk}\right)^{\frac{1}{p}}$, $j\overline{1,n}$, $k=\overline{1,p}$ is the most possible value and $w_{ju}=\max_k y_{jk}$, $j=\overline{1,n},k=\overline{1,p}$ is the maximal possible value of the jth criterion.

After applying the fuzzy ANP based on the manner mentioned above, a decision matrix is ready to be used in the next step by examining the FARAS method to rate the Islamic banks based on the criteria chosen from the CAMEL model by Grey Relation.

i. Fuzzy ARAS Examination to Assess Banks' Performance

The ARAS method [97] is based on the argument that a complicated world could be understood using simple relative comparisons. It is argued that the ratio of the sum of normalized and weighted criteria scores, which describe alternatives under consideration, to the sum of the values of normalized and weighted criteria, which describes the optimal alternative, is a degree of optimality that is reached by the alternative under comparison. According to the ARAS method [87], a utility function value determining the complex relative efficiency of a reasonable alternative is directly proportional to the relative effect of values and weights of the main criteria considered in a project. The first stage here is the fuzzy decision-making matrix (FDMM) forming. In the FMCDM of the discrete optimization problem, any problem that has to be solved is represented by the following DMM of preferences for m reasonable alternatives (rows) rated on n criteria (columns):

$$\tilde{X}=\begin{bmatrix} \tilde{x}_{01} & \cdots & \tilde{x}_{0j} & \cdots & \tilde{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{x}_{i1} & \cdots & \tilde{x}_{ij} & \cdots & \tilde{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mj} & \cdots & \tilde{x}_{mn} \end{bmatrix}, i=\overline{0,m};j=\overline{1,n} \quad (6)$$

where m is the number of alternatives, n is the number of criteria describing each alternative; $\tilde{x}_{ij}$ is the fuzzy value representing the ith alternative's performance value in terms of the j criterion, and $\tilde{x}_{0j}$ is the optimal value of the jth criterion. A tilde '~' will be placed above a symbol if it represents a fuzzy set. If the optimal value of the jth criterion is unknown, then:

$$\tilde{x}_{0j}=\max_i \tilde{x}_{ij}\text{ , if }\max_i \tilde{x}_{ij}\text{ is preferable, and }\tilde{x}_{0j}=\min_i \tilde{x}_{ij}\text{ , if }\min_i \tilde{x}_{ij}\text{ is preferable.} \quad (7)$$

The performance value $\tilde{x}_{ij}$ and the criteria weight $\tilde{w}_j$ are usually viewed as the entries of a DMM. Experts determine the system of criteria and the values and initial weights of criteria. The interested parties can correct the information with their goals and opportunities. Then, the determination of the priorities of alternatives is carried out in several stages. Usually, the criteria have different dimensions. The purpose of the next stage is to receive dimensionless weighted values from the comparative criteria. The ratio of each value to the optimal value is used to avoid the difficulties caused by the criteria' different dimensions. Various theories are describing this ratio. However, the values are mapped either on the interval [0;1] or the interval [0; ∞) by applying a DMM's normalization. In the second stage, the initial values of all the criteria are normalized by defining the values of $\tilde{\tilde{x}}_{ij}$ of the normalized decision-making matrix $\tilde{\tilde{X}}$:

$$\tilde{\tilde{X}}=\begin{bmatrix} \tilde{\tilde{x}}_{01} & \cdots & \tilde{\tilde{x}}_{0j} & \cdots & \tilde{\tilde{x}}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\tilde{x}}_{i1} & \cdots & \tilde{\tilde{x}}_{ij} & \cdots & \tilde{\tilde{x}}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\tilde{x}}_{m1} & \cdots & \tilde{\tilde{x}}_{mj} & \cdots & \tilde{\tilde{x}}_{mn} \end{bmatrix}, i=\overline{0,m};j=\overline{1,n} \quad (8)$$

Criteria with preferable values at the maxima have been normalized as follows:

$$\tilde{\tilde{x}}_{ij}=\frac{\tilde{x}_{ij}}{\sum_{i=0}^{m}\tilde{x}_{ij}} \quad (9)$$

Criteria with preferable values at the minima have been normalized by applying a two-stage procedure:

$$\tilde{x}_{ij}=\frac{1}{\tilde{x}^*_{ij}};\ \tilde{\tilde{x}}_{ij}=\frac{\tilde{x}_{ij}}{\sum_{i=0}^{m}\tilde{x}_{ij}} \quad (10)$$

When the criteria' dimensionless values are calculated, all the criteria originally having different dimensions can be compared with each other. The third stage defines the normalized weighted matrix $-\tilde{\hat{X}}$. It is possible to evaluate the criteria with the weights $0 < \tilde{w}_j < 1$. Only well-founded weights should be used because weights are always subjective and influence the solution. The values of weight w_j are usually determined by the expert evaluation method. The sum of weights w_j would be limited as follows:

$$\sum_{j=1}^{n} w_j = 1 \quad (11)$$

$$\tilde{\hat{X}}=\begin{bmatrix} \tilde{\hat{x}}_{01} & \cdots & \tilde{\hat{x}}_{0j} & \cdots & \tilde{\hat{x}}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\hat{x}}_{i1} & \cdots & \tilde{\hat{x}}_{ij} & \cdots & \tilde{\hat{x}}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\hat{x}}_{m1} & \cdots & \tilde{\hat{x}}_{mj} & \cdots & \tilde{\hat{x}}_{mn} \end{bmatrix}, i=\overline{0,m};j=\overline{1,n} \quad (12)$$

Normalized weighted values of all the criteria are calculated as follows:

$$\tilde{\tilde{x}}_{ij}=\tilde{\bar{x}}_{ij}\tilde{w}_j \; ; \; i=\overline{0,m}, \quad (13)$$

where w_j is the weight (importance) of the j criterion and $\tilde{x}_{ij}$ is the normalized rating of the j^{th} criterion. The following task is to determine the values of the optimality function:

$$\tilde{S}_i=\sum_{j=1}^{n}\tilde{\tilde{x}}_{ij} \; ; \; i=\overline{0,m}, \quad (14)$$

where $\tilde{S}_i$ is the value of the ith alternative's optimality function.

The biggest value is the best, while the smallest one is the worst. In the calculation process, the optimality function $\tilde{S}_i$ has a direct and proportional relationship with the values $\tilde{x}_{ij}$ and the weights $\tilde{w}_j$ of the investigated criteria and their relative influence on the final result. Therefore, the greater the value of the optimality function $\tilde{S}_i$ is, the more effective the alternative. The priorities of alternatives can be determined according to the value $\tilde{S}_i$. Consequently, it is convenient to evaluate and rank decision alternatives when this method is used. The result of fuzzy decision-making for each alternative is fuzzy number $\tilde{S}_i$. There are several methods for defuzzification. The center-of-area method is the most practical and simple to apply:

$$S_i=\frac{1}{3}(S_{il}+S_{im}+S_{iu}) \quad (15)$$

The alternative utility degree is determined by comparing the variant analysed with the ideal one, S_0. The equation used for the calculation of the utility degree of the alternative A_i is given below:

$$K_i=\frac{S_i}{S_0} \; ; \; i=\overline{0,m}, \quad (16)$$

where S_i and S_0 are the optimal criterion values obtained from Eq.(15) to Eq. (16).

It is clear that the calculated values of K_i are within the interval [0; 1] and can be ordered in an increasing sequence, which is the wanted order of precedence. The reasonable alternative's complex relative efficiency can be determined according to the utility function values [88].

4. Calculations and Results (MENA region Islamic Banks Case)

We applied our synthetic model to 19 Islamic banks in MENA region (Table 2). We evaluated them based on their performances from 2014 to 2019. First, we applied the CAMEL rating system with 24 criteria. Next, we selected the representative indicators of ratios using the Grey Relation technique (Table 4). Cluster analysis or clustering groups a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense) to each other than to those in other groups (clusters). From an economic point of view, it can be expected that close indicators in terms of the degree of similarity to different decisions in the field of asset and liability management are in the same cluster. For example, there are two indicators of net wealth protection and capital adequacy ratio in the first cluster, which are most similar in measuring the Islamic bank's total risk. There are two indicators, debt ratio, and leverage ratio, in the second cluster, which measure financial risk. It is also evident in other clusters, and the creation of clusters has a significant economic intuition. Of course, it may be said that the placement of some indicators in a cluster seems obvious, and there is no need to use the clustering method at all. For example, the placement of ROE and ROA ratios in a cluster is obvious.

Nevertheless, this is not always so easy. For example, the placement of net wealth protection and capital adequacy ratio are not close to each other in terms of economic logic. However, when we look at the type of these two ratios dealing with the financial institution's risk level, we confirm them to be in the same cluster and what the clustering method does by a machine learning system based on the historical data of the Islamic banks is outstanding.

Table 4. Representative indicators

Category	Cluster	Ratios Within Each Cluster	Representative indicator Of Each Cluster
Capital Adequacy	C1	C1 C3	C1
	C2	C2 C4	C2
Asset Quality	C3	A1 A2	A1
Management Quality	C4	M1 M3 M5	M1
	C5	M2 M4	M4
Earning	C6	M6 M7	M7
	C7	E1 E2	E1
	C8	E3 E4	E3
Liquidity	C9	L1 L2 L6 L7	L1
	C10	L3 L4 L5	L5

After finding the representative criteria, criteria weights were calculated by the fuzzy ANP method (Table 5). The fuzzy weight of each criterion is shown in Table 6. Then, we created a fuzzy normalized weighted matrix to form the fuzzy decision matrix for 19 Islamic banks based on the ten chosen representative criteria.

Table 5. The weight of each criterion according to each expert by fuzzy ANP Method

W_j by fuzzy ANP		Decision-makers									
		D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Capital Adequacy	C1	0.097	0.108	0.128	0.114	0.113	0.082	0.072	0.089	0.100	0.108
	C2	0.124	0.117	0.115	0.138	0.089	0.119	0.092	0.093	0.102	0.093
Asset Quality	A1	0.064	0.057	0.061	0.055	0.099	0.056	0.091	0.069	0.071	0.083
Management Quality	M1	0.088	0.085	0.146	0.090	0.085	0.115	0.082	0.069	0.077	0.159
	M4	0.072	0.064	0.051	0.063	0.066	0.094	0.094	0.084	0.067	0.066
	M7	0.097	0.113	0.098	0.098	0.120	0.079	0.090	0.116	0.096	0.087
Earning	E1	0.135	0.135	0.112	0.129	0.125	0.140	0.144	0.159	0.149	0.097
	E3	0.109	0.112	0.108	0.101	0.129	0.126	0.133	0.104	0.140	0.067
Liquidity	L1	0.147	0.140	0.114	0.159	0.108	0.135	0.121	0.120	0.122	0.148
	L5	0.068	0.069	0.068	0.053	0.066	0.056	0.081	0.097	0.077	0.092

Table 6. The fuzzy weight of each criterion

Criteria		$\tilde{\omega}j$		
		l	m	u
Capital Adequacy	C1	0.072	0.100	0.128
	C2	0.089	0.107	0.138
Asset Quality	A1	0.055	0.069	0.099
Management Quality	M1	0.069	0.096	0.159
	M4	0.051	0.071	0.094
	M7	0.079	0.099	0.120
Earning	E1	0.097	0.131	0.159
	E3	0.067	0.111	0.140
Liquidity	L1	0.108	0.130	0.159
	L5	0.053	0.071	0.097

Table 7. Fuzzy normalized decision matrix of 19 Islamic banks for 2017 to 2019

Criteria	Bank 1			Bank 2			Bank 3			…	Bank 19		
C1	0.00	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	…	0.00	0.00	0.01
C2	0.44	0.76	1.40	0.46	0.73	1.15	0.58	0.71	0.85	…	0.16	0.88	4.19
A1	0.01	0.02	0.03	0.01	0.01	0.02	0.00	0.01	0.03	…	0.00	0.01	0.03
M1	0.01	0.02	0.05	0.01	0.03	0.07	0.05	0.06	0.07	…	0.02	0.03	0.07
M4	0.01	0.05	0.13	0.05	0.07	0.11	0.06	0.08	0.10	…	0.01	0.01	0.04
M7	0.05	0.10	0.20	0.07	0.11	0.20	0.09	0.11	0.14	…	0.02	0.03	0.08
E1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	…	0.00	0.00	0.00
E3	0.00	0.02	0.04	0.01	0.01	0.02	0.01	0.01	0.01	…	0.02	0.03	0.07
L1	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	…	0.00	0.01	0.02
L5	0.00	0.01	0.01	0.01	0.01	0.02	0.00	0.01	0.01	…	0.00	0.01	0.02

Here we needed to normalize our data through Equations (1) and (2). After normalization, the resulting matrix was weighted (Tables 7 and 8).

Table 8. Fuzzy normalized weighted decision matrix 19 Islamic banks for 2017 to 2019

Criteria	Bank 1			Bank 2			Bank 3			…	Bank 19		
C1	0.000	0.001	0.001	0.000	0.001	0.001	0.000	0.001	0.001	…	0.000	0.000	0.001
C2	0.039	0.082	0.194	0.042	0.078	0.158	0.052	0.076	0.118	…	0.014	0.094	0.579
A1	0.001	0.001	0.003	0.000	0.001	0.002	0.000	0.001	0.003	…	0.000	0.001	0.002
M1	0.001	0.002	0.007	0.001	0.003	0.011	0.004	0.006	0.012	…	0.001	0.003	0.012
M4	0.001	0.004	0.012	0.002	0.005	0.010	0.003	0.005	0.009	…	0.000	0.001	0.004
M7	0.004	0.010	0.025	0.005	0.011	0.024	0.007	0.011	0.017	…	0.001	0.003	0.010
E1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	…	0.000	0.000	0.000
E3	0.000	0.002	0.006	0.001	0.002	0.003	0.001	0.001	0.002	…	0.001	0.003	0.010
L1	0.000	0.001	0.002	0.001	0.001	0.002	0.000	0.001	0.001	…	0.000	0.001	0.003
L5	0.000	0.001	0.001	0.001	0.001	0.002	0.000	0.000	0.001	…	0.000	0.000	0.002

After the defuzzification of Si and S0, the FARAS method was applied to rate the Islamic banks. Table 9 shows the final ranking result.

Table 9. Defuzzification of Si and S0 and ranking results through FARAS

No.	Islamic Bank	period 2014-2016				period 2017-2019			
		Si	S0	Ki	Ranking	Si	S0	Ki	Ranking
1	Bank 1	0.1148	0.2498	0.4597	12	0.1134	0.2689	0.4217	13
2	Bank 2	0.1188		0.4756	9	0.1230		0.4573	5
3	Bank 3	0.1223		0.4897	7	0.1112		0.4138	16
4	Bank 4	0.1198		0.4795	8	0.1171		0.4355	9
5	Bank 5	0.1240		0.4965	5	0.2489		0.9256	1
6	Bank 6	0.1139		0.4559	15	0.1105		0.4109	17
7	Bank 7	0.2275		0.9110	1	0.1333		0.4959	3
8	Bank 8	0.1175		0.4703	10	0.1181		0.4394	8
9	Bank 9	0.2188		0.8761	2	0.1229		0.4572	6
10	Bank 10	0.1087		0.4351	19	0.1081		0.4020	18
11	Bank 11	0.1148		0.4596	13	0.1188		0.4420	7
12	Bank 12	0.1118		0.4477	16	0.1136		0.4226	12
13	Bank 13	0.1147		0.4593	14	0.1157		0.4303	10
14	Bank 14	0.1103		0.4415	17	0.1020		0.3792	19
15	Bank 15	0.2068		0.8280	3	0.1276		0.4745	4
16	Bank 16	0.1158		0.4635	11	0.1342		0.4991	2
17	Bank 17	0.1268		0.5075	4	0.1115		0.4146	15
18	Bank 18	0.1230		0.4926	6	0.1126		0.4187	14
19	Bank 19	0.1102		0.4413	18	0.1155		0.4297	11

For testing the consistency of this synthetic approach, we ran (Table 10) two other techniques, FTOPSIS and FVIKOR, with the same data and compared their results with the results obtained by using the FARAS method. The results based on FARAS and FTOPSIS in the different bank types on different periods were close to each other. However, the FVIKOR method gave a relatively different rating compared with the other two methods. So, for increasing the reliability of the results, one may use the average results of the three methods, which is shown in the last column of Table 10.

Table 10. Comparison of methods across two periods

Bank types	Periods	Period 2014-2016				Period 2017-2019			
	Banks	This paper (FARAS Rank)	Other methods		Average of FTOPSIS, FVIKOR, and FARAS results	This paper (FARAS Rank)	Other methods		Average of FTOPSIS, FVIKOR, and FARAS results
			FVIKOR Rank	FTOPSIS Rank			FVIKOR Rank	FTOPSIS Rank	
Iran	Bank 1	12	9	11	11	13	6	13	11
	Bank 2	9	7	9	8	5	4	3	4
	Bank 3	7	5	10	7	16	10	15	14
	Bank 4	8	4	7	6	9	15	8	11
Saudi Arabia	Bank 5	5	3	6	5	1	3	1	2
	Bank 6	15	19	14	16	17	8	17	14
	Bank 7	1	8	3	4	3	2	4	3
UAE	Bank 8	10	1	13	8	8	9	7	8
	Bank 9	2	14	2	6	6	5	6	6
	Bank 10	4	11	1	5	15	7	14	12
Qatar	Bank 11	6	12	5	8	14	1	11	9
	Bank 12	18	10	19	16	11	16	16	14
	Bank 13	19	15	18	17	18	11	19	16
Kuwait	Bank 14	11	6	5	7	2	13	2	6
	Bank 15	13	16	12	14	7	18	9	11
Bahrain	Bank 16	16	13	16	15	12	19	12	14
	Bank 17	14	17	15	15	10	17	10	12
Oman	Bank 18	17	18	17	17	19	14	18	17
Egypt	Bank 19	3	2	4	3	4	12	5	7

5. Conclusion

The development of a new approach to evaluating Islamic banks performance is of high importance. Our synthetic method examines how precisely the integrated use of Grey Relation, fuzzy ANP, and FARAS techniques in the banking context can promote evaluation of the Islamic banks' performance. We propose an applicable synthetic model to evaluate the banks' performance by combining the Grey Relation, fuzzy ANP, FARAS models, and the CAMEL rating framework.

The proposed model assists banking policy-makers, financial managers, and regulators to have a better, more accurate, and faster model for assessing the Islamic banks' condition. This synthetic model helps Islamic banks to have a complete performance evaluation in comparison with their competitors. Also, financial market players can have broader and clear insights into the effects of managers' decisions on the Islamic bank's situation.

The CAMEL framework, as a global rating model, using our hybrid model becomes more practical to Islamic banks performance appraisal. This study provides a solution for filtering criteria overlaps and preventing the important criteria from being omitted.

We use Grey Relation as an operational research method to answer the following question: Using the Grey Relation technique, how will the best representative criteria be chosen through the CAMEL model to remove the criteria with overlapping effects and keep the highly important criteria? The mixture of the Grey Relation model and the CAMEL model is an innovation preventing the overlap of indicators and the elimination of important indicators in the banking evaluations. [29, 23, 77] mentioned some of these problems in their studies. Some others attempted to solve such problems by creating similar mixed models such as [80, 20, 58, 72]. In these studies, they have only combined mathematical models with the CAMEL model to improve the output. None of them have been able to solve overlapping indices and use a suitable model to select a representative index among many indices; The point that distinguishes this paper from the same works.

Moreover, after choosing the representative indices, we should have a model to compare the Islamic banks. To test for the consistency of the proposed synthetic approach, we answer the following question on the three main decision-making models: Which one of the multi-criteria decision-making models amongst FVIKOR, FTOPSIS, and FARAS is preferable for ranking the Islamic banks based on the selected indices? We show that there is almost no difference between using FARAS and FTOPSIS methods, but the results from FVIKOR are different from those obtained from the other two methods. We suggest that one may use the average of the rankings produced by two or three methods to correct such inconsistency.

While generalizable to any other banking system, applying this hybrid model also brings economic results for the MENA region Islamic banks system. First, instead of calculating many indicators, it provides an easier method for managers to make financial decisions by selecting more important indicators. Second, using a more efficient decision-making model among the three important models introduced, banks' ranking is more accurate, reliable, and less based on personal judgment. In comparison with the other studies such as [80, 20, 58, 72] works, in our synthetic model, we firstly find the parsimonious amount of relevant indices. Moreover, you will rarely find a work that improve the appraisal process by suggesting a suitable method for each performance appraisal step while ours did. Finally, future research may involve a broader sensitivity analysis by using different clustering techniques, weighting, and decision-making to find other possible synthetic models in Islamic or conventional banking or other industries to improve the outputs.

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