EVALUATION OF CRYPTOCURRENCY INVESTMENT WITH FUZZY LOGIC IN ON-CHAIN ANALYSIS

ENGİN TÜRELİ

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ABSTRACT

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TÜRELİ, Engin

Master of Science in Computer Engineering

Supervisor: Assist. Prof. Dr. Roya CHOUPANI

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Recently, cryptocurrencies, a technology that does not need any authority or center, have been increasing the scrutiny of all dimensions with unprecedented interest. Especially with the Covid-19 pandemic, it has been observed that the active trading volume of cryptocurrencies has increased, and qualitative and quantitative applications of the studies have been determined in the literature in this context. For this reason, this study deals with the interpretation of mathematical transactions between two blocks of 4 crypto-assets (Bitcoin, Ethereum, Chainlink, Maker) that are actively traded in the market, in other words, on-chain analysis as a decision problem that has not yet been studied as far as is known from the literature. The proposed methodology includes the combination of the Random Forest Regression algorithm, which performs exceptionally in the prediction error of the data set with a series of comparisons of cryptocurrencies, and the Pythagorean fuzzy sets, which offer strong and large scale in the multi-criteria decision-making branch of decision science in fuzzy logic. In this conceptual framework, the fuzzy logic method is used while prioritizing the metrics that will affect the investment decision. In addition, the strong ranking of these metrics is achieved with the TOPSIS algorithm. In addition, sensitivity analyses to obtain stable rankings will provide an important projection to the literature by rationalizing the high uncertainty on the investors' side of crypto-assets traded in the markets. The results show that the Exchange Reserve metric of the crypto asset is the most important criterion among the stock market flow data, even

when an investment preference is required for a crypto asset that is relatively new or whose historical data is not available for analysis.

Keywords: Cryptocurrency, On-chain Analysis, Machine Learning, Pythagorean Fuzzy Sets, TOPSIS

ÖZ

ON-CHAIN ANALİZİNDE KRİPTO PARA YATIRIMININ BULANIK MANTIK İLE DEĞERLENDİRİLMESİ

TÜRELİ, Engin
Bilgisayar Mühendisliği Yüksek Lisans
Danışman: Dr. Öğretim Üyesi Roya CHOUPANI
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Son zamanlarda herhangi bir otorite ya da merkeze ihtiyaç duymayan bir teknoloji olan kripto para birimlerinin, benzeri görülmemiş bir ilgiyle her boyutta incelemesi artmaktadır. Özellikle Covid-19 pandemisi ile kripto para birimlerinin aktif olarak işlem görme hacmi arttığı gözlemlenmiş ve literatürde de bu bağlamda çalışmaların nitel ve nicel uygulamaları da tespit edilmiştir. Bu nedenle bu çalışma piyasada aktif olarak işlem gören 4 kripto varlığın (Bitcoin, Ethereum, Chainlink, Maker) iki blok arasında yapılan matematiksel işlemlerin yorumlanması diğer bir deyişle on-chain analizinin literatürden bilindiği kadarıyla henüz çalışılmamış bir karar problemi olarak ele almaktadır. Önerilen metodoloji kripto para birimlerinin bir dizi karşılaştırma ile veri setinin tahmin hatasında olağanüstü performans sergileyen "Random Forest Regression" algoritmasının bulanık mantıkta karar biliminin çok kriterli karar verme dalında güçlü ve geniş ölçek sunan Pisagor bulanık setlerle kombinasyonunu içermektedir. Bu kavramsal çerçevede yatırım kararına etki edecek metrikleri önceliklendirirken bulanık mantık yöntemi kullanılmasının yanı sıra bu metriklerin güçlü sıralamasının TOPSIS algoritması ile elde edilmesi de sağlanmaktadır. Buna ek olarak stabil sıralamalar elde etmek için yapılan duyarlılık analizleri piyasalarda işlem gören kripto varlıkların yatırımcılar tarafındaki yüksek belirsizliği, rasyonel kılarak literatüre önemli projeksiyon sunacaktır. Elde edilen sonuçlar göstermektedir ki nispeten yeni olan veya analiz yapacak kadar geçmiş verisine ulaşılamayan bir kripto varlık için yatırım tercihi yapılması gerektiğinde bile

kripto varlığa ait Borsa Rezervi metriği borsa akış verileri arasındaki en önemli ölçüttür.

Anahtar Kelimeler: Kripto Paralar, On-chain Analizi, Makine Öğrenmesi, Pisagor Bulanık Kümeler, TOPSIS

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

USD	: United State Dollar(s)
BTC	: Bitcoin
ETH	: Ethereum
LINK	: Chainlink
MKR	: Maker
RFR	: Random Forest Regressor
TOPSIS	: Technique for Order of Preference by Similarity to Ideal Solution
AHP	: Analytical Hierarchy Process
PFAHP	: Pythagorean Fuzzy AHP
BCH	: Bitcoin Cash
LTC	: Litecoin
ETN	: Electroneum
XMR	: Monero
ZEC	: Zcash
LSTM	: Long Short-Term Memory
SVM	: Support Vector Machine
ANN	: Artificial Neural Network

CHAPTER I

INTRODUCTION

1.1 INTRODUCTION

In recent years, a new type of currency, called cryptocurrency, has emerged due to the use of digital assets as means of exchange designed as virtual currency. Cryptocurrencies are a digital element that uses encryption techniques to make payments and verification processes more secure [1]. These techniques and the underlying technology include blockchain technology. It represents a super-fast growing distributed technology that includes the hashing structure of blocks by enabling an increasing number of records to be interconnected via encryption/cryptography. In blockchain technology, each block holds the cryptographic hash, timestamp, and transaction data of the previous block.

The development of this technology has enabled blockchain-based cryptocurrencies to gain increasing popularity in the last decade. Considering the pre- and post-COVID-19 outbreak, when the crypto money market is the most flourished, it has been determined that more than 7000 cryptocurrencies are actively traded as of the second quarter of 2020 [2]. In addition, Bitcoin, the first coin with the largest volume, is registered in April 2021 with a volume of 64 billion USD and a market capitalization of 1.304 billion USD [3].

Another reason for its increased efficiency in the markets is related to the technology it contains. In cryptocurrency, the public keys of the sender and receiver and the number of coins transferred are a kind of ledger that keeps track of every transaction exchange. These public keys are called wallet addresses and must be signed by the sender with a personal key in every transaction. Once the transaction has been approved and broadcasted within the network, miners can confirm exchanges or transactions by solving a cryptographic puzzle. After miners approve the swap or any exchange, they must stamp it and distribute it on the system. Thus, the transactions that take place are added to the databases. And after the change is approved, the transaction process ends. As a result of this process, the miner or sender is rewarded in addition to his expenses for expenditure payments. This reward ensures the vitality of the crypto economy [2], [4].

With such a development and an unprecedented interest due to the technology it contains, researchers are also analyzing the future values of cryptocurrencies by establishing prediction models with many abstract and tangible attributes. The correct estimation of these analyzes not only provides decision support to investors but also contributes to the development of regulatory policies in their governments and the creation of competitive strategies of enterprises [5], [6]. Therefore, the interpretation of mathematical operations between two blocks, in other words, on-chain analysis, is a decision problem that has not yet been studied as far as is known from the literature.

However, since this problem includes both dependent and independent qualitative and quantitative attributes between two blocks, it has been studied with four crypto assets with the highest market dominance, whose exchange flow data on all exchanges for the last three years can be accessed. These are Bitcoin (BTC), Ethereum (ETH), Chainlink (LINK), and Maker (MKR). First, the metrics used in the on-chain analysis of the cryptocurrencies considered in the study were calculated for each crypto asset with Random Forest Regressor (RFR), one of the artificial intelligence and machine learning algorithms. In addition, Pearson correlation analysis was also used to observe a statistically based relationship.

Then, the Fuzzy Set Theory developed by Zadeh [7] was used to determine which crypto asset is important in this analysis. Thus, importance weights were obtained for decision-makers by using the Pythagorean Fuzzy Analytic Hierarchy Process, in which the membership and non-membership degrees of the uncertainty and complexity set theory in a fuzzy environment have quadratic elasticity by Yager [8]. These weights provided input to the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) algorithm in ordering the alternatively selected metrics in the decision matrices created by RFR and Pearson correlation analysis.

Alternatively, the metrics used are Reserve, Inflow, Outflow, Inflow Address Count, Outflow Address Count, Inflow Transaction Count, and Outflow Transaction

Count flow data for all exchanges, respectively. To observe the stability and accuracy in the ranking of these metrics, sensitivity analyses were performed.

As a result, the "Exchange Reserve" relationship, in which the price effect is observed in the BTC crypto asset that dominates the market, gave obvious high results both in the correlation account and in Bitcoin, which is the market's driver and the highest market dominance.

In addition, Exchange Inflow/Outflow and Transaction Count importance weights are observed to be significantly lower in both regression and fuzzy analysis. For this reason, when it is desired to decide on a crypto asset investment by supporting exchange reserve data from the on-chain analysis, it will give healthy results to look go though at the Exchange Reserve value and then the Exchange Inflow/Outflow Addresses Count values.

1.2 THESIS CONTRIBUTION

In this thesis, we aim to suggest which ones should be used and prioritized when analyzing the stock market flow data by creating a decision support system for investment with on-chain analysis in the blockchain ecosystem, a very new research area.

In on-chain analysis, it is not possible to access the historical data set for every crypto asset. Also, changes in the price of Bitcoin and Ethereum coins impact other crypto assets. This effect is different from market dominance data that can be measured quantitatively, so verbal expert opinion comes into play at this point. For these reasons, decision-making methods in a fuzzy environment have been preferred. Furthermore, as far as the literature knows, "on-chain" analysis has not yet been studied as a decision problem in a fuzzy environment.

On the other hand, the Random Forest Regression algorithm, one of the machine learning methods, was used to measure the factors affecting the price in time series. And we evaluated by comparing both results.

1.3 RESEARCH QUESTION

This study aims to answer whether the exchange flow data has a determining impact on the prices of crypto assets, and if so, which features and how much.

1.4 THESIS ORGANIZATION

In the second chapter of the study, there are academic studies on blockchain technology and crypto-assets and the contributions provided, along with the problem aforementioned.

The methodology of the proposed machine learning and statistical-based decision model are mentioned in the third chapter.

In chapter four, the analytical study of the question of which metrics are effective in crypto-asset investment is applied in the on-chain analysis.

In the fifth chapter, the results of the implementation phase and comments are given.

In the sixth chapter, which is the last part, the general results of the application study are given, and suggestions are made about future studies.

CHAPTER II

LITERATURE REVIEW

Cryptocurrencies, which recently operated without the need for any authority or center, are virtual element technologies that are used to transfer any funds in order to offer transparency to their users [9], [10]. This currency, developed based on blockchain technology, is a basic example of a distributed computing framework. In other words, it leverages the public transaction capabilities of blockchain technology by offering a decentralized environment, unlike the central banking system without a federal cloud environment [11]. The increasing interest in cryptocurrencies and their basic algorithms due to the transparency, decentralization, and encryption strength they contain in their technology have been the concept that researchers in the academic world have studied in many aspects.

To summarize a brief classification of the studies in this context, the related studies include artificial intelligence-based studies in the first part focusing on price predictions of cryptocurrencies, input parameters (determinants) used in price predictions, and measuring the reactions of the social media/outside world to price fluctuations. The second part covers fuzzy logic-based multi-criteria decision-making problems, which include the perspectives of eliminating the uncertainty in the application areas of the multi-agent and multi-process structure of blockchain technology in different sectors.

The review of the relevant literature with artificial intelligence and fuzzy multi-criteria decision-making methods provides a perspective that will bring analytical solutions to the problems that will facilitate the investment process in addition to technical and fundamental analysis in cryptocurrencies. With this point of view, at the end of the chapter, on-chain analysis, and the evaluation of cryptocurrency investment with fuzzy logic, as far as is known from based on the studies cited, the contributions of the study to the gaps in the literature.

There are challenges, opportunities, or applications about the share of blockchain technology in many different industries around the world. Researchers have discussed that blockchain technology plays an active role due to its strong encryption and decentralized structure, from its technological effects to its political aspects. Recently, the common thought is the problems in data privacy, security, and integration in studies where different aspects of health [12], [13], energy [14], urbanization [15], finance [16], agriculture, and livestock [11], [17] have been discussed from an interdisciplinary perspective is pointing.

However, cryptocurrencies, one of the most important and popular applications of blockchain technology, offer unprecedented opportunities in information discovery and data mining, thanks to rich information and transparent tracking of financial activities. For this reason, the focus of researchers has turned to artificial intelligence-based studies in cryptocurrencies.

From this perspective, as a result of examining the studies of the last five years with the titles of "Blockchain", "Cryptocurrency" and "Artificial Intelligence", it was determined that the researchers focused on the studies based on estimating the prices of cryptocurrencies and focused on the fluctuation in prices with artificial intelligence-based algorithms (Table 2.1).

The main reason for this is that the trend of transition from printed currency to virtual currency has been increasing in recent years, and considering its decentralized structure, whether it varies according to the economic conditions of the countries has been another subject of research [4], [18]–[21].

Related to this, Liu et al. [18] presented not only parameters such as daily turnover, total market, the average hash rate related to cryptocurrencies, but also a detailed list including stock market indices, exchange rates, current oil prices, and keywords in search engines in order to determine the Bitcoin price in their study. For Bitcoin price prediction, Chen et al. [19] developed a two-stage price estimation model by measuring the potential importance of the information hidden in economic and technological parameters. For the Ethereum price prediction model, another cryptocurrency that is different from Bitcoin, Kim et al. [20], examined the relationship between other coins and generic blockchain information unlike other studies.

In many studies in the literature, studying the determinants of the price prediction models of other cryptocurrencies, in addition to the globally known Bitcoin and Ethereum cryptocurrencies, price prediction models have also been established for Litecoin, EOS, Digital Cash, and Ripple [22]–[31]. Among these studies, Zhang et al. [24] conducted a study that established the price forecasting models of cryptocurrencies on the broadest scale. Zhang et al. [24] differentiated them from the literature by taking into account the fluctuation in price momentum in order to design crypto money investment strategies to realize more profitable transactions.

In addition, the studies include not only economic parameters but also studies in which hypotheses are established on the motivation of users to hold cryptocurrencies and the effect of social media on the value of cryptocurrencies, and the way they are associated with many behavioral measures [32]–[38].

The commonality of the studies is based on finding empirical evidence to exploit the relationship between price changes and social media posts. In this context, the value of focusing on the emotions of investors or users in digital forums and social media platforms, in other words, users with different activity levels on online platforms, instead of traditional descriptors, has been frequently investigated in the literature (Table 2.1). In addition, data belonging to a single platform were not used to examine the relationships between different user groups and different platforms between price changes of cryptocurrencies and social media posts.

Poongodi et al. [32] designed the Bitcoin price change model using data from different platforms (Reddit, Twitter, and Bitcoin Talk). Wolk et al. [34] analyzed the predictive relationship between cryptocurrency value and social media by designing complex machine learning models, using data from Google Trends and Twitter platforms for Bitcoin, Electroneum, Ethereum, Monero, Ripple, and Zcash.

All these studies show a common decision problem for users of different buyer statuses of cryptocurrencies. For example, this situation serves to predict future price fluctuations for investors and design legislation for policymakers. The clarification of this uncertain decision problem in at least one dimension in the financial sector plays a role in helping to reduce the risks. For businesses, removing uncertainty about cryptocurrencies can serve as a proxy for market confidence and perceived use-value for information systems while serving their decision to introduce their digital currencies.

Table 2.1: Literature Summary About Cryptocurrencies

References	Purpose	Method	Assets	Journal	Index
[32]	Trend prediction of global cryptocurrencies with social media analysis	Topic models Latent Dirichlet Allocation (LDA)	BTC	Information Processing and Management	SCI
[24]	Predict the daily closing price and intraday trends of cryptocurrencies	Weighted & Attentive Memory Channels (WAMC)	BTC, BCH, LTC, ETH, EOS, XRP	Expert Systems with Applications	SCI
[23]	Developing price prediction and trading strategy using static Bitcoin data	Proximal Policy Optimization (PPO)	BTC	Applied Soft Computing	SCI
[22]	Analysis of trends in Bitcoin prices and price prediction	Wavelet Transform (WT) and Casual Multi-Head Attention (CA) Temporal Convolutional Network (TCN)	BTC	Decision Support Systems	SCI
[18]	Price prediction by creating a feature set that determines Bitcoin price	Stacked Denoising Autoencoders (SDAE)	BTC	Finance Research Letters	SSCI
[19]	Price prediction by creating a feature set that determines Bitcoin price	Long Short-Term Memory (LSTM)	BTC	International Journal of Forecasting	SSCI
[33]	Short-term price prediction using Bitcoin's various exchange rates and Twitter data	Gradient Boosting, LSTM, Neural Network	BTC	The Journal of Finance and Data Science	Other
[39]	Price prediction by creating a feature set that determines Ethereum price	Artificial Neural Network (ANN), Support Vector Regression (SVR)	ETH	Expert Systems with Applications	SCI

Table 2.1: Literature Summary About Cryptocurrencies (Continued)

References	Purpose	Method	Assets	Journal	Index
[4]	Creating an investment risk strategy by resampling financial series on a cryptocurrency exchange	Logistic Regression, Random Forest, Support Vector Classifier, Gradient Tree Boosting	-	Applied Soft Computing	SCI
[25]	Analysis of trends in Bitcoin prices and price prediction	SVR, Gaussian Poisson regressions (GRP), Regression Trees (RT), k-nearest neighbors (kNN), Bayesian Regularization (BRNN), Radial Basis Function Networks (RBFNN).	BTC	Chaos, Solitons & Fractals	SCI
[26]	Analysis of trends in Ethereum prices and price prediction	Linear Regression (LR), Support Vector Machine (SVM)	ETH	Computers & Electrical Engineering	SCI
[27]	Analysis of trends in Bitcoin prices and price prediction	Logistic Regression, Linear Discriminant Analysis, and more complex ML models	BTC	Journal of Computation al and Applied Mathematics	SCI
[21]	Predicting and analyzing factors affecting cryptocurrency prices	Gated Recurrent Unit (GRU), LSTM	LTC, XMR	Journal of Information Security and Applications	SCI
[28]	Analysis of trends in Bitcoin prices and price prediction	Recurrent Neural Network (RNN), LSTM	BTC	Journal of Risk and Financial Management	SCI
[34]	Cryptocurrency price prediction with social media data	Complex machine learning models	BTC, ETN, ETH, XMR, XRP, ZEC	Expert Systems	SCI

Table 2.1: Literature Summary About Cryptocurrencies (Continued)

References	Purpose	Method	Assets	Journal	Index
[29]	Intraday analysis of trends in Bitcoin prices and price prediction	ANN, SVM	BTC	Applied Soft Computing	SCI
[30]	Prediction of cryptocurrency prices	LSTM	BTC, Digital Cash, XRP	Chaos, Solitons & Fractals	SCI
[31]	Prediction of cryptocurrency prices	SVR-GARCH	BTC, ETH	Expert Systems with Applications	SCI
[35]	Examining the relationship between media sentiment and Bitcoin's intraday price unit	Sentiment Score	BTC	Journal of Risk Finance	SCI
[36]	Predicting prices by analyzing user reviews in online cryptocurrency communities	VADER	BTC, ETH, XRP	Plos ONE	SCI

All these benefits show that the evaluation of cryptocurrency investment with fuzzy logic in on-chain analysis, a detailed analysis, is a multi-criteria decision problem. In this context, revealing the effective examination factors of this problem, which includes high complexity and uncertainty in the technological, economic, and social sense, will improve the theory in determining the roles of its different sides in the new financial technology. In this context, the uncertainties in the applications that contain blockchain technology in different application areas have been a subject frequently discussed by researchers in the literature (Table 2.2).

Table 2.2: Literature Summary on Blockchain and MCFD Algorithms

References	Application Area	Application Purpose	Method
[40]	Supply chain (SC), Finance	Analyzing supply chain financial risks in terms of blockchain technology	Fuzzy Hierarchy Analysis and Cognitive Maps
[41]	SC, Food	Investigation of the strategies of the food supply chain in terms of the effectiveness of blockchain technologies during the pandemic period	Fuzzy Analytical Hierarchy Process and Weighted Assessment Sum Product Assessment (WASPAS)
[42]	Risk	Risk assessment in blockchain technology	Hesitant fuzzy Z-numbers, DEMATEL
[43]	Platform	Platform selection in blockchain technology	Combined solution proposal: SAW, WASPAS, MABAC, CODAS, and MARCOS
[6]	Banking	Evaluation of banks' blockchain-based business models	BWM, VIKOR, Fuzzy set theory
[44]	SC, Drug	Classifying the risks of blockchain implementation in the pharmaceutical supply chain	BWM, VIKOR
[45]	Platform	Selection of a suitable blockchain platform for enterprise system development	Simple Multi-Attribute Rating Technique (SMART)
[46]	Platform	Blockchain platform assessment	Double Normalization-based Multi-Aggregation (DNMA), Criteria Importance Through Intercriteria Correlation (CRITIC), Linguistic D Numbers (LDNs)
[47]	Platform	Blockchain platform assessment	Entropy and CRITIC
[48]	Marine	Identification of key application factors in blockchain technology of shipping companies in Taiwan	BOCR (Benefits, Opportunities, Costs, and Risks) and the Fuzzy Analytical Hierarchy Process
[49]	SC	The use of blockchain applications in different sectors in supply chain management	Hesitant Fuzzy AHP, TOPSIS
[50]	Risk	Evaluating possible risks that may arise in blockchain technology using decision methodology	Pythagorean Fuzzy AHP

Table 2.2: Literature Summary on Blockchain and MCFD Algorithms (Continued)

References	Application Area	Application Purpose	Method
[5]	Platform	Development of decision model for blockchain platform selection	TOPSIS, AHP, BDT
[51]	SC, Agriculture	Investigating barriers to blockchain adoption in the Indian agricultural supply chain	Integrated ISM-DEMATEL and Fuzzy MICMAC
[52]	Finance	Development of a new approach to evaluating blockchain crowdfunding projects	TOPSIS, Grey correlation analysis (GRA)

Researchers have focused on accelerating the sharing services and resources of blockchain technology in different industries. In this context, it has been determined that with the completion of various encryption verifications, savings can be achieved in accelerating time-consuming workflows in the process. The most common example of this determination is in the studies in the literature in which the supply chain is made in the dimensions of medicine, food, agriculture, and finance [40], [42], [45], [49], [51]. Apart from this, there is also some research that discusses the risks for investors about in which cryptocurrency to invest [42], [50]. Differences in commercial transactions and management automation in various industries also present a different decision problem about which platform or software to choose. Considering this situation, the lack of a guide for the applicability, evaluation, and selection of blockchain technology shows that the problem is suitable for fuzzy multi-criteria decision structures. Many of the researchers focused on this problem and evaluated different platforms in the relevant criteria sets [5], [6], [43], [45], [47], [48], [52], [53].

In the light of all these studies, as far as is known from the literature, the limitations of the study and the gaps in the literature are as follows.

- There are many potential factors influencing the price changes of cryptocurrency in traditional approaches, and there is no standard set for this yet.
- Although many hybrid models have been presented on how to design accurate forecasting models that can describe price fluctuations in cryptocurrencies, the unpredictability of trading volume growth limits the input data in these models.
- Although it has been frequently studied which core features to consider in forecasting models in price fluctuation, there is no systematic analysis of the strong

positive correlation between them and the correlation weights in an environment of uncertainty.

- Although there are strong approaches to Bitcoin and Ethereum cryptocurrencies, the study, in which other cryptocurrencies in the market meet on a common denominator, has not been analyzed with fuzzy multi-criteria decision-making methods in an environment of uncertainty as far as is known from the literature.

Considering the limitations of the study, as far as is known from the literature, its contributions provide an important projection in terms of both the field of application and the developed methodology and applicability. The literature shows that the most critical step in the price prediction of cryptocurrencies is the creation of feature sets. In this context, this study, which examines the correlation in the determinant alternatives that make up the price unit between cryptocurrencies, will make an important contribution to standardization in feature sets. Another critical contribution is the use of fuzzy sets for problems with high uncertainty and complexity in blockchain-based applications. In this context, there is no research yet on the determinants of cryptocurrencies in on-chain analysis in a fuzzy environment. This aspect of the study allows the establishment of a fuzzy multi-criteria decision-making model based on artificial intelligence. Therefore, the creation of a decision support mechanism will standardize the current situation and enable the concretization of abstract data. Scenario-based sensitivity analyzes were carried out in order not only to ensure the accuracy and validity of the proposed approach but also to present analyzes in hourly, weekly, and monthly changing situations. Thus, the uncertainty in the evaluation process will be rationalized with the proposed artificial intelligence-based hierarchical model and will provide an important projection to the literature.

CHAPTER III

METHODOLOGY

3.1 FEATURE IMPORTANCE BY RANDOM FOREST ALGORITHMS

The random forest has the role of a meta-estimator, which creates decision trees for its various sub-samples in the dataset. It achieves forecast accuracy by controlling the risk of overfitting. Although "squared_error" is often used for this process, it can be used in Poisson deviance to measure the quality of splits or predictions [54].

It is also known that it is possible to explain the high dimensionality in feature sets, in other words, to easily calculate multivariate feature importance (FI) scores with random forest algorithms. This is called variable importance and has the ability to describe which attributes are relevant. Calculated importance values are a descriptor of how important features are to machine learning models. It is an approximation of the question of how important the features in the data are and how their relationship contributes to the model [55].

The random forest algorithm has built-in feature importance that can be calculated in three ways:

3.1.1 Gini Importance

There are many nodes and leaves in the set of decision trees for both the classifier (Random Forest Classifier) and the regressor (Random Forest Regressor). The feature selected in the internal node is used to decide how to split the dataset into other clusters containing similar responses. Features in internal nodes are selected for the classifier by some criteria, which are "Gini impurity" and "information gain". For the regressor, some criteria that are "variance reduction" are selected and continued. The average value of all trees in the forest represents the feature importance measure. For the classifier or regressor, it is measured how each feature reduces its health in the split. However, the relative values of the importance values calculated here should be checked [56]. The disadvantages of the method are the predominance of categorical features with numerical and high cardinality. In addition, when associated features are found in the dataset, only one of the features is selected; the second can be neglected. In this case, it can lead to wrong results. On the other hand, the biggest advantage is the computational speed because all the necessary values are calculated during the training [57].

3.1.2 Permutation Based FI

It is preferred to overcome the disadvantages of the default feature importance calculated with "mean impurity decrease". With this operator, each feature is randomly mixed with calculating the change in the performance of the model. Thus, the feature that affects the performance the most is marked as the most important. However, it is computationally difficult because it can report highly correlated features as unimportant [56].

3.1.3 FI Computed with SHAP Values

It uses the model as agnostic in calculating feature importance degrees. It draws on game theory science to interpret how it affects the prediction for each feature. Here it can provide extra information such as decision graphs or dependency graphs using Shapley values. However, this operator is expensive due to its informatic computing feature [54].

3.2 FUZZY SET THEORY: PYTHAGOREAN NUMBERS

The ambiguity and complexity in the decision-making process create difficulty in expression for decision-makers. Fuzzy set theory for this problem entered the literature in 1965 [7]. The theory reveals the mathematical approach that can model linguistic expressions, that is, many qualitative and quantitative considerations in the decision-making phase. As a result, it was possible to measure the uncertainty in the information. He solved this problem by associating the uncertainty with the degrees of membership μ_P (x) and non-membership ν_P (x) in the set. However, using this theory, which is used in different fields of application, a different version was published by adding the degree of hesitancy in 1986 [58]. This development, called Intuitionistic fuzzy sets, has been used by many researchers and has been enriched in the academic literature. Over the years, it has been noticed that this proposed approach is insufficient when the sum of membership degrees is greater than 1 [59]. As a result, Pythagorean fuzzy sets, which are a different extension of heuristic fuzzy sets, entered the literature in 2014 [8]. The biggest difference and advantage of Pythagorean fuzzy sets compared to intuitive fuzzy sets is that, unlike the sum of membership and non-membership degrees, the sum of the squares of these degrees does not exceed 1 [60]. This is $0 \leq (\mu_P (x))^2 + (\nu_P (x))^2 \leq 1$. In the following section, important mathematical operators and linguistic scales of Pythagorean fuzzy sets are mentioned.

The degree of indeterminacy of x to P is shown as in Eq. (3.1):

$$\pi_P (x) = \sqrt{1 - \mu_p^2 (x) - \nu_p^2 (x)} \tag{3.1}$$

For simplicity, Zhang and Xu [61] named $P (\mu_P (x), \nu_P (x))$ a Pythagorean fuzzy number (PFN) represented by $p = (\mu_P, \nu_P)$.

Table 3.1: Weighting Scale for the PFAHP Method

Linguistic terms	**Abbr.**	**Pythagorean fuzzy numbers**			
		μ_L	μ_U	ν_L	ν_U
Definitely Low Significance	DLS	0	0	0,9	1
Very Low Significance	VLS	0	0	0,8	0,9
Low Significance	LS	0,2	0,35	0,65	0,8
Below Average Significance	BAS	0,35	0,45	0,55	0,65
Average Significance	AS	0,45	0,55	0,45	0,55
Above Average Significance	AAS	0,55	0,65	0,35	0,45
High Significance	HS	0,65	0,8	0,2	0,35
Very High Significance	VHS	0,8	0,9	0,1	0,2
Definitely High Significance	DHS	0,9	1	0	0
Exactly Equal	EE	0,1965	0,1965	0,1965	0,1965

Source: [59]

3.3 RANKING ALGORITHMS: PYTHAGOREAN FUZZY AHP & TOPSIS

Multi-criteria decision-making methods, which are the sub-branch of decision science, model the decision process according to the criteria. As a result, quantitative results are obtained about the alternatives in a way that maximizes the benefit for the decision-maker. In the literature, many classical or fuzzy-based methods are used to solve the solution of different multi-criteria decision-making problems. One of the methods that has proven to be algorithmic operations and consistent results is the Analytical Hierarchy Process (AHP) [62]. There are many examples in the literature where AHP is used with fuzzy numbers as it is used in this study [63]–[66]. In addition, AHP can be used in decision problems in combination with both criterion weighting and ranking methods. There are many academic studies on the combined use in the literature [67]–[69]. In combined use cases, the criteria weights calculated in the AHP method are used as inputs in the ranking algorithm. One of these combined uses is the AHP-TOPSIS combination. The TOPSIS method can calculate a sequence of positive and negative ideal solutions that alternative decision points can take made with certain criteria [70]. In this direction, the conceptual framework of the algorithm and application of the combination of Pythagorean fuzzy AHP-TOPSIS is as in Figure 3.1.

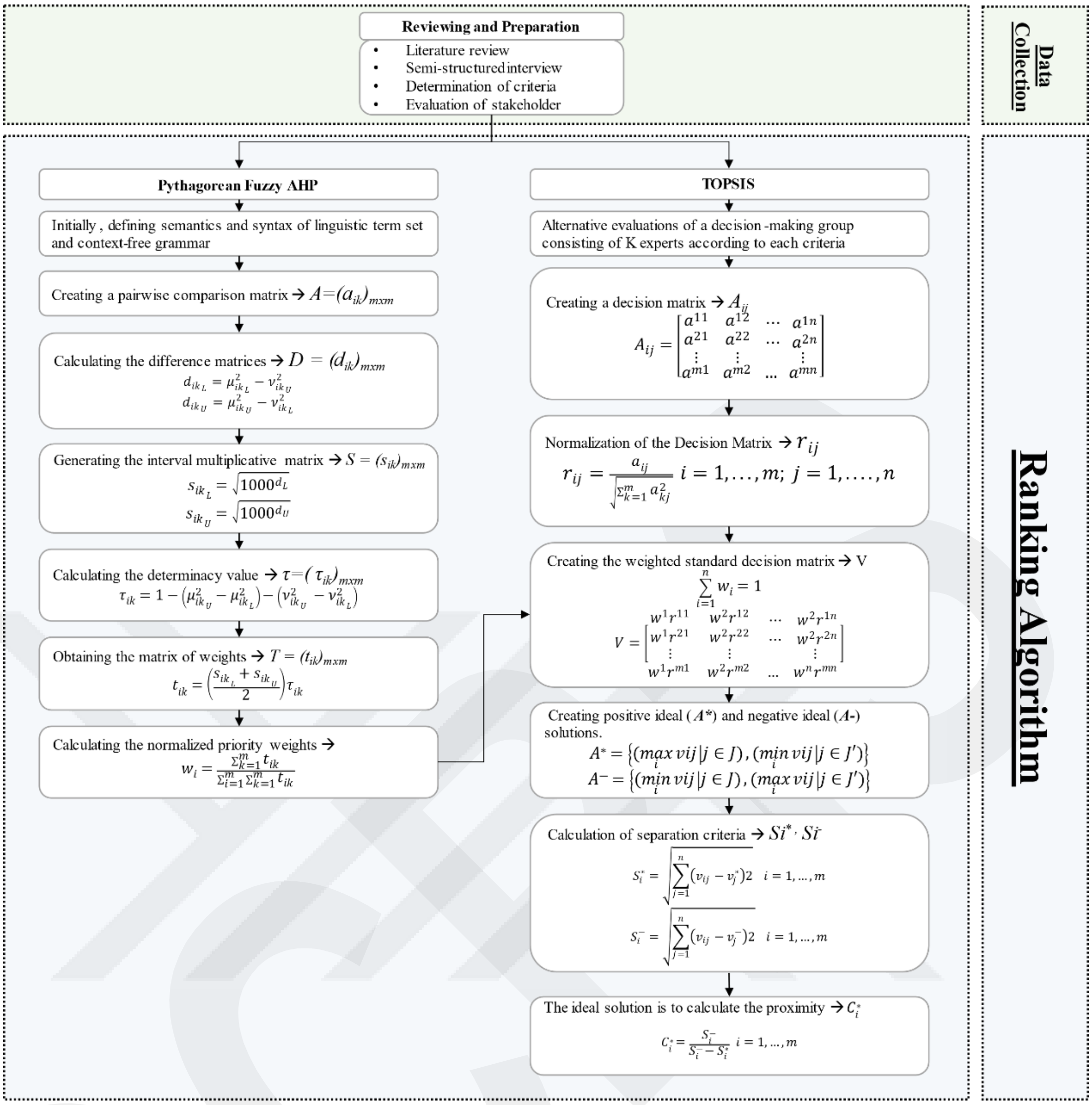


Figure 3.1: Application Steps of the Ranking Algorithm

CHAPTER IV

CASE STUDY

A new type of currency called cryptocurrency has emerged due to the use of digital assets as means of exchange designed as virtual currency [20], [24], [32]. Another reason for its increased efficiency in the markets is related to the technology it contains. With such a development and an unprecedented interest due to the technology it contains, researchers are also analyzing the future values of cryptocurrencies by establishing prediction models with many abstract and tangible attributes. The correct estimation of these analyzes not only provides decision support to investors but also contributes to the development of regulatory policies in their governments and the creation of competitive strategies of enterprises [10]. Therefore, the interpretation of mathematical operations between two blocks, in other words, on-chain analysis, is a decision problem that has not yet been studied as far as is known from the literature.

In this study, access to exchange flow data on all stock markets for the last three years was provided, and four crypto assets with the highest market dominance were studied. These are Bitcoin (BTC), Ethereum (ETH), Chainlink (LINK), and Maker (MKR), respectively. The selected crypto assets are included in the criteria set and have been weighted with PFAHP by five experts in the industry (Table 4.1).

Table 4.1: Expert Profile Particulars

Expert number	Actor Types*	Stakeholder	Title	Duration of experience
E1	Enactor	Technology development (University)	Designing the financial and technological architecture of systems developed on the blockchain	15
E2		Financial Services (University)		12
E3		Blockchain Software Developer - Researcher	Cryptocurrency policy and system modeling	6
E4	Selector	Economist - Researcher (University)	Financial Planner	5
E5		Investor	Production and service, planning, lobby-advocacy groups	9

**: Enactors, developers, and people who directly contribute to technology. E.g., technology developers, R&D ownership, etc. Selectors are those who are remotely involved in more than one alternative. E.g., investors, financiers, etc.* [71].

After this stage, in the on-chain analysis, since the effect of the analyzed movement is not expected instantly or even hourly, seven alternative data of crypto-assets were drawn daily, since it would be necessary to average again to capture the effect in hourly or minute data correctly. The time shift between the price and the metrics in order to calculate the effect time of the metric used on the price was not made within the scope of this study. At this stage, CryptoQuant [72] stock market flow data is used. This paid data is accessed via an API. To use this API, it is necessary to obtain an API_KEY first and then make an HTTP Request.

The metrics used in the study are Reserve, Inflow, Outflow, Inflow Address Count, Outflow Address Count, Inflow Transaction Count, and Outflow Transaction Count flow data for all exchanges. The views of the graphs of the related data are given in Figure 4.1 – 4.4, respectively.

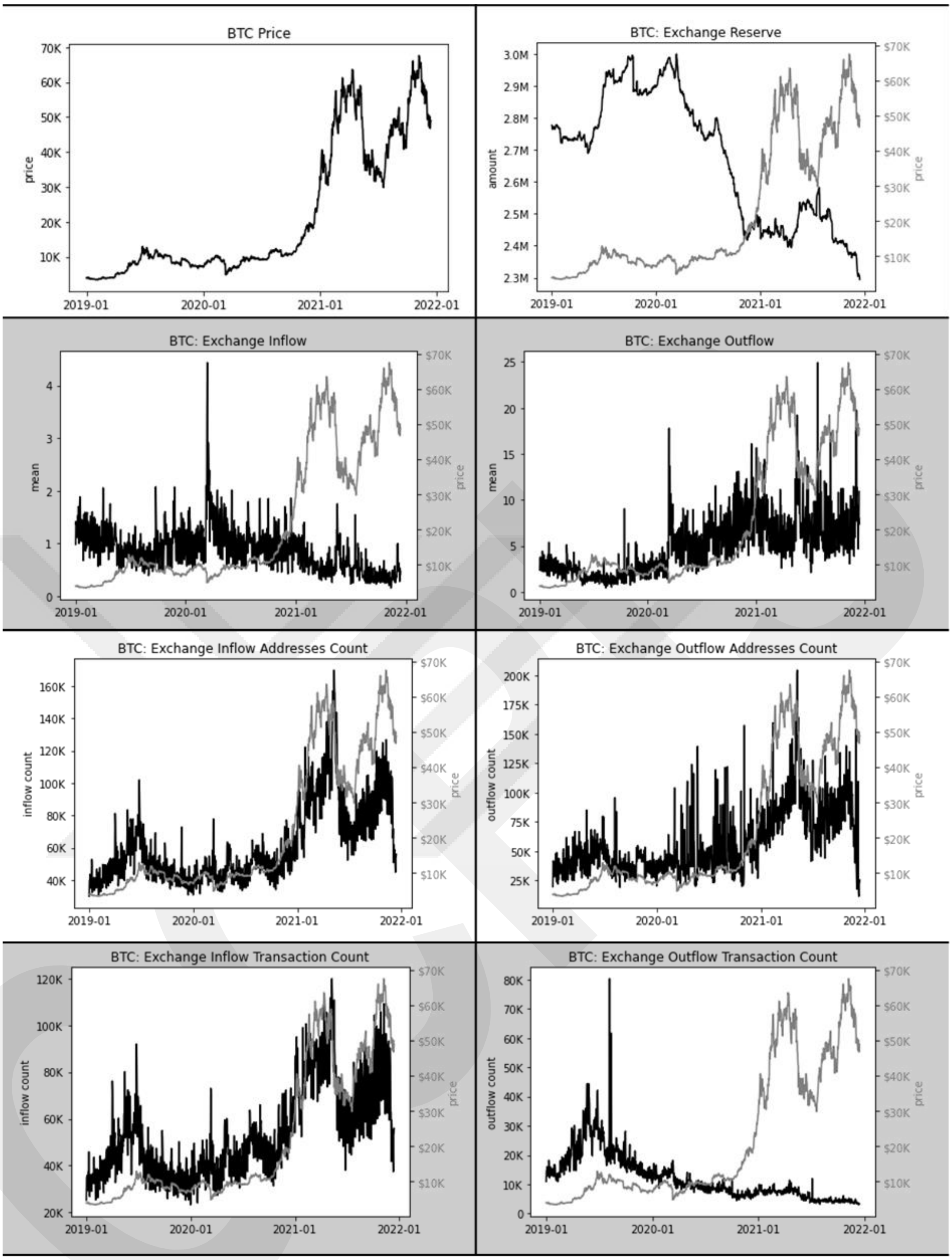


Figure 4.1: Graphs of BTC Data

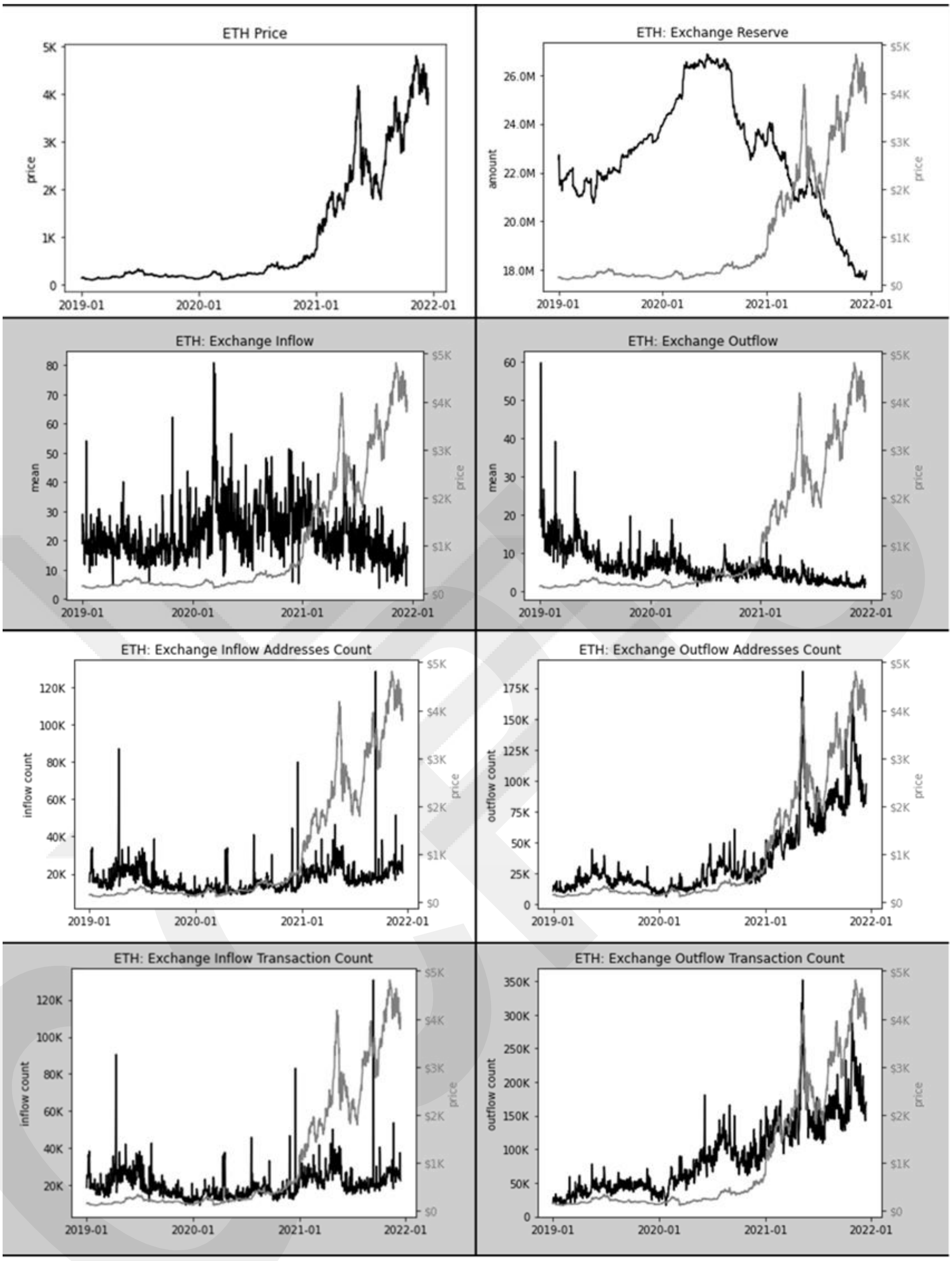


Figure 4.2: Graphs of ETH Data

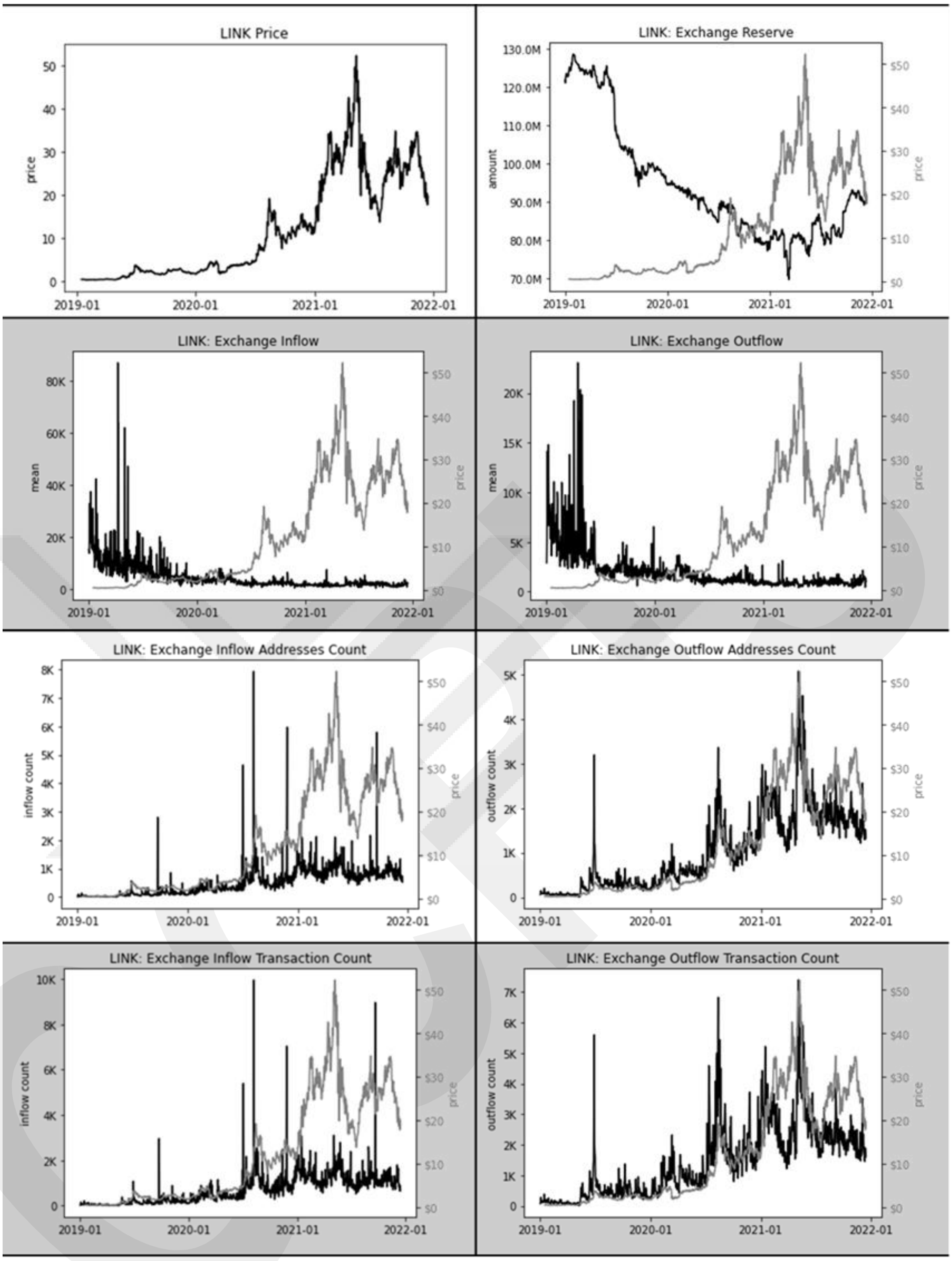


Figure 4.3: Graphs of LINK Data

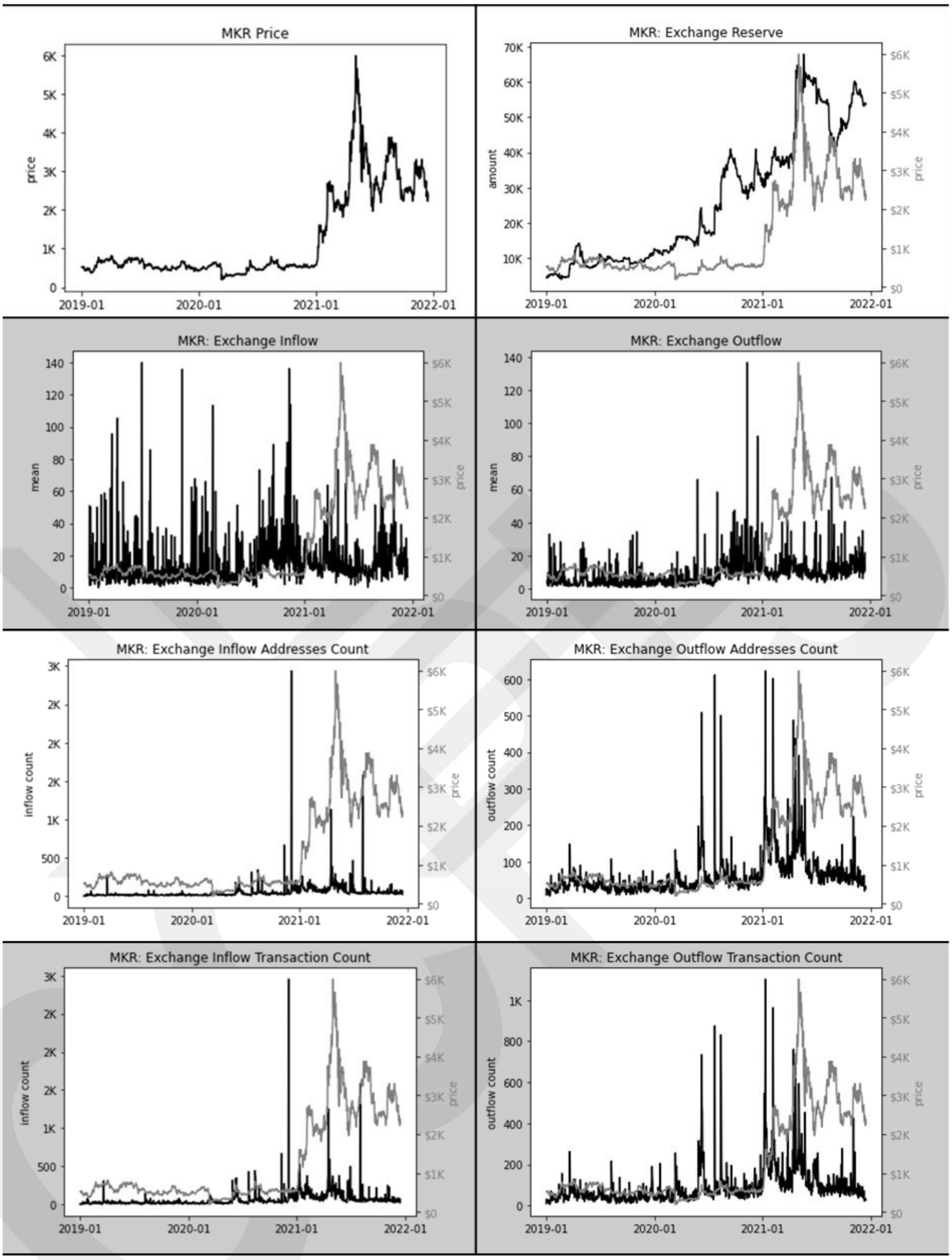


Figure 4.4: Graphs of MKR Data

Data in JSON or CSV format; It can be taken as a daily, hourly, minutely, or block time interval. The data of a single stock exchange can be obtained, as well as the data of all stock exchanges. It is possible to reach the data within the desired date range. Detailed information about the metrics considered is presented in Table 4.2.

Table 4.2: Detailed Explanations of On-Chain Metrics (Alternatives)

Alternative number	**Alternative**	**Definition**
A1	Exchange Reserve	It shows the total amount of crypto assets (coin or token) available on exchanges. It is an important indicator that is generally used for medium-long term forecasts. A high value means selling pressure as it indicates potential crypto assets ready for sale. A low value indicates that money is probably withdrawn from exchanges to cold wallets; thus, trust is established, and an increase in prices is expected. Therefore, there is an inverse relationship between price and stock market reserve.
A2	Exchange Inflow	It is an indicator of the amount of crypto-asset deposited on exchanges. It can be used for short, medium, and long-term forecasts. A large amount entered usually means that it was sent to sell on the exchange. It is known that not only money is sent to the stock market for sales, but also money can be sent to exchanges to trade in derivatives markets, to make exchanges, or to benefit from the exchange's own services such as staking. Even those who hold large amounts of coins can enter large amounts instantly to manipulate the market. These conditions should be considered, especially for short-term evaluations.
A3	Exchange Outflow	It is an indicator of the amount of crypto-asset coming out of exchanges. The price is expected to rise, possibly as it signals an exit from exchanges for a safe and long-term hold.
A4	Exchange Inflow Addresses Count	Indicates the number of wallets that have entered the exchanges. The fact that the number of addresses entering the stock market is in an increasing trend indicates that the probability of selling increases as well. Considering the cost of sending to a different number of wallets from the exchange wallet, the number of wallets can be considered close to the number of investors. It is more prone to manipulation as it only shows the wallet or even the number of investors, regardless of trading low or high amounts. Therefore, it is a more reliable indicator than Exchange Inflow.
A5	Exchange Outflow Addresses Count	It refers to the number of wallets exiting the exchanges. If it shows an upward trend in the long term, it indicates that the price will increase as well. As with all indicators, it should be considered that suddenly rising or falling values can be deception.
A6	Exchange Inflow Transaction Count	Indicates the number of crypto asset transactions entered on the exchanges. Returns the number of each transaction, regardless of the amount and number of wallets. In an ascending trend, it indicates that there is selling pressure, and the price may decrease.
A7	Exchange Outflow Transaction Count	Indicates the number of crypto asset transactions exited from exchanges. As in Exchange Outflow Addresses Count, it is expected that the price will be positively affected by the rising trend.

Source: [72]–[74]

In addition, only stock market flow data were examined in the study. While there are dozens of other analyzes that can be used in on-chain analysis like this, it is an innovative perspective to standardize presenting the effect on the price units of crypto assets with on-chain analysis. In this context, Feature importance was calculated using Pearson correlation calculation and Random Forest regressor in order to observe the direction and stability of the relationship between critical metrics that can determine the effect on the price of crypto assets. This stage created two different decision matrices and provided input to TOPSIS, the ranking algorithm. Then, the calculated values were followed by the TOPSIS ranking algorithm steps, and the importance weights between the metrics were obtained. Sensitivity analysis was performed to observe the results under different conditions. The flow chart of this application is briefly given in Figure 4.5.

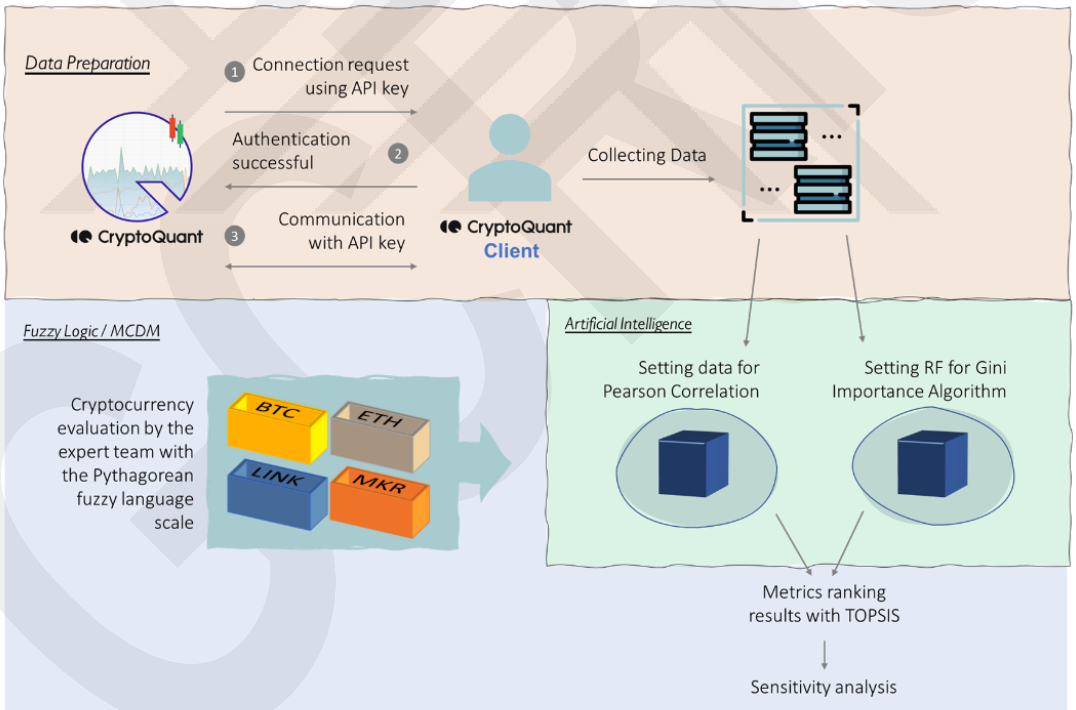


Figure 4.5: Flow Chart of the Case Study

4.1 DATA COLLECTION

In the study, CryptoQuant stock market flow data was used for four crypto assets, where it is easier and more interpretable to reach healthy data. These are Bitcoin (BTC), Ethereum (ETH), Chainlink (LINK), and Maker (MKR). The metrics used are Reserve, Inflow, Outflow, Inflow Address Count, Outflow Address Count, Inflow Transaction Count, and Outflow Transaction Count flow data for all exchanges. In order to determine the effect on the price, first of all, a Pearson Correlation calculation was made (Table 4.3).

However, by only looking at the correlation, it is not possible to make an inference about which metric should be looked at first. For this reason, the "RandomForestRegression" model was used to see the effect of on-chain exchange flow metrics, as an independent variable in time series, on the crypto asset price, which is a dependent variable. The significance of the effect of each metric on the price was also calculated with the "feature_importances_" attribute of the regression model. The results are given in Table 4.3.

Table 4.3: Importance Weights of Metrics in Crypto Assets (Decision Matrices)

Pearson Correlation Decision Matrix					**Random Forest Regressor Decision Matrix**				
	BTC	**ETH**	**LINK**	**MKR**		**BTC**	**ETH**	**LINK**	**MKR**
A1	-0,82	-0,73	-0,65	0,84	**A1**	0,76	0,09	0,09	0,87
A2	-0,61	-0,23	-0,41	0,03	**A2**	0,02	0,00	0,02	0,01
A3	0,5	-0,51	-0,46	0,21	**A3**	0,01	0,00	0,04	0,01
A4	0,86	0,37	0,62	0,22	**A4**	0,15	0,00	0,04	0,02
A5	0,72	0,95	0,86	0,4	**A5**	0,00	0,89	0,77	0,06
A6	0,84	0,33	0,62	0,26	**A6**	0,01	0,00	0,01	0,01
A7	-0,55	0,88	0,78	0,35	**A7**	0,05	0,01	0,02	0,01

4.2 WEIGHTING ASSETS WITH PFAHP IN FUZZY ENVIRONMENT

The opinions of the experts in Table 4.1 about the four crypto assets considered in the study were regarded. The expert team was asked to compare each crypto asset with one another. These evaluations were made using the linguistic scale defined in Table 2.1, where Pythagorean fuzzy numbers are presented. At this stage, the decision matrix for the Pythagorean Fuzzy Analytical Hierarchy Process was created by transposing the language variables to the interval-valued Pythagorean fuzzy numbers. This decision matrix includes the average of 5 expert opinions and the numerical transformations. The pairwise comparison matrix is as in Table 4.4. Afterward, the weights of 4 crypto-assets were obtained by following the algorithm steps given in Figure 4.5 in Chapter 3. All the matrices in the algorithm steps are presented as a supplementary file. Finally, the calculated criteria weights are plotted in Figure 4.6.

Table 4.4: Reconciled Pairwise Comparison Matrix for Four Crypto Assets

Criteria	Pythagorean fuzzy numbers: $\{[\mu_L,\mu_U],[v_L,v_U]\}$															
	BTC				ETH				LINK				MKR			
	μ_L	μ_U	v_L	v_U	μ_L	μ_U	v_L	v_U	μ_L	μ_U	v_L	v_U	μ_L	μ_U	v_L	v_U
BTC	0,2	0,2	0,2	0,2	0,5	0,6	0,2	0,2	0,8	0,9	0,1	0,2	0,9	1,0	0,0	0,1
ETH	0,2	0,2	0,5	0,6	0,2	0,2	0,2	0,2	0,5	0,6	0,4	0,5	0,8	0,9	0,1	0,2
LINK	0,1	0,2	0,8	0,9	0,4	0,5	0,5	0,6	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2
MKR	0,0	0,1	0,9	1,0	0,1	0,2	0,8	0,9	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2

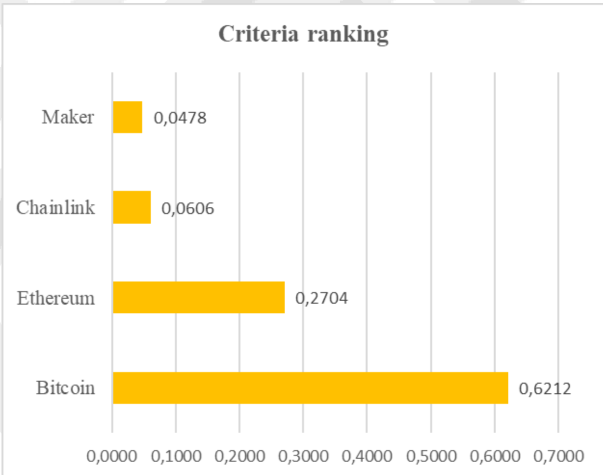


Figure 4.6: Weights of Crypto-Assets (Criteria) Calculated with PFAHP

4.3 PRIORITIZING ON-CHAIN METRICS USING TOPSIS

At this stage, the rankings of the stock market flow data obtained for four crypto assets are presented with the TOPSIS algorithm using decision matrices prepared based on machine learning and statistics. A combined method was created by including the criteria weights obtained by PFAHP using Table 4.3 (decision matrices) into the algorithm. The ranking results of this method are as in Figure 4.7.

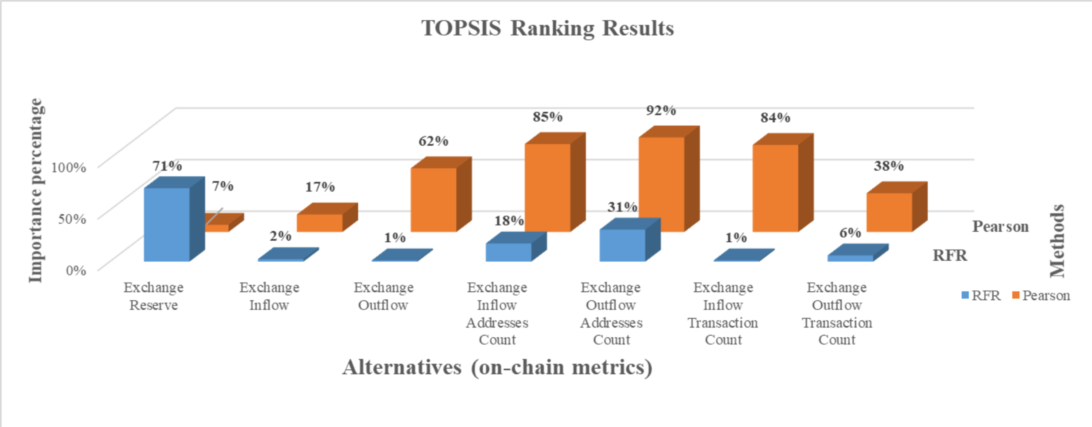
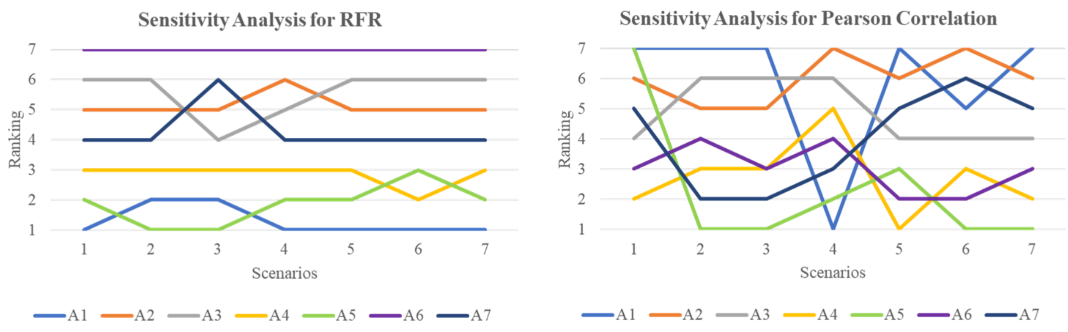


Figure 4.7: TOPSIS Ranking Results

As can be seen in Figure 4.7, the order of importance in statistical and artificial intelligence-based algorithms is not stable, which metrics are prioritized in terms of the effect on the price of crypto assets. However, it is known that the effect of on-chain metrics on price is based on interpretation as well as numerical values. For example, if there is an outflow of crypto money from the stock markets rather than the effect of the increase of rain clouds on the rain, it means that there is a relationship based on interpretation, as investors believe that the price will rise. For this reason, it is necessary to analyze the situations when the weights of crypto assets are calculated with the Pythagorean Fuzzy AHP change.

Accordingly, a scenario-based sensitivity analysis was performed using both the Pearson correlation decision matrix and the RFR decision matrix. The analysis includes a valid inquiry into the robustness of the proposed model and the correctness of the conceptual framework. Paired combinations of criteria were created to obtain a stable observation. Six scenarios were created for both decision matrices.

Table 4.5 summarizes the results calculated for each scenario. Calculation results are visualized and given in Figure 4.8 for ease of interpretation and comparison of the statistical and artificial intelligence methods that make up the decision matrices.



(a) (b)

Figure 4.8: Ranking Results of Sensitivity Analysis

Table 4.5: Sensitivity Analysis for Decision Matrices

	Scenarios		Criteria weights				Alternative Weights							Alternative Ranking						
			Bitcoin	Ethereum	Link	Maker	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**
Sensitivity Analysis for RFR Decision Matrix	***Current***		*0,6212*	*0,2704*	*0,0606*	*0,0478*	*0,7115*	*0,0239*	*0,0124*	*0,1761*	*0,3108*	*0,0120*	*0,0596*	*1*	*5*	*6*	*3*	*2*	*7*	*4*
	1	C1-C2	**0,2704**	**0,6212**	0,0606	0,0478	0,3307	0,0103	0,0062	0,0738	0,6978	0,0052	0,0265	2	5	6	3	1	7	4
	2	C1-C3	**0,0606**	0,2704	**0,6212**	0,0478	0,1489	0,0135	0,0349	0,0358	0,8993	0,0013	0,0127	2	5	4	3	1	7	6
	3	C1-C4	**0,0478**	0,2704	0,0606	**0,6212**	0,7129	0,0022	0,0035	0,0175	0,3249	0,0010	0,0056	1	6	5	3	2	7	4
	4	C2-C3	0,6212	**0,0606**	**0,2704**	0,0478	0,7172	0,0247	0,0193	0,1781	0,3067	0,0120	0,0600	1	5	6	3	2	7	4
	5	C2-C4	0,6212	**0,0478**	0,0606	**0,2704**	0,9073	0,0239	0,0124	0,1767	0,1054	0,0120	0,0595	1	5	6	2	3	7	4
	6	C3-C4	0,6212	0,2704	**0,0478**	**0,0606**	0,7136	0,0239	0,0123	0,1760	0,3086	0,0120	0,0596	1	5	6	3	2	7	4
	Scenarios		**Criteria weights**				**Alternative Weights**							**Alternative Ranking**						
			Bitcoin	Ethereum	Link	Maker	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**
Sensitivity Analysis for Pearson Correlation Decision Matrix	***Current***		*0,6212*	*0,2704*	*0,0606*	*0,0478*	*0,0552*	*0,1697*	*0,6170*	*0,8554*	*0,9203*	*0,8461*	*0,3770*	*7*	*6*	*4*	*2*	*7*	*3*	*5*
	1	C1-C2	**0,2704**	**0,6212**	0,0606	0,0478	0,0509	0,2779	0,2729	0,6864	0,9596	0,6656	0,7469	7	5	6	3	1	4	2
	2	C1-C3	**0,0606**	0,2704	**0,6212**	0,0478	0,0555	0,1917	0,1423	0,7913	0,9683	0,7850	0,9077	7	5	6	3	1	3	2
	3	C1-C4	**0,0478**	0,2704	0,0606	**0,6212**	0,6251	0,1382	0,2086	0,3708	0,5809	0,3921	0,5313	1	7	6	5	2	4	3
	4	C2-C3	0,6212	**0,0606**	**0,2704**	0,0478	0,0563	0,1332	0,6377	0,9197	0,9184	0,9187	0,3502	7	6	4	1	3	2	5
	5	C2-C4	0,6212	**0,0478**	0,0606	**0,2704**	0,2681	0,1187	0,6775	0,7798	0,8124	0,7889	0,2236	5	7	4	3	1	2	6
	6	C3-C4	0,6212	0,2704	**0,0478**	**0,0606**	0,0690	0,1695	0,6175	0,8525	0,9169	0,8437	0,3756	7	6	4	2	1	3	5

CHAPTER V

RESULTS AND DISCUSSION

In the application part of the study, the proposed method combination of crypto assets and the stages that will provide a decision support system to on-chain analysis are explained. In this section, detailed interpretations of the results are given, and important notes about the validity and consistency of the results are presented:

The "Exchange Reserve" relationship is an expected result both in the calculation of the feature importance value in the RFR model Figure 4.7 and in the sensitivity analysis of the relevant model Figure 4.8. Because Bitcoin, which dominates the market in Figure 4.6, sheds light on this result. As the amount of the current reserve is the most important indicator supporting the market confidence interpretation for the medium-long term [72]–[74]. Therefore, the first metric to look at among the exchange flow data should be the "Exchange Reserve" metric.

The "Inflow/Outflow Addresses Count" is the most important indicator that shows the "movement" in and out of the stock market. Because it can be assumed that the number of wallets entering and exiting is equal to the number of investors. In Figure 4.7, it is in the second and third ranks with the values of 31%, 18%, and 92%, 85% in the Pearson correlation and the RFR model. In this sense, it is more secure than "Exchange Inflow/Outflow" data and especially "Transaction Count" data. Addresses count values rank second in total in both regression analysis and fuzzy logic analysis.

It is observed that the importance weights of Exchange Inflow/Outflow and Transaction Count are significantly lower in both regression and fuzzy analysis.

Therefore, when it is necessary to decide on a crypto asset investment by supporting the "Exchange Flow" data from on-chain analyses, the conclusion that the "Exchange Reserve" value should be looked at first and then the "Exchange Inflow/Outflow Addresses Count" values should be looked at as presented with detailed analyses.

CHAPTER V

CONCLUSIONS

A new type of currency called cryptocurrency has emerged due to the use of digital assets as a medium of exchange designed as virtual currency. Another reason for its increased efficiency in the markets is related to the technology it contains. With such a development and an unprecedented interest due to the technology it contains, researchers analyze the future values of cryptocurrencies by establishing prediction models with many intangible and tangible attributes [1], [12], [16].

The review of the relevant literature with artificial intelligence and fuzzy multi-criteria decision-making methods provides a perspective that will provide analytical solutions to the problems that will facilitate the investment process in addition to technical and fundamental analysis in cryptocurrencies.

The correct estimation of these analyzes not only provides decision support to investors but also contributes to the development of regulatory policies in their governments and the creation of competitive strategies of enterprises. Therefore, the interpretation of mathematical operations between two blocks, in other words, on-chain analysis, is a decision problem that has not yet been studied as far as is known from the literature. In this direction, the results of the study and the projection it presents will make the following contributions to the literature:

- Although it is frequently studied which core features to consider in forecasting models in price fluctuation, there is no study on the systematic analysis of the strong positive correlation between them and the correlation weights in an environment of uncertainty.
- Although there are strong approaches to Bitcoin and Ethereum cryptocurrencies, the study, in which other cryptocurrencies in the market meet on a common denominator, has not been analyzed with fuzzy multi-criteria decision-making methods in an environment of uncertainty as far as is known from the literature.

- As far as we know from the literature, it is the first study in which machine learning and statistics-based approaches are presented in terms of providing robust and robust results in a world where strong data flow is provided.

In this direction, in the future versions of the study, machine learning algorithms that can obtain different feature importance values can be tested, and results in multi-criteria decision-making methods can be obtained. In addition, studies on the accuracy of the size of the input set used and the results obtained as output benefit the development of legislation and policies about crypto assets discussed in the literature and globally, and further studies can be carried out in which artificial intelligence and decision science are added to human behavior.

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