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Application of Metasynthesis in Identifying New Combined Genetic Algorithm Methods to Solve Problems in Oil Price Forecasting

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ABSTRACT

The current research seeks to identify new combined genetic algorithm methods to solve price forecasting for oil. Effective factors were identified using a systematic and meta-composite review approach, and by following the 7 steps of the Sandelowski and Barroso method. Out of 4340 articles, 54 were selected based on the CASP method. To assess reliability and quality control, the Kappa index was utilized, and it indicated excellent agreement with the identified indicators. The results of the data analysis collected in the ATLAS TI software led to the identification of 7 categories and 26 primary codes for new combined genetic algorithm methods to solve complex problems. Based on the coding performed, 7 categories and 26 primary codes were identified. The identified categories are: component design, supply network, planning, forecasting, inventory control, information security, segregation, and evaluation. The combination of genetic algorithms with various methods, due to their ability to distinguish features and optimize parameters, can lead to significant improvements in the field of oil price prediction. The use of genetic algorithms in solving oil price forecasting problems as an evolutionary and artificial intelligence approach makes it possible to integrate diverse and complex information into forecasting models. By designing the appropriate components as genes that represent important economic, geographic, and political features, the most optimal genetic combinations can be created to enhance the accuracy and performance of prediction models. ©**authors**

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1. Introduction

In today's world, markets and industries are rapidly evolving, and the factors influencing predictions are also growing (Hasan, Abedin, Hajek, Sultan, and Lucey, 2022; Shapley, 1951). In this context, machine learning and artificial intelligence can serve as powerful and effective tools for price prediction and market analysis (Asgharpour and Vafamand, 2014). Therefore, data-driven decision-making is strongly needed. In price prediction, machine learning machines are able to analyze a huge amount of data and hidden patterns in them (He, Sun, Li, and Mensah, 2023). Using machine learning algorithms, historical patterns can be identified, and based on them, predictions about future prices can be made. These algorithms can analyze historical data from various markets such as the stock market, foreign exchange market, real estate market, and more, identifying significant patterns and making predictions based on them. The use of artificial intelligence in price prediction allows researchers to automatically and quickly analyze large datasets and identify hidden patterns within them (Karathanasopoulos, Zaremba, Osman, and Mikutowski, 2019). Additionally, by using deep learning models and neural networks, it is possible to extract more complex features from the data and achieve more accurate predictions (Sen, Dutta Choudhury, and Kumar Datta, 2023).

Given the volatility and complexity of markets, the utilization of machine learning and artificial intelligence in price prediction assists individuals in making better decisions regarding investment and risk management. Furthermore, these tools can help in detecting various patterns in markets, leading to the identification of successful investment opportunities and the reduction of risks associated with price fluctuations (Manickavasagam, Visalakshmi, and Apergis, 2020). Therefore, this technique is highly effective in predicting oil prices, which involve multi-dimensional data (Hasan et al., 2022; Jovanovic et al., 2022; Jahanshahi et al., 2022). Crude oil is the primary source of energy supply worldwide and is recognized as a cornerstone of the global economy. Additionally, it plays a fundamental role in the financial market and global economic development, as fluctuations in crude oil prices impact a country's economic activities, social stability, and national security (Lu, Sun, and Duan, 2021). Data recorded regarding crude oil fluctuations are influenced by all environmental aspects and exhibit a multi-modal nature. Multi-modal data in crude oil price prediction refer to data collected from various sources and with different characteristics. In the oil industry, multi-modal data includes temporal, economic, geographical, social, and technical information. For accurate crude oil price prediction and reducing possible errors, time series data, geographical data, economic data, political data, technical data, and other factors are required (He et al., 2022).

Examples of such data include production capacity, consumption levels, storage amounts, drilling equipment, and pipeline networks. Multi-modal data in crude oil price prediction may also consist of data from other sources, but these examples illustrate the general nature of multi-modal data in this domain. The use of this multi-modal data helps in better analyzing and predicting oil prices, as these data sources feed from various aspects of the oil market and its influencing factors, interacting with each other to determine investment conditions (Zhao, Wang, Wang, and He, 2019). Therefore, in the coming years, oil prices will continue to be a major determinant of investments. Additionally, as a key variable in assessing economic development, energy policy decisions, and stock markets, oil prices will play a crucial role. Through price predictions, better timing for transactions and investments can be achieved. Having accurate and up-to-date information about price changes enables more informed decisions regarding buying or selling assets and capitalizing on investment opportunities. While international fuel prices are highly volatile, their impact on domestic prices varies significantly from one country to another. Furthermore, in some countries, international fuel price changes are fully and promptly transmitted to retail prices (Kpodar

and Imam, 2020). However, from another perspective, by using deep learning models and neural networks, it is possible to extract more complex features from the data and make more accurate predictions regarding crude oil prices (Huang and Wang, 2018).
Therefore, being aware of future fluctuations in oil prices can be instrumental in making better decisions at managerial levels (Mohammadi Almoti, Haddadi, & Nadimi, 1399). Economists and researchers have long been concerned with the impact of crude oil price fluctuations on economic performance. Therefore, achieving more accurate predictions of crude oil prices is a concern and priority for organizations, institutions, and research communities (Chen, 2020; Bristone et al., 2020; Zhao et al., 2019). Accordingly, this study, given the importance of predicting crude oil prices, seeks to investigate and evaluate specific algorithms, especially machine learning algorithms, for crude oil price prediction. In this regard, the results of this research can be important in paving the way for more useful and impactful research in the future, whether quantitative, qualitative, or mixed-method approaches, in various fields. Another significant aspect of this research is its methodological approach. This research employs both positivist and post-positivist paradigms and ultimately, its analysis with a highly generalizable quantitative method highlights the importance of the research methodology. So what are the new methods of hybrid genetic algorithm to solve oil price forecasting problems?

2. Literature Review

Crude oil prices have always been one of the most complex and challenging subjects to predict due to their relatively irregular, nonlinear, and unstable fluctuations. For this reason, many researchers have made significant efforts in developing various models for predicting crude oil prices (Shabri and Samsudin, 2014). In fact, predicting the trend of crude oil prices and their fluctuations has always been one of the challenges faced by traders in the oil markets. Since World War II, scientists, sociologists, and practitioners in the field of operations research, among others, who referred to themselves as futurists, have undertaken the establishment and expansion of both quantitative and qualitative methods for rational future prediction. Therefore, forecasting methods have always been essential tools in the hands of futurists (Asghari, Omid, Maleki Nia, and Omid, 2018). The importance of predicting oil prices stems from the fact that it is not only necessary for stakeholders such as the petroleum industry, investors, financial institutions, and risk managers, but also for central banks to measure financial and economic stability (Degiannakis and Filis, 2018). To gain a deeper understanding of this phenomenon, the influential factors on oil prices and forecasting tools for global oil prices need to be examined based on the theories presented in this context.
Many researchers have conducted studies in the field of crude oil prices, price prediction, and forecasting tools and algorithms. For instance, Elyakov etal. (2018) found that factors such as changes in a country's macroeconomic conditions, global economic development, geopolitical changes, oil reserves, exchange rate fluctuations, and more are influential factors that significantly impact crude oil prices. Similarly, Peng et al. (2020) consider economic and financial factors such as trade cycles and market sentiment, which increase the volatility of oil markets, as impactful elements on oil prices. Additionally, Liu et al. (2018) discovered that factors affecting oil prices can be multidimensional financial factors. Sehgal and Pandey (2015) conducted research using artificial intelligence methods to examine and predict oil prices. They believe that artificial intelligence methods are widely used as an alternative approach to conventional techniques for oil price prediction. They also argue that artificial intelligence methods encompass a wide range of techniques that can be employed to overcome the complexities and irregularities in oil price series. GAO and Lei (2017) utilized machine learning paradigms for oil price prediction. They state that the advantage of this algorithm is its ability to capture changes in oil prices, as the model

continuously updates whenever new oil price data becomes available.

In Iran, studies have also been conducted on the influential factors and prediction of crude oil prices. For example, Takroosta, Mohajeri, Mohammadi, Shakeri, and Ghasemi (2020) analyzed the factors affecting oil prices. They found that factors such as risks arising from sub-indices of government stability, socio-economic conditions, domestic conflicts, external conflicts, corruption, religious tensions, law and order, and others can be influential factors. Furthermore, in the field of algorithms and price forecasting software, some studies have been mentioned. Razavi, SalimiFar, Mostafavi, and Baki Heskooyi (2014) considered financial markets as influential on crude oil prices in Iran. Also, Asgharpour and Vafamand (2014) used non-linear smooth transition models and genetic algorithm optimization to examine oil price prediction. They believe that this algorithm is a more suitable model for investigating the behavior of crude oil prices and predicting future values. In another article, Shahbazi and Salimian (2014) conducted an evaluation and assessment of oil price prediction using the meta-analysis method. The new meta-analysis method, which is a combination of weighted least squares methods, was used for estimating oil prices, and they believe The present study seeks to identify new hybrid genetic algorithms to solve completely difficult problems in studies based on a component approach in terms of qualitative study approach, and with a library research method, with a combined technique in the field of genetic algorithm Is. In meta synthesis, the information and findings extracted from other studies are analyzed and analyzed. In this regard, the data compiled from these studies are qualitative and not quantitative. As a result, the sample is formed for a combined, elected, and based on their relationship with the research question. Combatively, the integrated review of the qualitative principles of the case or the analysis of secondary data and the main data is not selected, but also the analysis of these studies. In other words, the composition of the data interpretations is the main data of

that the meta-analysis method has the best predictive power.

Although many studies have been conducted in the field of oil price prediction, these models have both advantages and many disadvantages and limitations. Member countries of OPEC are often developing countries, and the economic indicators used in prediction models in these countries are subject to significant fluctuations even in the long term due to the unstable economic structure of these nations. This economic instability reduces the accuracy of oil price predictions by these models and can lead to long-term instability in the economic policies of these countries. Therefore, accurate short-term oil price prediction can mitigate the undesirable effects of political and economic events at the international level. To use these mentioned models and make accurate oil price predictions, it is essential to understand the international oil pricing system's structure. However, from the perspective that a study solely focuses on examining global oil price predictions and is a new study with fresh investigations, there is a noticeable research gap. We are seeking to address this gap and search for new and up-to-date information to better understand this subject.

3. Methodology

selected studies. ATLAS TI software is used for analysis. The main steps of Sandluski and Barrosu (2007) are as follows:

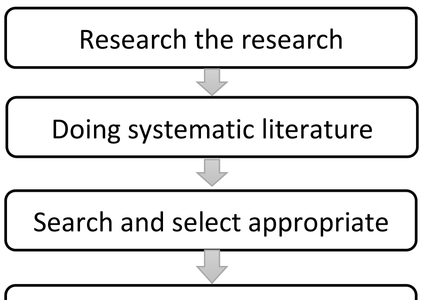

Figure 1. *The process of metasynthesis*

As mentioned, the analytical analysis contains seven steps. In this section, the results of each step of this analysis are presented separately.

Step One: Set up the basic research questions

The first step in Sandulusky's and Barrosu method is to arrange research questions. These questions are generally based on four parameters what, who, when and how; Adjustable. Once the research questions are arranged based on the purpose of the research, the systematic examination of the texts begins. Table 1 shows the answer to these fundamental and fundamental questions about the component method:

4. Findings

Table 1. *Basic Research Questions*

Research Question	Parameter
Identification of new hybrid genetic algorithm to solve problems completely difficult	(What)
Based on the specified keywords	(Who)
Various works, including books, articles, reports on identifying new combination genetic algorithm methods to solve completely difficult problems	(When)
Includes all works from 2000 to 2023	(How)

Stage Two: The systematic review of texts

For the formation of data from the database, the data is used to be used. As mentioned earlier, the research databases were considered by the two prominent Scopus and Web of Science bases, which focused on the following collection of publishing databases: Emerald insight- Springer Link- Science Direct- Taylor & Francis Online- SAGE journals- Wiley Online Library

In addition, in the field of Persian articles, the database of the Academic Jihad Scientific Information Center and the Comprehensive Humanities Portal were also taken into account.

Step Three: Search and Selection of Texts

Table 3 shows the steps taken to refine the extracted articles. Based on this table, for refining the articles of literature, four stages went through the final stage based on the views of 5 experts in this study. In order to evaluate the final quality of the approach -based articles, these experts presented their views for each signed final article, and the articles that earned a lower rating from the applied race were removed from the process.

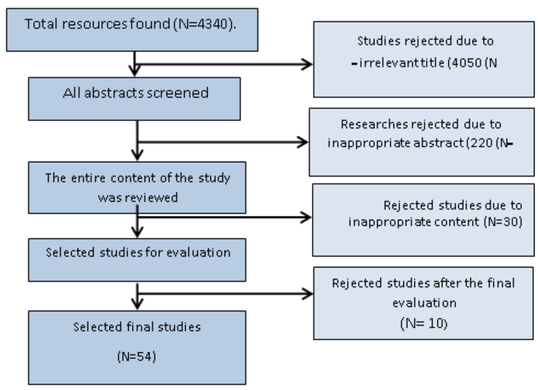

Figure 2. *Review and selection process*

In this step, 4340 studies found in the previous step will be carefully reviewed in several stages to abandon studies that are not commensurate with the research questions and finally identify the most relevant studies for extracting answers to questions. The review process involves examining the title, abstract and content of the research along with the research method. The steps of the review process in this study are as follows:

1. At this stage, the title of studied studies and studies that were not related to research questions were abandoned. By examining the title of the studies, 4050 studies were abandoned due to their lack of relevance to the research questions
2. At this stage, the abstracts of studied studies and studies that were not related to research questions were abandoned. According to studies, 220 studies were abandoned for lack of relevance to research questions.
3. At this stage, the content of the studies was studied, in other words, the whole study was studied and studies that were not related to research questions were abandoned. By examining the content of the studies, 30 studies were unlawful to the research questions.
4. Since this study intends to extract the research framework by using the composition of past studies, according to the expert opinion, the studies are examined with qualitative and quantitative research methods. Therefore, at this stage a study was not eliminated because of the research method.

After removing inappropriate studies with research goals and questions, the researcher must evaluate the methodological quality of the research. The purpose of this step is to eliminate research in which the researcher does not trust the findings provided. A tool commonly used to evaluate the quality of initial qualitative research studies is the "Vital Evaluation Skills Program" that helps with the ten questions to determine the accuracy, validity and importance of qualitative studies of the research. These questions focus on the following: 1. Research goals 2. Methodology logic 3. Research project 4. Sampling method 5. Data collection 6. Reflection (which is to the relationship between the researcher and the participation The people refers to) 7. Ethical considerations 8. Data analysis accuracy 9. Clearly expression of the findings 10. Research value.

Table 2. *Selected Articles*

Total points	Title	Article code
40	.A Blending Ensemble Learning Model for Crude Oil Price Prediction	S01
35	An analysis of crude oil prices in the last decade (2011-2020): With deep learning approach	S02
39	A novel crude oil price trend prediction method: Machine learning classification algorithm based on multi-modal data features	S03
40	Oil Forecasting Using Artificial Intelligence.	S04
39	A novel hybrid approach to forecast crude oil futures using intraday data.	S05
44	Multi-Step Crude Oil Price Prediction Based on LSTM Approach Tuned by Salp Swarm Algorithm with Disputation Operator	S06
34	Artificial Intelligence-Based Prediction of Crude Oil Prices Using Multiple Features under the Effect of Russia–Ukraine War and COVID-19 Pandemic	S07
32	Analysis and forecasting of crude oil price based on the variable selection-LSTM integrated model	S08
33	Predicting Oil Prices: An Analysis of Oil Price Volatility Cycle and Financial Markets,	S09
37	To Pass (or Not to Pass) Through International Fuel Price Changes to Domestic Fuel Prices in Developing Countries: What Are the Drivers?	S10
37	Global crude oil price prediction and synchronization-based accuracy evaluation using random wavelet neural network	S11
33	Investigating the Weak Efficiency Hypothesis in Two Low-Volatility and High-Volatility Regimes of the OPEC Crude Oil Market	S12
35	CPPCNDL: Crude oil price prediction using complex network and deep learning algorithms,	S13
33	Daily Crude Oil Price Forecasting Using Hybridizing Wavelet and Artificial Neural Network Model,	S14
38	Forecasting global crude oil demand by using vector autoregressive, autoregressive distributed lag, and gravitational search algorithms	S15
39	World oil prices: a retrospective analysis and elevation of factors	S16
37	Dynamic Characteristics of Crude Oil Price Fluctuation—From the Perspective of Crude Oil Price Influence Mechanism	S17
44	Financial factors affecting oil price change and oil-stock interactions: a review and future perspectives,	S18
40	Artificial intelligence methods for oil price forecasting: a review and evaluation,	S19
37	A new approach for crude oil price prediction based on stream Learning	S20
38	An Analysis of Oil Prices Considering the Political Risk of OPEC	S21

Total points	Title	Article code
35	Short-term impact of financial markets on the behavior of heavy Iranian crude oil prices	S22
45	Predicting oil prices using meta-analysis method.	S23
33	Application of genetic algorithm in optimization of neural network architecture and oil price prediction (GADDN)	S24
39	Oil market volatility model based on regime choice approach	S25
35	How crude oil consumption impacts on economic growth of Sub-Saharan Africa?	S26
33	Detecting method for crude oil price fluctuation mechanism under different periodic time series	S27
44	A novel multiscale forecasting model for crude oil price time series.	S28
45	Forecasting crude oil prices by a semiparametric Markov switching model: OPEC, WTI, and Brent cases	S29
43	Crude oil time series prediction model based on LSTM network with chaotic Henry gas solubility optimization.	S30
43	Dynamic Cross-Market Volatility Spillover Based on MSV Model: Evidence from Bitcoin, Gold, Crude Oil, and Stock Markets	S31
35	A Novel Agricultural Commodity Price Forecasting Model Based on Fuzzy Information Granulation and MEA-SVM Model	S32
39	Seasonal forecasting of agricultural commodity price using a hybrid STL and ELM method: Evidence from the vegetable market in China.	S33
41	Agricultural commodity futures prices prediction via long- and short-term time series network.	S34
33	A comparison of artificial neural network and time series models for forecasting commodity prices.	S35
35	Commodity price prediction using neural network case study: Crude palm oil price.	S36
37	Forecasting commodity price indexes using macroeconomic and financial predictors	S37
40	Cash Soybean Price Prediction with Neural Networks.	S38
41	Development of fuzzy logic and genetic fuzzy commodity price prediction systems—An industrial case study	S39
38	Automated Agriculture Commodity Price Prediction System with Machine Learning Techniques	S40
35	Forecasting model for crude oil price using artificial neural networks and commodity futures prices	S41
45	Development and performance evaluation of hybrid KELM models for forecasting of agro-commodity price	S42
33	A novel decomposition ensemble model with extended extreme learning machine for crude oil price forecasting	S43
39	Optimizing the monthly crude oil price forecasting accuracy via bagging ensemble models	S44
35	A novel hybrid model for forecasting crude oil price based on time series decomposition	S45
34	Assessing Potentiality of Support Vector Machine Method in Crude Oil Price Forecasting.	S46
44	Interval decomposition ensemble approach for crude oil price forecasting.	S47
46	A new approach for crude oil price prediction based on stream learning	S48
43	Global crude oil price prediction and synchronization based accuracy evaluation using random wavelet neural network.	S49
43	Forecasting Crude Oil Prices: a Deep Learning based Model.	S50
36	A compressed sensing based AI learning paradigm for crude oil price forecasting	S51
39	Financial time series forecasting model based on CEEMDAN and LSTM	S52
42	Crude Oil Price Prediction Using LSTM Networks	S53
44	Effect of inventory announcements on crude oil price volatility	S54

Step Four: Extraction of Information

This step involves reviewing the remaining articles and extracting texts for coding in the next step. This step focuses on the separation of the outputs and interpretations of these outputs along with the final discussion and conclusion of the researchers. At this stage, 54 articles were entered into ATLAS TI software and selectively reviewed and selectively reviewed by some of the study articles and random coding articles to complete the researcher's acquaintance with existing data. The researcher thus became familiar with the general discussions and the atmosphere governing it.

Table 3 examines an example of coding on the articles. The first column describes the initial specifications of the article and in the last column of the main keywords that became the original codes:

Table 3. *Check a number of articles information*

Source	Initial code (concept)	Field

Source	Initial code (concept)	Field
S2,S3, S4,S5,S6,S7,S8,S10,S11	Genetic algorithm, hierarchical genetics, multi -objective genetic algorithm, parallel genetic algorithm	Design of components
S12, S13, S16, S19, S22	Genetic Algorithm, NSGA-II, Genetic Algorithm + Particle Crowd, Multi-Objective Genetic Algorithm, Genetic Algorithm + Fuzzy Approach,	Supply Network
S1,S9.S14,S15,S17,S18,S19,S20,S21 S24,S27,S28,S29,S30,S31,S32, S33	Branch algorithm and branch+genetic algorithm; Genetic Algorithm, Optimization Algorithm+Genetic Algorithm, NSGA-II, Multi-Objective Genetic Algorithm, Parallel Genetic Algorithm	planning

Step Five: Analytics of Qualitative Findings

In the course of analysis, it sees the topics that are in the field of study in the field. This is the case (s). To what, it has been meticulously, the formation of the mining, gives the mining and the modesty and the bodies in the case that gives it to the body. It does. The requirements and the basis of the advice provides patterns and theories or theories. In this case, the full -fledged segregation of the studies was found to be in the field. Then, considering the meaning of each of them, a common conceptual host ID was defined.

Similar concepts were then categorized in the explaining categories to identify the axes of the research indicators in the form of the main and sub -research components of the research.

Table 4. *The main categories and relevant codes*

Source	The issue of examination	Subject domain	Algorithm
S2,S3, S4,S5,S6,S7,S8,S10,S11	Design of components layout	Design of components	Genetic algorithm, hierarchical genetics, multi -objective genetic algorithm, parallel genetic algorithm
	The dynamics of components		
	Flexible components		
S12,S13,S16,,S19,S22	Multi -product, multi -period	Supply Network	Genetic Algorithm, NSGA-II, Genetic Algorithm + Particle Crowd, Multi-Objective Genetic Algorithm, Genetic Algorithm + Fuzzy Approach,
	Multi -product, single -product		
	Single -product, single -period		
S1,S9.S14,S15,S17,S18,S19,S20,S21 S24,S27,S28,S29,S30,S31,S32,S33	vehicles navigation	planning	Branch algorithm and branch+genetic algorithm; Genetic Algorithm, Optimization Algorithm+Genetic Algorithm, NSGA-II, Multi-Objective Genetic Algorithm, Parallel Genetic Algorithm
	Share resource and scheduling		
	Car planning		
	Flexible planning		
S23,S25,S26,S34	Financial planning	Forecast	Genetic Algorithm, Particle Chaosing Optimization Algorithm, Self -Organization Algorithm, Genetic Algorithm+Neural Network
	Planning time		
	Planning inflation		
S43,S44,S45	Routing	Inventory control	Genetic algorithm, NSGA-II,
	Identify the masses of the market		
	Inventory Optimization		
S35,S36,S37	Ensure costs	Information security	Genetic algorithm, NSGA-II, parallel genetic algorithm, nsga
	Hiding information		
S38,S39,S40,S41,S42,S43	Grouping	Separation and evaluation	Genetic algorithm, NSGA-II, Combined Genetic Algorithm, Self-Organization Algorithm, Parallel Genetic Algorithm, NSGA
	Improvement		
	Diagnosis		
	Reduce noise (transparency)		
	Cognition of the process		
	Classification		
	Optimal identification		
	Stop identifying		

Step Six: Output quality control

In this study, the researchers also used to compare their views with another expert to control the concepts of the extracted studies. For this purpose, a 26 questionnaire consisting of identified indicators was designed. Then the data obtained were analyzed through SPSS software version 23 and the transcript index. The results of the calculations are shown below, the value index of 0.711, which is at the valid agreement.

Step Seven: Final Collection

In this step, the findings are presented. The following is the identification of research indicators. The indicators extracted from the texts of the relevant articles were derived from the elimination of synergistic and recurrent indicators, and finally the category and categorization of the final indicators, 7 categories and 26 codes. At this stage of coding, the main and sub -research categories were identified.

After identifying the research indicators based on the analytical analysis and the determination of analytical units (words and themes), the Shannon Entropian method will be used for data analysis:

First, the frequency of each of the identified categories should be determined by content analysis.

The matrix of the desired abundance should be normative. Linear normalization method is used for this purp**ose:**

$$n_{ij} = \frac{x_{ij}}{\sum x_{ij}}$$

The information load of each category must be calculated. The following relationship is used for this purpose:

$$k = \frac{1}{Ln(a)};\ \text{a} = \text{No. of Options}$$

$$E_j = -k \sum \left[n_{ij} LN(n_{ij})\right]$$

The importance coefficient of each category must be calculated. Any category that has more information load is more important. The following relationship is used for this purpose:

$$W_j = \frac{E_j}{\sum E_j}$$

So in the first step, the matrix decision is made. The privileges from the matrix decision on the problem are presented in the table below:

Table 10. *Determine the Importance and Emphasis of Past Research*

Rank	Wj	Ej	$\sum P_{ij} \times knP_{ij}$	Frequency	Code
2	0.14487	0.695459	-0.31652	9	Design of components
4	0.109103	0.52376	-0.23837	5	Supply Network
1	0.168354	0.808199	-0.36783	17	planning
5	0.095975	0.460735	-0.20969	4	Forecast
6	0.080386	0.385898	-0.17563	3	Inventory control
7	0.080386	0.385898	-0.17563	3	Information security
3	0.120271	0.577371	-0.26277	6	Separation and evaluation

Finally, based on the analysis, the codes extracted are shown in a initial model.

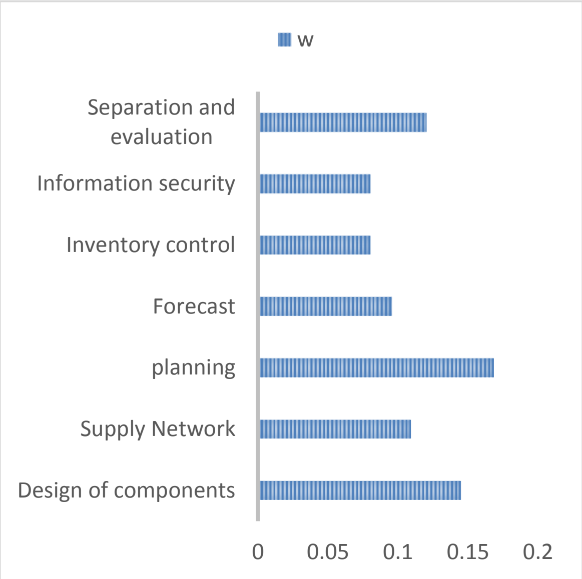

Figure 3. *Entropy obtained based on past research*

5. Discussion

The purpose of the present study was to apply a combination of new hybrid genetic algorithms to solve oil forecasting problems. Based on the coding, 9 categories and 33 initial codes were identified. Identified categories include layout design, supply network, planning, forecasting, inventory control, information security, imagery, medical imaging and wireless network.

The genetic algorithm is an artificial intelligence algorithm documentary to the evolutionary processes in nature that is used to optimize and combine information through genes and genetic compounds. In solving oil prices forecasting issues, the new hybrid genetic algorithm methods can be used. The components needed to predict oil prices are considered as genes. These genes can be different features of the oil market such as inflation, global oil production, the world economy, and so on. In the supply network, using the genetic algorithm, the supply network is optimized related to the various issues that affect the price of oil. The network can include information on oil production sources, transport routes, warehouses and sales points using genetic algorithm, processes planning and activities in the field of production, transportation, warehousing and distribution. This optimization can be used to reduce costs and increase efficiency in the oil supply system. The genetic algorithm can be used to predict oil prices from past data and provide a prediction model. Genes are used as input features to the prediction model and different genetic combinations to optimize the model parameters.

The genetic algorithm can help optimize the oil inventory in the supply system. According to the forecast of oil prices and market needs, the level of oil inventory in warehouses and distribution points is optimized. In information security, the genetic algorithm can provide appropriate solutions to improve the security of information related to the oil trade. This may include encryption, access management and information monitoring strategies. In separation and evaluation, the genetic algorithm can be used to separate various items related to oil prices, such as processes, resources, analysis and reports. Evaluation of the results of the implemented improvements and decisions on the best solutions are also made through the genetic algorithm. Given the complex and dynamic nature of the oil market, the genetic algorithm as an evolutionary and hybrid method can have significant improvements in oil price management and forecasting. Metathesis, a linguistic phenomenon involving the transposition of sounds or letters within a word, might seem unrelated to genetic algorithms and oil price forecasting at first glance. However, metaphorically speaking, the concept of metathesis can be applied in identifying new combined genetic algorithm methods to enhance oil price forecast accuracy.

In the realm of genetic algorithms, combining different methodologies and techniques is akin to a metathesis of sorts, where elements are rearranged and recombined to create novel solutions. Just as metathesis can produce new words with altered meanings, combining genetic algorithm methods can yield innovative approaches for optimizing complex systems such as oil price forecasting.

By leveraging metathesis-inspired strategies in the context of genetic algorithms, researchers can explore unconventional combinations of algorithms, parameters, and data sources to improve the accuracy of oil price forecasts. This approach involves experimenting with various genetic algorithm components, such as selection mechanisms, crossover and mutation operators, and population initialization techniques, and reconfiguring them in novel ways to adapt to the dynamic and multifaceted nature of oil markets.

The application of metathesis in identifying new combined genetic algorithm methods offers a promising avenue for advancing oil price forecasting capabilities. By embracing the principles of flexibility, adaptability, and innovation inherent in metathesis, researchers can uncover synergies between disparate genetic algorithm approaches and create sophisticated forecasting models that better capture the complexities of oil market dynamics. As a result, stakeholders in the energy industry can make more informed decisions, mitigate risks, and optimize their strategies in response to evolving market conditions.

6. Conclusion

The use of genetic algorithm to solve oil price forecast problems as an evolutionary and artificial intelligence approach enables the integration of varied and complex information into predictive models. By designing appropriate components as genes that represent important economic, geographical and political characteristics, the most optimal genetic compounds can be created to enhance the accuracy and performance of predictive models. The supply network has also been improved and optimized by the genetic algorithm, which can increase the efficiency of oil prices. This optimization in the distribution of oil inventory, transportation routes, and warehousing helps us to counter market fluctuations and prevent rising costs. This combined method of genetic algorithm in the field of oil forecasting becomes a comprehensive and efficient framework by integrating planning, inventory control, information security and segregation and evaluation. This new hybrid approach can significantly improve the accuracy of the oil supply system and help the oil industry to adapt to the challenges facing market fluctuations. In terms of forecasting oil prices using the genetic algorithm, a new combination of this algorithm with other methods and concepts can be used to improve accuracy and performance. The following is a few practical suggestions based on the results:

-Genetic algorithm can be used as a combination method with neural networks. Various genes can code important features for predicting oil prices, and neural network can learn these features and improve prediction accuracy.

- Using a combination of genetic algorithm with other artificial intelligence algorithms such as Learning machine algorithms, adding side information and improving precision and prediction performance can be effective.

- Often oil prices are very dependent on time. The combination of genetic algorithm with time series models, such as ARIMA or Prophet, can help improve prediction capability based on existing time patterns.

- Merging genetic algorithm with statistical methods and data analysis such as regression analysis can improve the effect of different variables on oil prices.

- The combination of genetic algorithm with other evolutionary algorithms such as evolutionary evolutionary algorithms or multi -objective algorithms (MOEA) can help obtain optimal answers at multiple points related to oil price forecasts.

-Instead of using only historical data, the genetic algorithm can be combined with expert oil knowledge to benefit from auxiliary information and specialized knowledge.

Combining genetic algorithm with learning reinforcement methods such as Deep Q-Learning can be helpful in improving performance and interacting with complex environments.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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