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Optimizing Water Pipeline Route Selection Using a Sparse Deep Neural Network and the Fuzzy VIKOR Method (Case study: water pipeline transmission)

Alireza Ghorbani [1], Mohammad Khajehzadeh [2], Farima Seifi [3] Nadhir Al-Ansari[4]* and Himan Shahabi[5]*

[1] Statistics Department, Shahid Beheshti University, Tehran 1635648954, Iran; alcstat@outlook.com (A.G.)
[2] Industrial Engineering Department, Iran University of Science and Technology, Tehran 1513754415, Iran; khajezadeh.sina@gmail.com (M.K.)
[3] Management Department, UCLA Anderson School of Management, Los Angeles 90095, CA; farima1378@gmail.com (F.S.)
[4] Civil, Environmental and Natural Resources Engineering, Lulea University of Technology, Lulea 97187, Sweden; nadhir.alansari@ltu.se (N.A.A)
[5] Department of Geomorphology, Faculty of Natural Resources, University of Kurdistan, Sanandaj 6617715175, Iran; h.shahabi@uok.ac.ir (H.S.)
* Correspondence: nadhir.alansari@ltu.se | h.shahabi@uok.ac.ir

Abstract: Due to the limited availability of natural resources like water, an efficient approach in selecting water pipeline routes is so crucial for sustaining human life. Exposed to weaknesses such as time-consuming procedures and a lack of comprehensive data processing inherent in traditional route selection methods, this study is aimed to present an integrated model using a Sparse Deep Neural Network (DNN) and the Fuzzy VIKOR method to optimize water pipeline route selection. A case study involving six new water pipeline routes between two provinces is presented to develop the model. The study employs a penalized multi-task deep learning model to train on elements of a fuzzy decision matrix which was built on data from 71 existing pipeline routes. The model then predicts the new fuzzy decision matrix elements for six new routes. Finally, the Fuzzy VIKOR method is applied to this new decision matrix to prioritize the six new routes for transmitting water between two areas. The results show that routes 04, 06, and 03 have been identified as optimal choices. This integrated approach streamlines route selection, enhancing the efficiency and effectiveness of decision-making problems.

Keywords: Deep Learning, Penalized Neural Network, Variable Selection, Fuzzy VIKOR

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1. Introduction

Water covers about 71% of the Earth's surface, though only 2.5% of it is consumable by people which makes it so crucial in sustaining human life. Nowadays, a vast amount of water is being conveyed through an extensive network of pipelines that span millions of kilometers globally. In this regard, a systematic approach in selecting the most appropriate route can potentially reduce project costs, mitigate negative impacts, and ensure long-term benefits; thus, pipeline routing is essential infrastructure for the efficient, effective, and reliable conveyance of natural resources like water (Ayadi et al.[1]). Moreover, determining an appropriate approach for selecting the water pipeline route is also crucial for governments, as it helps prevent economic losses and ensures the safe conveyance of consumable water (Almheiri et al.[2]). Conventionally, identifying pipeline routes entailed a manual process of determining the shortest distance between two locations on a topographic map and gathering all relevant data along the route to evaluate its feasibility. Despite the capabilities of this method, its efficacy is considerably constrained due to its time-consuming nature and limited ability to process information that can ultimately undermine the accuracy of the final result (Bayramov et al.[3]). An additional requirement is to ensure that the chosen routes do not disrupt the daily activities of the region, while also minimizing any losses and avoiding future failures; thus, a proper route selection method can effectively mitigate any negative impacts on society (Sivakumar et al. [4]). Concerning these multi-criteria problems, an integrated data-driven model in the terms of decision support systems can facilitate the decision-making process while enhancing the accuracy of problem outcomes (He et al. [5]). Accordingly, this paper provides an integrated approach involving a Sparse Deep Neural Network and Fuzzy VIKOR method to optimize route selection for a water transmission project. The criteria were categorized into three sections: operational, environmental, and socio-economic. A case study was chosen to implement the research model and determine the best routes for transmitting water through the pipeline network.

In the following, we will begin with a literature review of related methods and concepts. Subsequently, we will discuss the models and research methodologies in detail, followed by the application of the method in a real case in section four. Finally, we will interpret the analytical results in the Discussion section to draw conclusions in the final part of this research.

While earlier research has applied fuzzy techniques and optimization methods to optimize pipeline route selection (Davarpanah [6]), the recent increase in the complexity and scale of data have rendered traditional approaches inadequate in some scenarios. Moreover, the importance of multi-criteria evaluation in assessing the performance of pipeline route selection projects has become increasingly recognized. Therefore, the need for efficient decision-making systems that incorporate the latest advances in artificial intelligence techniques is more important than ever (He et al. [5]). As a result, the following literature review is divided into two sections including the pipeline studies for defining all determinant factors in selecting optimum routes and the combination of machine learning and multi-criteria decision-making method in related studies.

According to the topic of transmission lines and pipelines, studies can be categorized into four groups, including spatial analysis and routing selection based on multi-criteria decision-making (MCDM) methods, determining geomatics indexes for optimal pipeline route selection, optimization methods via evolutionary algorithms (EA), and improvement of route optimization algorithms in water transmission pipeline routes.

The first group of studies,which is the focus of this article, uses various multi-criteria decision-making techniques and spatial analyses in GIS for optimizing the routing of transmission lines and roads. For instance, Ghasemi et al.[7] used both quantitative and qualitative criteria, like road slope, infrastructure, soil type, and environmental factors, to determine the water transmission route to agricultural lands. Naseri et al.[8] used a combination of GIS and MCDM to select suitable sites for fluid distribution points to provide artificial irrigation for underground water. The study's criteria were almost geological types including distances from wells and roads, depth of groundwater, soil permeability, quality of groundwater, topographic slope, and lithological units. Asgharipour Dasht Bozorg et al[9] used the AHP method in GIS to select suitable areas for providing artificial irrigation using flood-spreading practices. They examined seven effective factors, including slope, permeability, fluid quality, runoff thickness, conveyance capacity, drainage density, and land use in the study area, and calculated the weight of each factor using the "AHP" method. Then, they integrated the "GIS" analytical functions and the "AHP" method to determine routes in four classes ranging from very suitable to unsuitable. Similarly, Sadeghi [10] used a multi-criterion feature to determine the shortest water transmission line, while Abedian et al.[11] used the shortest path algorithm in routing the road network. Bagli et al. [12] applied a combination of the least cost path analysis (LCPA) and MCDM method to determine power line routes. In this study, several criteria with different weights were considered to compare and rank routes. Peng [13] performed a similar study to determine the road route, but used sensitivity analysis to determine the final route while considering multi-criteria decision-making methods. Yildirim et al.[14] carried out a study on selecting pipeline routing in which they used an integrated multi-criteria decision making including an analytic hierarchy process and the TOPSIS method. Additionally, there are several studies concerning the optimal route selection projects which are used the integration of GIS and MCDM approaches that are included Fu [15]; Aguda and Uyeh[16]; Akıncı et al.[17]; Jelokhani-Niaraki et al.[18]. Finally, Yildirim and Kadi [19] used multi-criteria decision-making and the GIS method to suggest solutions for new path construction.

The second group of studies relates conceptually to studies conducted with the aim of providing an index for routing that can be leveraged in other routing studies. In this regard, Moradgholi [20] conducted research to determine the optimal path by utilizing three methods including the Ordered Weighted Averaging (OWA), integrated Boolean and WLC approaches, and the cost layer in routing. The resulting index was developed with the intent of being effectively utilized in routing problems. Hamid-Mosaku et al. [21] also developed an index for routing gas transmission lines using artificial neural networks.

The third group of studies utilizes evolutionary and swarm intelligence algorithms for optimization purposes in transmission line routing. Beheshtifar et al. [22] determined the suitable route for power transmission lines based on GIS method in which they applied a multi-objective genetic algorithm for this purpose. This method has been implemented for the optimal routing of a 400 kilo-volt power transmission line. Li et al. [23] presented a route design using a modified ant colony optimization algorithm (ACO) and GIS to maximize population coverage using it. Ebrahimipour et al. [24] utilized Global Positioning System (GPS) techniques and genetic algorithms to solve problems related to optimal path determination for water transmission lines. comparing the paths extracted from the genetic algorithm with the existing path, it is shown that the cost decreases by 20%, mainly due to the reduction in pipeline length and fewer intersections with the river and road. As newer solutions, researchers are currently conducting preliminary studies on using game theory and combining it with evolutionary approaches for routing (Vahidnia et al[25]). A study of pipeline systems selection was conducted by Marcoulaki et al.[26] which examined optimization objectives for capital cost and energy consumption when the project is operated in terms of reparation cost, risk of project to the environment and maintenance issues. De Lucena et al.[27] applied genetic algorithm to solve multi-objective problem concerning route optimization of submarine pipeline. Liang et al.[28] used general genetic algorithm to solve the automatic route model for optimizing pipeline selection. Baeza et al.[29] compared two algorithms, Ant Colony optimization and Dijkstra algorithm for optimal ore concentrate pipeline routing. Kang and Lee [30] applied methods of least cost path (LCP) and smoothing algorithm in pipeline route selection. Maliki and Farizal [31] developed a goal programming model included a genetic algorithm for selecting the optimum route for a pipeline project. Gitau and Mundia [32] proposed Geographic Information System technique (GIS) and Remote Sensing (RS) for selecting pipeline route.

The fourth category of research is comprised of studies that focus on improving the routing algorithm and its technical aspects. As an example, Antikainen et al. [33] presented a method to minimize the complexity of the model for extracting the minimum cost path. Murekatete and Shirabe [34] evaluated the effect of the raster scale on routing results, and also provided solutions for situations where standard maps are not at the same scale.

The table 1 below provides a concise overview of the significant research carried out on the pipeline routing topic.

Table 1. Relative Studies.

Papers	Methodologies	Results
[24] Ebrahimipour et al. 2006	GPS, genetic algorithms	Reduction of pipeline length and fewer intersections with river and road in optimal path determination
[7] Ghasemi et al. 2009	Quantitative and qualitative criteria, GIS	Determined the water transmission route to agricultural lands by considering quantitative and qualitative criteria, such as road slope, infrastructure, fault and soil type, and environmental factors. Showed that significant reductions in environmental damage can be achieved by considering even a small percentage of environmental objectives.
[8] Naseri et al. 2009	GIS, MCDM	Used an integrated decision support system, including GIS and MCDM, to select suitable locations for fluid distribution points in order to provide artificial irrigation for underground water.
[20] Moradgholi 2005	Ordered Weighted Averaging (OWA), integrated Boolean and WLC approaches, and the cost layer in routing	Conducted research to determine the optimal path by utilizing three methods including the OWA, integrated Boolean and WLC approaches, and the cost layer in routing. Developed an index for routing problems.
[23] Li et al. 2009	Modified ant colony optimization algorithm	Route design using ACO and GIS to maximize population coverage
[12] Bagli et al. 2011	Least cost path analysis (LCPA), multi-criteria decision-making method	Used the combination of the LCPA and multi-criteria decision-making method to determine the routing of power lines. Considered various criteria with different weights to compare and rank proposed routes and determined the final score of each route using a weighted linear combination method.
[13] Peng 2011	Sensitivity analysis, multi-criteria decision-making methods	Used sensitivity analysis to determine the final road route while considering multi-criteria decision-making methods.
[22] Beheshtifar et al. 2012	GIS-based method, multi-objective GA	Optimized routing of a 400-kilovolt power transmission line
[26] Marcoulaki et al. 2012	Optimization objectives	Examined optimization objectives for capital cost and energy consumption in pipeline systems selection
[9] Asgharipour Dasht Bozorg et al. 2013	AHP method, GIS	Used AHP method in GIS to select suitable areas for providing artificial irrigation using flood-spreading practices. Examined seven effective factors, including slope, permeability, fluid quality, runoff thickness, conveyance capacity, drainage density, and land use, and determined routes in four classes ranging from very suitable to unsuitable.
[17] Akıncı et al. 2013	Integration of GIS and MCDM approaches	Used the integration of GIS and MCDM approaches for optimal route selection projects.
[33] Antikainen et al. 2013	Model simplification	Method to minimize model complexity and reduce calculation time for extracting minimum cost path
[10] Sadeghi 2014	Multi-criterion feature	Used a multi-criterion feature to determine the shortest water transmission line.
[27] De Lucena et al. 2014	Genetic algorithm	Optimization of submarine pipeline route
[11] Abedian et al. 2015	Shortest path algorithm in routing the road network	Used the shortest path algorithm in routing the road network of Kordkoi, Bandargaz, and Golugah cities.
[16] Aguda and Uyeh 2016	Integration of GIS and MCDM approaches	Used the integration of GIS and MCDM approaches for optimal route selection projects.
[14] Yildirim et al. 2017	Integrated multicriteria decision making, analytic hierarchy process, and the TOPSIS method	Conducted a study on selecting pipeline routing and used an integrated multicriteria decision-making approach including the analytic hierarchy process and the TOPSIS method.
[28] Liang et al. 2017	General genetic algorithm	Automatic route model for optimizing pipeline selection
[29] Baeza et al. 2017	Ant Colony Optimization, Dijkstra algorithm	Comparison of algorithms for optimal ore concentrate pipeline routing
[30] Kang and Lee 2017	Dijkstra least cost path, Laplacian	Comparison of two methods for pipeline route selection
[32] Gitau and Mundia 2017	GIS, Remote Sensing	Selection of pipeline routes using GIS and remote sensing
[15] Fu 2018	Integration of GIS and MCDM approaches	Used the integration of GIS and MCDM approaches for optimal route selection projects.
[18] Jelokhani-Niaraki et al 2018	Integration of GIS and MCDM approaches	Used the integration of GIS and MCDM approaches for optimal route selection projects.
[25] Vahidnia et al. 2019	Game theory, evolutionary approaches	Preliminary studies on using game theory and evolutionary approaches for routing
[31] Maliki and Farizal 2019	Goal programming, genetic algorithm	Selection of optimum route for a pipeline project using goal programming and a genetic algorithm
[19] Yildirim and Kadi 2020	Multi-criteria decision-making and GIS routing	Used multi-criteria decision-making and GIS routing to improve existing forest paths and proposed solutions for new path construction.
[21] Hamid-Mosaku et al. 2020	Artificial neural networks for developing an index for routing gas transmission lines.	Developed an index for routing gas transmission lines using artificial neural networks.
[34] Murekatete and Shirabe 2021	Raster scale evaluation	Evaluation of effect of raster scale on routing results and solutions for situations with non-standard maps

The paper aims to explore the intersections between MCDM and Deep Learning (DL) in pipeline route selection, an area that has not been thoroughly investigated. While a few contributions have attempted to combine MCDM with forecasting and machine learning techniques (Repetto [35]), the studies in pipeline route selection remains relatively unexplored. For instance, Bhowmik [36] applied an integrated optimization approach included machine learning algorithms to select optimal pipeline routes. This study caused a significant reduction of operation costs up to 20% in comparison with conventional process. The method also incorporated on-bottom stability criteria and other constraints to evaluate potential routes and minimized the length and cost of mitigating procedures. In another study, Rolka et al. [37] presented a hybrid logical-arithmetic method for selecting optimal flight routes, incorporating multi-criteria decision-making using the technique for order preferences by similarity to an ideal solution (TOPSIS) method. Furthermore, Koohathongsumrit and Meethom [38] proposed a combination of MCDM and ML approach for route selection in multi-modal supply chains, addressing the complexities of this domain. Additionally, Stoilova and Munier [39] introduced a novel fuzzy multiple criteria time series modeling method based on fuzzy linear programming and sequential interactive techniques. They successfully applied this method to urban transportation planning.

1.1. Contributions of Current Study

However, applying an appropriate integrated technique for selecting pipeline route could be perplexing considering wide range of variations in the water pipeline route selection which are included operational, environmental, economic and social issues; moreover, according to the former studies, there are different MCDM models, all of which are integrated with weighting methods using decision-makers opinion like AHP, ANP, ELECTRE and so forth, though these methods have some considerable disadvantages including the different number of decision-makers could have varying effects on determining the weights of criteria (Kaya and et al. [40]), lack provision to check the consistency of decision-makers' opinions (Alinezhad and Khalili [41]), additional analysis is needed for results verification (Siksnelyte-Butkiene et al. [42]), interdependence between criteria which might lead to inconsistencies between judgment and rankings (Velasquez and Hester [43]). Moreover, these methods rely on extensive data collection through questionnaires' that can be so time-consuming, costly, and labor-intensive.

The issue of interdependence is a concern for MCDM methods, as they may encounter situations where some criteria used in decision-making are interdependent. The inclusion of such irrelevant criteria introduces unnecessary complexity and inconsistency in the decision-making process. Moreover, an abundance of features or criteria in a problem, like in high-dimensional settings, intrinsically accumulates noise by the existence of many redundant factors that do not contribute to the decision-making process (Ghorbani [44]). Penalized models like LASSO, QUADRO, and Penalized Neural Network address these issues by selecting the main contributing features through dimension reduction (James et al. [45] Fan et al. [46] Sato [47]). Therefore, an integrated deep learning model with MCDM method can bring more reliable decision-making processes. It would also address the issue of interdependence and reduce the need for manual interventions like data gathering and analysis in making decisions. Given these disadvantages, this paper proposes an integrated model that combines a deep learning approach with the fuzzy VIKOR method to select the optimal water transmission route based on sustainable development criteria.

2. Material and Methods

2.1. Principal Component Analysis

Principal Components Analysis (PCA) represents an unsupervised learning approach involving the computation of principal components. These components are subsequently utilized to comprehend the data. One valuable aspect of PCA is its ability to discover a low-dimensional representation within a variation dataset. The idea is that each n observation lives in p-dimensional space, but not all these dimensions are equally interesting. PCA aims to identify a concise set of dimensions that maximize interest, where the concept of interest is measured by the amount that the observations vary along each dimension. All the principal components of a set of features $X_1, X_2, ..., X_p$ are the normalized linear combination of the features:

$$Z_i = \phi_{11}X_1 + \phi_{21}X_2 + + \phi_{p1}X_p,$$

that has the largest variance. Where $(i = 1, \ldots, p)$. In this case, normalized would mean that

$$\sum_{j=1}^{p} \phi_{ji}^2 = I; (i = 1, ..., p).$$

After computing the principal components, we attain a low-dimensional view of the data. It is important to know how much information is lost by projecting the observations onto the first few principal components. Stated differently, it reveals the portion of data variant not contained by these primary components. To argue this, we look at the proportion of variance explained by each principal component. If the cumulative proportion of those few selected principal components covers a significant proportion of the data variance, selecting those few components instead of the entire features can be notably reliable (James et al. [45]).

2.2. *Artificial Neural Network (ANN)*

A neural network is a subset of machine learning that employs a network of functions to comprehend and transform input data from one form into a desired output. In other words, a neural network takes an input vector comprising of p variables $X = (X_1, X_2, ..., X_p)$ and builds a nonlinear function $f(X)$ to forecast the response Y. These networks are inspired by early models of sensory processing in the human brain, simulating the way biological neurons transmit signals to each other (Krogh [48]). Neural networks consist of an input layer, one or more hidden layers, and an output layer. Each layer consists of multiple nodes or units that perform mathematical operations on the input data and pass it to the next layer. In the figure below, you can see an ANN architecture with one hidden layer (James et al. [45]).

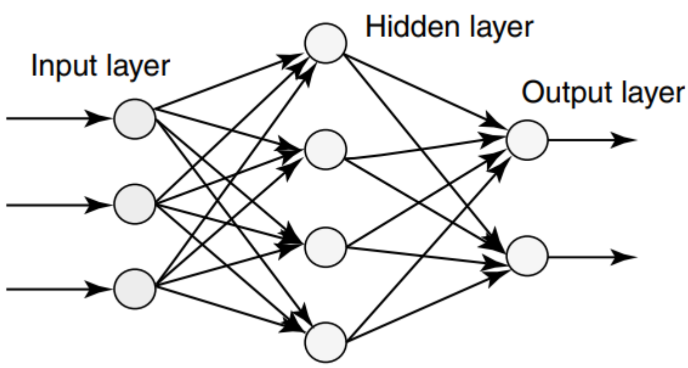

Figure 1. Architecture of a neural network with a single hidden layer. (Abraham [49])

2.3. *Regularization by l_1 Penalty*

When fitting a model, a technique exists that regularizes the coefficient estimates through pulling the coefficient estimates closer to zero. It turns out that shrinking the coefficient estimates can significantly reduce the variance. In ANN, the loss function, the loss optimization algorithm or other techniques have these various properties (Kukačka et al. [50]). The application of an l_1 penalty function is a prevalent approach in regression, initially introduced by Tibshirani [51]. He outlined a method known as the LASSO, which stands for 'least absolute shrinkage and selection operator for parameter estimation. Regularization through the l_1 penalty yields simpler and more interpretable models, involving only a subset of predictors. This leads to a coefficient estimate vector with a relatively small number of non-zero elements which is called sparsity. In the context of ANNs, regularization eliminates units that don't contribute to the prediction task (Florkowski [52]). The following figure 2 shows this concept:

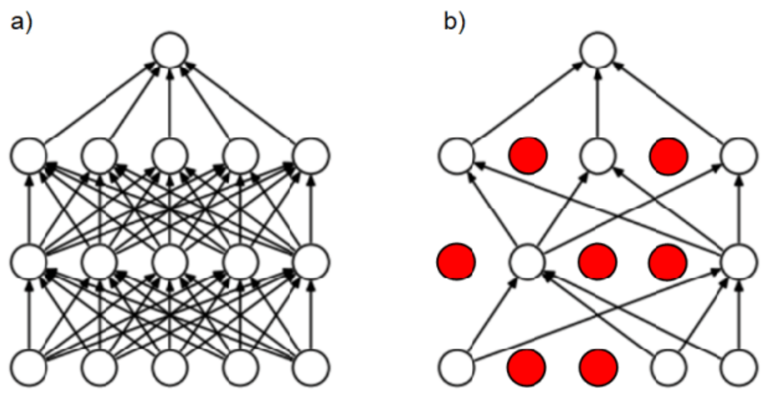

Figure 2. Sparse neural network in comparison with standard neural network. Figure (a) is a standard neural network in which coefficient for nodes' function are non-zero. Figure (b) is a neural network with l_1 penalization where nodes functions has small number of non-zero coefficient [52]. As a result, some nodes are dropped out of the calculation for the next layer.

2.4. VIKOR

VIKOR, which stands for Vlsekriterijumska Optimizacija I Kompromisno Resenje, was developed in 1998 by Opricovic [53]. This method is used to optimize the multi-criteria of complex systems. VIKOR is a powerful technique for resolving MCDM problems involving various alternatives and conflicting criteria. Moreover, to address the issues of uncertainty more effectively, Fuzzy VIKOR (or FVIKOR) was introduced. This model interprets the linguistic preference of each criterion assigned by the experts to a fuzzy set (Rezaei [54]). To implement FVIKOR, first a decision-making matrix should be formed which is assumed that the problem has y alternatives and x criteria. where X_{ij} refers to the fuzzy set of i-th alternative with respect to j-th criterion, (l_{ij}, m_{ij}, u_{ij}). To assign weight to each criterion based on its preferential value, it is necessary to interview several experts in the field to gather their opinions. Subsequently, these linguistic terms can be translated into numerical values using the table 2 (Sadeghi et al. [55]).

Table 2. Triangular fuzzy number of five-point Likert scale.

Triangular Fuzzy Number (l, m, u)	Fuzzy Number	Linguistic Variables
(0,0,0.25)	1	Very Unimportant (VU)
(0,0.25,0.5)	2	Unimportant (U)
(0.25,0.5,0.75)	3	Moderately Important (MI)
(0.5,0.75,1)	4	Important (I)
(0.75,1,1)	5	Very Important (VI)

All the experts' opinions will be gathered and aggregated into a single triangular fuzzy number for further analysis on each criterion. Then equations (1) and (2) utilized to determine the best f_j^* and the worst f_j^- values of all criterion functions (Opricovic [53])

$$f_j^* = \max(x_{ij}),\ f_j^- = \min(x_{ij}),\ \text{for positive criteria.} \tag{1}$$

$$f_j^* = \min(x_{ij}),\ f_j^- = \max(x_{ij}),\ \text{for negative criteria.} \tag{2}$$

The next steps are to compute the ideal and anti-ideal values through measuring the values of S_i and R_i and Q_i as following equations:

$$S_i = \sum_{i=1}^{n} \frac{w(f_j^* - fij)}{(f_j^- - fij)}.$$

$$R_i = \max_i \frac{w(f_j^* - fij)}{(f_j^- - fij)}.$$

$$Q_i = \frac{v(S_i - S^*)}{(S^- - S^*)} + \frac{(1-v)(R_i - R^*)}{(R^- - R^*)},$$

Where $S^* = \min_j S_j$, $S^- = \max_j S_j$, $R^* = \min_j R_j$ and $R^- = \max_j R_j$. Furthermore, a parameter v is introduced to balance the weight between the strategy of maximum group utility and the weight of individual regret, denoted as $(1 - v)$. By minimizing $\min_j S_j$, the solution achieves maximum group utility, whereas minimizing $\min_j R_j$ results in the solution with minimum individual regret for the "opponent." Normally, the value of v is taken as 0.5. However, v can take any value between 0 to 1. Then rank the alternatives based on their values for S, R, and Q in decreasing order. Next, propose alternative A^1 as the compromise solution, as it is the best-ranked alternative according to the measure Q (minimum), if the following two conditions are satisfied:

a description Acceptable advantage is defined as $Q((A^2)) - Q((A^1)) \leq DQ$, where $DQ = 1/(j-1)$, and A^2 represents the alternative with the second position in the ranking list based on the parameter Q.
b Acceptable decision-making stability is achieved when alternative A^1 is ranked as the best option by either S or R or both. This compromise solution ensures stability within the decision-making process, which could be based on the strategy of maximizing group utility (when $v > 0.5$ is required), reaching a consensus ($v > 0.5$), or utilizing a veto ($v < 0.5$).

If any of the conditions are not satisfied, a set of compromise solutions can be proposed as follows:

1 If only condition b is not satisfied, the following alternatives can be considered: Alternative A^1 and A^2.
2 Alternatives A^1, A^2, ..., A^M if condition 1 is not satisfied. A^M is determined by the relation $Q(A^M - A^1) < DQ$ for maximum M (the positions of these alternatives are "in closeness").
3 If condition 1 is not satisfied, a range of alternatives, including A^1, A^2, ..., A^M, can be explored. Here, A^M is determined by the relation $Q(A^M - A^1) < DQ$ for maximum M, where the positions of these alternatives are ordered in terms of their closeness.

2.5. Sustainable Development

Sustainable development is an inclusive approach that seeks to balance diverse needs while taking into account environmental, social, and economic constraints in decision-making processes. It involves anticipating the broader and long-term consequences of development activities (Sonal [56]). Numerous studies have proposed frameworks and methodologies for identifying sustainable development factors in the context of route selection. Zhang [57] considered economic development factors in optimizing dispositions of water resources. Batisha et al. [58] extended this perspective by maintaining efficient operational and functional factors in transmitting process while taking to account the objectives of optimization, climatic fluctuation, and economic aspects. Zhang and Zeng [59] considered environmental conditions and environmental protection as major factors in sustainable development of water resources. Mohamadi & Shojaie [60] introduced a comprehensive criterion containing environmental, economic and construction aspects in establishing a sustainable development system for selecting pipeline routes. Evidently, route selection process requires a holistic approach involving a range of social, environmental, economic, and operational criteria. Accordingly, the following criteria within three primary aspects of sustainable development were derived from prior research to define features in the ongoing case study of water pipeline transmission. These criteria have been organized in the subsequent table 3, maintaining the essential problem features.

Table 3. Problems Features based on Sustainable Development Indexes.

Sections	Features (Criteria)	Context in Current Study	Variables
Operational	Water Pipeline Length	Capacity Requirements for the Entire Water Conservancy Pipeline Project (Dimension, Km)	X_{01}
	Water Resource Pooling (liquidity aggregation)	When encountering extreme changes in height, such as in very high or very low regions, the phenomenon of liquid aggregation occurs at turning points (Dimension, Number).	X_{02}
	Pressure variation (elevation head)	In places with liquidity aggregation, there is twice as much pressure variance compared to other areas (Dimension, Number).	X_{03}
	Water Pumping Station	To enhance the water pressure within the pipeline (Dimension, Station).	X_{04}
	Pipe Corrosion	In swampy areas, where water can cause corrosion, the installation of additional stations is crucial to prevent pipeline corrosion (Dimension, Station)	X_{05}
	Line break valve	Enhancing Pipeline Safety and Efficiency: Mitigating Water Hammer Phenomenon by Adjusting the Closing Rate of Line Break Valve (Dimension, Number)	X_{06}
	Freezing of water pipelines	Moisture in winter can freeze and form ice crystals, leading to blockages within pipelines (Dimension, Number)	X_{07}
	Road Construction with Level Terrain (Being flat to build ROW)	Topography or Slope of the terrain, ensuring roads are built on flatter surfaces, the process of constructing ROWs becomes significantly smoother and more efficient (Dimension, Percent)	X_{08}
	Natural Twists and Curves of the Route for Constructing the Pipeline	More meandering twists and curves found along the route cause displacement of certain farms along the way (Dimension, inch)	X_{09}
	Crossing Natural Barriers	Pipeline routes encounter various natural obstacles like lakes, mountain passes, and other geographical features (Dimension, Number)	X_{10}
	Crossing Passing from artificial barrier	These barriers include asphalt roads, paths, and railways (Dimension, Number)	X_{11}
Environmental	Pig running	Pollution been subsiding in the pipeline should be cleaned off (Dimension, Yearly)	X_{12}
	Deforestation (cutting the trees)	Cutting down trees should be avoided to preserve forest and nature for transmitting water pipeline (Dimension, Km)	X_{13}
	Pasture damage	Mitigating pasture damage (Dimension, Km)	X_{14}
	Water Pipelines passing from lakes, rivers and ponds	Making construction impossible and interfering with our environment (Dimension, Number)	X_{15}
Socio-economic	Crossing water pipelines in densely populated areas	To construct a water supply network, it is more appropriate to bypass crowded areas, ensuring greater efficiency and a reliable water supply to a great number of people (Dimension, Number)	X_{16}
	Crossing water pipelines within industrial areas and towns reliant on water	Main Industries such as power generation, chemical manufacturing, steel and metal manufacturing and electronics manufacturing etc (Dimension, Number)	X_{17}
	Payback period	Years required to recover the original cash investment (Dimension, Year)	X_{18}
	Crossing water pipelines within farms and gardens	Pipelines construction has detrimental effects on agriculture (Dimension, Km)	X_{19}
	Line class description in selecting route	Areas with third- and fourth-class rankings are excessively crowded and hazardous (Dimension, Number)	X_{20}

3. Case Study

This study was aimed at determining the best route of water pipelines from six new lines to transmit water between two provinces in an area. During the previous routing projects, civil engineers gathered a dataset consisting of a matrix that represents information from 71 existing water pipelines. This information was associated with the 20 features suitable for sustainable development goals. Moreover, a Fuzzy linguistic decision matrix was made based on this dataset. In this matrix, five committee of experts evaluated the relationship between twenty features and each of the 71 lines using a fuzzy linguistic approach (five-item Likert scale). The elements of this decision matrix illustrate decision-makes ideas based on certain decision criteria. Due to space limitations in presenting the complete data, this information is shown in the following abbreviated table 4 and table 5.

Table 4. Previous Fuzzy Decision Matrix (Committees' Views on Previous Constructed Water Pipelines Data) - **5 Decision-maker groups ideas for 71 routes by criteria.**

Decision Makers Groups Ideas	X_{01}	X_{02}	X_{03}	X_{04}	X_{05}	X_{06}	**...**	X_{15}	X_{16}	X_{17}	X_{18}	X_{19}	X_{20}
DM G1-Line 01	I	U	U	MI	MI	U	...	VI	I	MI	U	MI	I
DM G1-Line 02	I	U	U	MI	MI	U	...	VI	U	MI	U	MI	I
...	...	...	...	...	...	...	...	...	...	...	...	...	...
DM G5-Line 69	MI	U	U	I	MI	U	...	MI	U	MI	U	MI	MI
DM G5-Line 70	MI	MI	U	I	I	MI	...	MI	MI	MI	MI	MI	U
DM G5-Line 71	MI	MI	MI	I	I	MI	...	U	U	MI	MI	MI	U

355 rows*20 columns

Table 5. This is a table caption. Tables should be placed in the main text near to the first time they are cited.

	Line 01	**Line 02**	**Line 03**	**Line 04**	**Line 05**	**...**	**Line 67**	**Line 68**	**Line 69**	**Line 70**	**line 71**
X_{01}	84.6	84.8	86.5	88.4	89.8	...	92.5	94.2	95	96.7	97.5
X_{02}	14	14	16	12	13	...	9	9	8	6	5
X_{03}	28	27	32	25	26	...	18	18	17	13	10
X_{04}	2	2	2	2	2	...	2	1	1	1	0
X_{05}	2	2	2	2	1	...	2	2	2	3	3
X_{06}	9	10	10	9	9	...	7	7	8	7	6
X_{07}	9	9	10	8	8	...	6	6	6	4	3
X_{08}	39	36	28	42	42	...	59	60	55	63	68
X_{09}	1090	1060	1262	997	1028	...	700	668	608	410	311
X_{10}	27	27	32	26	26	...	18	18	18	13	11
X_{11}	3	3	3	4	3	...	4	4	4	4	4
X_{12}	4	4	4	4	4	...	3	3	3	3	2
X_{13}	36	36	42	33	34	...	23	22	21	15	12
X_{14}	12	12	9	14	16	...	18	19	20	23	25
X_{15}	2	2	2	2	2	...	3	3	3	3	4
X_{16}	19	7	4	20	17	...	36	36	12	15	16
X_{17}	2	2	1	2	2	...	3	3	2	2	2
X_{18}	23.9	23.9	23.7	21.9	23.3	...	21.3	21.6	22.6	22	21.7
X_{19}	33	34	28	35	38	...	43	44	45	50	52
X_{20}	8	9	8	9	6	...	10	11	14	16	17

20 rows* 71 columns

On the other hand, there was a complex situation in determining the optimal routes among the six new transmission lines for conveying water between two new districts. The experts intended to make decision about the appropriate routes to construct water pipelines. Accordingly, these route lines were associated with the same 20 features exited in previous dataset, categorized into three main sustainable development sections mentioned in the previous. The data is shown in table 6. Consequently, an integrated deep learning model was implemented to determine the best routes for construction to expedite the decision-making process and avoid extensive data collection. The following steps are outlined the study method which is elaborated in detail in following section:

- **Step 1 - Checking the interpretability of decision matrix data:** Using a combination of PCA and FVIKOR methods on 71 alternatives (existing water pipeline routes) to assess the interpretability of the available Fuzzy Decision Matrix data.
- **Step 2 - Developing Sparse Neural Network model :** We have trained a multi-task sparse neural network based on the old alternatives 20 criteria as the input variables and fuzzy combination of all expert groups' decision matrices which is a decision matrix called the output decision matrix as the output variables using TensorFlow in Python.
- **Step 3 - Applying model to predict Fuzzy Decision Matrix for six new alternatives:** Using the trained model, we have predicted the fuzzy combined ratings for the new alternatives. Then, we have stacked up the old and new alternatives data to use FVIKOR once again to rank the new alternatives alongside the old ones.

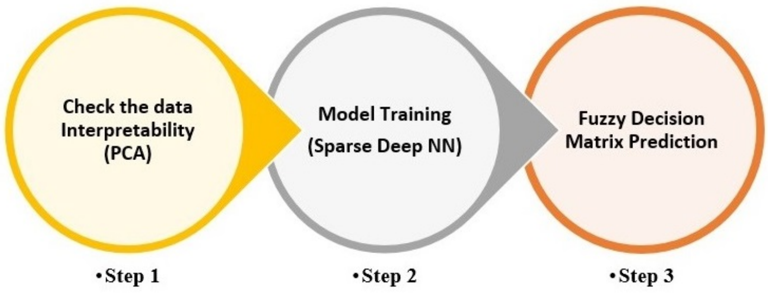

Figure 3. steps of the method.

Table 6. Case Study new Alternatives (Water Pipeline routes)

	Line 01	Line 02	Line 03	Line 04	Line 05	line 06
X_{01}	104.5	100	90	78	115	83
X_{02}	1	2	15	18	1	16
X_{03}	2	4	30	36	1	33
X_{04}	0	0	2	3	0	3
X_{05}	3	3	2	1	2	1
X_{06}	3	5	10	11	2	11
X_{07}	0	1	10	12	0	11
X_{08}	95	80	30	20	96	25
X_{09}	12	15	1200	1450	10	1325
X_{10}	3	5	30	35	1	33
X_{11}	6	5	3	2	4	3
X_{12}	1	2	4	5	0	5
X_{13}	0.5	2	40	48	0	44
X_{14}	30	30	10	6	40	8
X_{15}	4	4	2	1	2	2
X_{16}	69	20	5	2	58	4
X_{17}	5	3	1	1	3	1
X_{18}	18.14	20.83	24.3	25.83	21.14	23.127
X_{19}	60	60	30	24	75	27
X_{20}	15	19	8	5	7	7

20 rows* 6 columns

4. Results & Discussion

As discussed in the previous section, there is a dataset consisting of a matrix that represent 71 water pipelines as alternatives with 20 features (criteria). These pipelines' features were evaluated by five groups of decision-makers, utilizing a fuzzy Likert scale which resulted in a fuzzy decision matrix. To expedite the decision-making process and avoid extensive data collection approaches like using questionnaires to gather a new fuzzy decision matrix for 6 new water pipeline routes, a deep learning model was developed. This model was trained on the existing fuzzy decision matrix (refer to table 5) to predict the fuzzy Likert scale associated with each six new alternatives (routes). To do so, an initial stage is required to ascertain whether the present fuzzy decision matrix has the necessary information for predicting the combined ratings nor not. To check the interpretability of the data, PCA is employed alongside VIKOR scores for 71 existing routes. This allows us to determine whether it is actually possible to define a statistical classifier function in a reduced-dimensional space.

Using fuzzy VIKOR for available decision matrix of 71 existing routes, we can rank these alternatives as follows chart. Due to limitation space, the first top 25 alternatives are shown in figure 4.

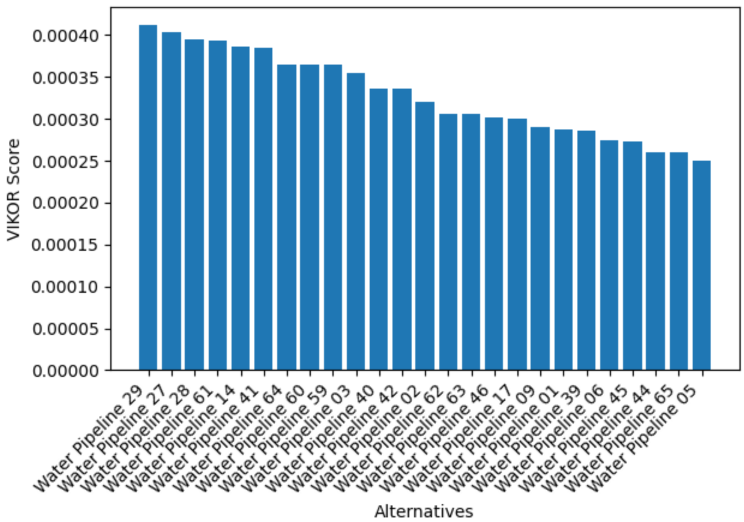

Figure 4. Fuzzy VIKOR scores for the top 29 constructed water pipelines.

All these 71 alternatives were classified by PCA method, while their ranking was determined through VIKOR. The results of these two methods are combined as follows:

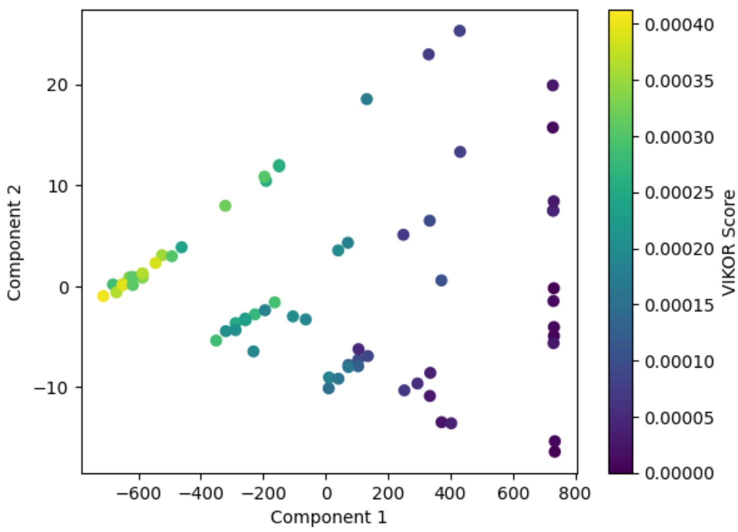

Figure 5. Combining PCA and FVIKOR .

In the figure 5, there are regions with alternatives uniformly received higher VIKOR scores, while other areas show alternatives with consistently lower scores. This implies that the data's internal variability is valuable for detecting alternatives with higher score, in other words, the laying information within the data is enough to build a classifier function. Therefore, fitting a model on the former alternatives can be reasonable.

4.1. Sparse Deep Learning ANN (Model Training)

As previously mentioned, a fuzzy decision matrix was available from previous water pipeline projects gathered by experts. As the idea behind each element of the decision matrix in each group of experts could be affected by different factors, it appears the function that can predict the elements of a new decision matrix could be quite complex. Also, we need a model to predict the elements of the decision matrix simultaneously for each alternative (or we would like the model to be a multi-task model) to save time and not train the same model multiple times with different elements of the decision matrix as the output variable. As a result, a multi-task deep learning model was developed to be trained on this dataset. This model led to prediction elements of the output decision matrix (fuzzy numbers) for six new alternatives (routes); these predicted elements show a combination of decision-makers ideas based on certain decision criteria (twenty features). Accordingly, neural network models can offer such a prediction using a complex function. In theory, a single hidden layer with a large number of units has the ability to estimate most functions. However, the process of learning for finding a solution becomes very smooth when we utilize several moderately-sized ones instead (James et al. [45]). Thus, we pick a deep neural network model with 2 hidden layers. To ensure the model achieves adequate accuracy in capturing the complexities among decision matrix elements during training, it is imperative to select an approach capable of addressing this challenge without yielding overfitted predictions. It was also discussed that some of the criteria (twenty features) could be interdependent and using all of them in our model can be noise accumulating and inconsistent. To ensure our model selects only the contributing features or criteria, the predictive model has to be l_1 -penalized. This kind of penalization leads to objective dimension reduction using sparsification of the models' parameters which is helpful for addressing the issue with stacked-up noise. The model architecture can be seen the Figure 6.

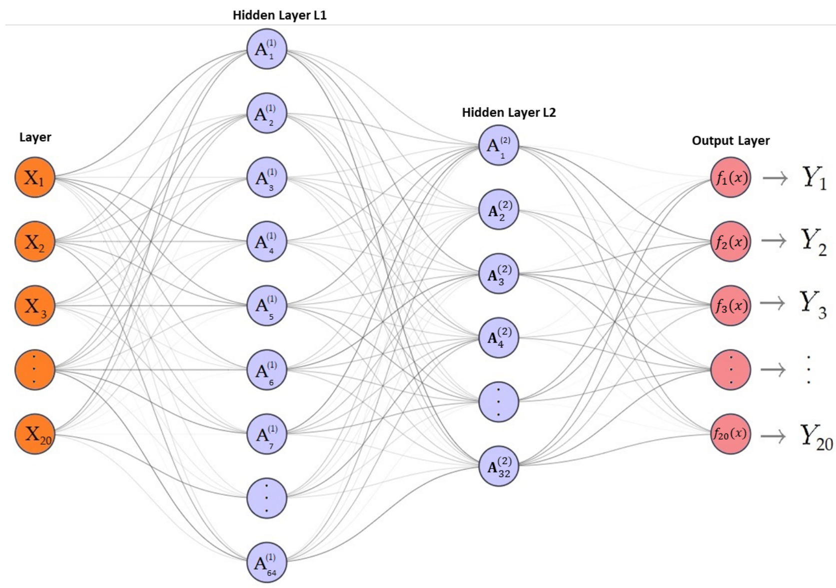

Figure 6. Model architecture of a multi-task deep neural network with 2 hidden layers.

After utilizing the multi-task penalized sparse deep neural network to predict the elements of the new fuzzy decision matrix for the six new alternatives, the Fuzzy VIKOR methodology was utilized to reassess and rank both the new and existing alternatives. This evaluation was conducted with the goal of determining the relative placement of these six new alternatives (routes) within the ranking scores among all 77 available water pipeline alternatives. Accordingly, if the rankings of the new alternatives were to place within the top 25, these options might be considered appropriate for implementing water transmission between the two areas. The first 25 alternatives are displayed in the figure 7.

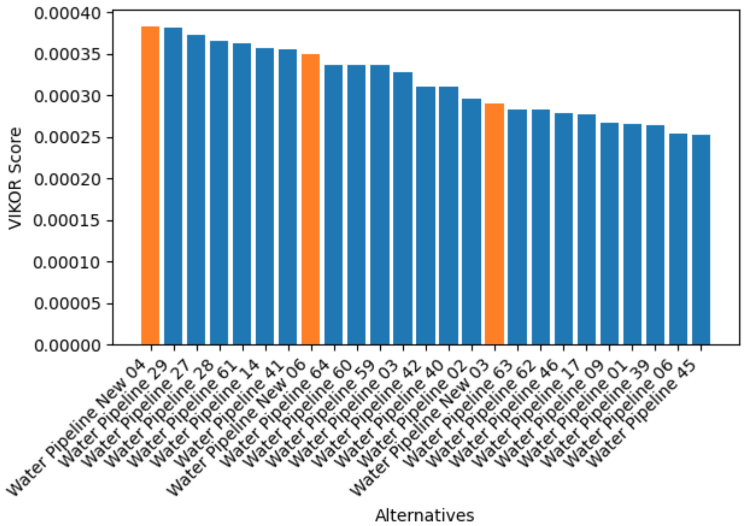

Figure 7. FVIKOR scores for the all the alternatives (77 routes). According to these new rankings, the 4th route of new water pipeline has received the highest score. Also, the 6th and the 3rd of new routes for proposed water pipelines have received a considerable score..

Clearly, among the six new alternatives considered for water transmission between two areas, routes of water pipelines 04, 06, and 03 are the appropriate choices for the study's goals since they were ranked among within the top 25 new routes based on the new FVIKOR scores.

Following the predictions from the DNN model, the Fuzzy VIKOR method was utilized to re-evaluate and rank all 77 pipeline alternatives. The table 7 represents the new rankings of all 77 water pipeline routes:

Table 7. New FVIKOR Scores for all 77 Water Pipeline Routes

Alternative	S-Value	R-Value	VIKOR Score	Ranking
Water Pipeline New 04	0.0003	0.0004	0.0004	1
Water Pipeline 29	0.0003	0.0004	0.0004	2
Water Pipeline 27	0.0003	0.0004	0.0004	3
...	...	...	...	...
Water Pipeline 14	0.0003	0.0004	0.0004	6
Water Pipeline 41	0.0003	0.0004	0.0004	7
Water Pipeline New 06	0.0003	0.0004	0.0003	8
Water Pipeline 64	0.0003	0.0004	0.0003	9
Water Pipeline 60	0.0003	0.0004	0.0003	10
...	...	...	...	...
Water Pipeline 40	0.0003	0.0003	0.0003	14
Water Pipeline 02	0.0002	0.0003	0.0003	15
Water Pipeline New 03	0.0002	0.0003	0.0003	16
Water Pipeline 63	0.0002	0.0003	0.0003	17
...	...	...	...	...

5. Conclusion

This study focused on the crucial task of optimizing water pipeline route selection through an integrated approach involving a Sparse Deep Neural Network (DNN) and the Fuzzy VIKOR method. Water scarcity and the limited availability of consumable water emphasize the importance of efficient water transmission projects. Traditional manual methods of pipeline routing, though effective, suffer from time constraints and limited data processing capabilities. To address these challenges, the study proposed an integrated approach leveraged by deep learning methodology in combination with a Fuzzy multi-criterion decision-making method (FVIKOR) for determining the optimal water pipeline route. Furthermore, the existence of interdependency among criteria is a concern in Multiple Criteria Decision Making (MCDM) methods, as it can introduce unnecessary inconsistency into the decision-making process. This issue becomes more pronounced in situations with numerous criteria, leading to noise resulting from redundant factors. A Penalized Neural Network provides a solution by selecting the most significant features through dimension reduction. In this regard, an integrated Deep Learning model with Fuzzy VIKOR was used to encounter this problem. A case study was presented to explain the proposed approach. The case study involved six new routes for transmitting water between two provinces. A comprehensive fuzzy decision matrix consisted of 71 existing water pipelines routes, evaluated against 20 sustainable development features, formed the foundation of this study. A multi-task deep learning model was developed to expedite the decision-making process for six new routes to see which ones are suitable for transmitting water between two areas. This model, comprising two hidden layers, was capable of predicting fuzzy decision matrix elements for the new alternatives. The model's complexity was addressed by l_1-penalization, which allowed for feature selection and noise reduction. Among the six new routes, options 04, 06, and 03 were deemed the most suitable choices for implementation, as they secured rankings within the top 25 alternatives. This integrated approach showcases the potential of modern technologies like Deep Neural Networks and multi-criteria decision-making methods like Fuzzy VIKOR in making decision challenges. This study contributes to an efficient and sustainable approach to transmitting water through a combination of a data-driven prediction model with a multi-criteria decision-making method which ultimately benefits the environment and society. However, it is advisable for future research to utilize resampling methods in combination with the fitting model to enhance the accuracy of the model since the limitation of data availability for these kinds of studies has negative effects on model precision. Moreover, in future studies, additional geographical factors such as soil composition, faults, and natural features could be incorporated into the assessment of water pipeline projects, enhancing the comprehensiveness of the evaluation.

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Data Availability Statement: The data used in the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest: We declare that we have no competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

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