A Goal Programming-Based Framework for Multi-Objective Optimization of Sustainable Concrete Pavements Mix Design

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Abstract

The use of concrete pavement has significantly increased due to its advantages over asphalt pavement. Determining the concrete mix ratio for asphalt is a vital and crucial step in the construction process. Concrete should be strong, durable, and resistant to environmental degrading factors. This means it needs to withstand freezing, thawing, shrinkage, and harsh environmental conditions (such as heat and cold. These characteristics result in concrete having a longer lifespan and creating robust structures). One of the challenges in design is balancing quality and cost, which comes with its own complexities.. Over the past few years, the application of models and algorithms for multi-objective problems has been a focus of research. This study introduces adaptive neuro-fuzzy inference system goal programming (NFGPM) and fuzzy-goal programming model (FGPM) as expanded variants of basic goal programming models, as alternative tools for allocating asphalt concrete pavement mixtures proportions with multiple, varied objectives. The actual data laboratory experiment datasets were generated and used to develop proposed models. The outcomes of the proposed NFGPM's mixture proportions and its prediction of concrete properties —such as slump, flexural strength, abrasion resistance, shrinkage and freeze–thaw behavior— are compared with experimental data. The study confirms that the adaptive neuro-fuzzy inference system

goal programming model proposed herein can deliver the most cost-effective and optimally performing concrete pavement mixture proportions.

Keywords: concrete pavement; mixture proportioning; multi-objective; goal programming; adaptive neuro-fuzzy inference system

1. Introduction

Today concrete pavement is employed owing to numerous advantages such as high rigidity, excellent fatigue performance, long service life and cost-effectiveness [1]. The first concrete pavement was constructed in 1891 in Ohio, USA, and remained surprisingly serviceable after centuries. Although concrete pavement require a higher initial investment than asphalt pavements, they are more economical over their long-term life cycle.

However, their longer service life and ease of maintenance relative to other pavement materials, including asphalt, are high desirable. Additionally, concrete pavements have an operating life that is at least 1.5 to 2 times longer than that of asphalt pavements [2].

Concrete pavements are important components due to exposure to environmental weather conditions. Therefore, certain standards, including Federal Aviation Administration of United State (FAA) and the International Civil Aviation Organization (ICAO), as well as some guidelines, attempt to provide method or process for determining mixture proportions [2-4]. However, the methods described in the cited standards or guidelines for selecting appropriate concrete pavement mixture proportions remain traditional, relying on trial mixes and the use of tabulated data or a table or charts [5]. Typical intended properties in guidelines for concrete pavements include achieving the desired workability, sufficient compressive or flexural strength, controlled plastic or drying shrinkage, durability and abrasion resistance. An important consideration is that, in addition to the stated objectives, the designed concrete mixture should be cost-effective [6,7]. In recent years, there has been growing use of algorithms and mathematical and statistical to predict concrete properties or to determine optimal mixture ratios by comparing regression methods, neural network and neuro-fuzzy network [8-10].Sobhani et al. [11] attempted to identify the best method for predicting 28-day compressive strength by presenting data from no-slump concrete mix designs. A notable aspect of the aforementioned study is that the models and algorithms considered only a single objective. For instance, only the attainment of compressive strength was targeted. The challenge of determining concrete pavement mixture proportions is highlighted here, because several goals may be conflicting, making it very difficult to address all of them using traditional approaches or single objective models [4, 12, and 13].

For example, in determining mixture proportions, the project owner or consulting foreconsiders several objectives, including reducing costs, improving mechanical properties, increasing the durability, minimizing shrinkage and cracking, and ensuring acceptable workability. However, to increase mechanical properties, special admixtures are required that raise costs or or may adversely affect the properties of the structure. Therefore, it is essential to use models that can optimize concrete mixture proportions for all purposes. In recent years, multiple studies have been explored multi-objective optimization in the construction industry. Muthukumar and Mohan [14] employed an optimization model to determine the optimal polymer concrete proportions to minimize mixture voids, evaluating mechanical properties such as compressive, flexural and tensile strength for each mix. Park et. al. [15] proposed a multi-objective approach that concurrently considers mechanical property and the cost in the early stage. Sahab et. al. [16] aimed to optimize the cost of buildings slabs. As noted above, there is no study that optimizes concrete pavement mixture proportions across multiple goals and objectives. Recent advances in data-driven and optimization-based concrete mix design have significantly improved the accuracy and sustainability of proportioning methods. Gao et al. [۱۷] proposed a generative modelling framework that enables automated mix design optimization by learning from existing datasets, resulting in more efficient and sustainable concrete compositions.

Similarly, Cao et al. [١٨] integrated Bayesian optimization with NGBoost and the NSGA-III algorithm to minimize cost, carbon emissions, and variability in concrete for low-carbon applications. Their hybrid framework achieved better convergence and predictive accuracy compared to conventional statistical methods and other metaheuristic approaches. Complementing these investigations, Wang et al. [١٩] proposed a multi-objective optimization framework for ultra-high-performance concrete (UHPC) that integrates evolutionary algorithms with machine learning models to achieve a more favorable balance between mechanical strength and material efficiency. Collectively, these contemporary studies underscore the expanding role of artificial intelligence and hybrid optimization techniques in advancing next-generation, sustainable concrete mix design methodologies.

2. Aims and methodology

In this article, goal programming is employed to determine the mix proportions of concrete pavements while simultaneously optimizing multiple objectives. A model is developed to yield the optimal proportions such that the combination of minimum cost and the optimal values of mechanical properties, durability and shrinkage adheres to the technical specifications of the project. Moreover, within the framework of the model, fuzzy logic and artificial neural networks were employed to develop the model. The proposed approach is capable of determining the usage or non-usage of different materials and quantifying their amounts while considering the defined objectives. The results of these models were benchmarked against the linear programming model. The schematic structure of applied optimization models in this study is depicted in Figure 1.

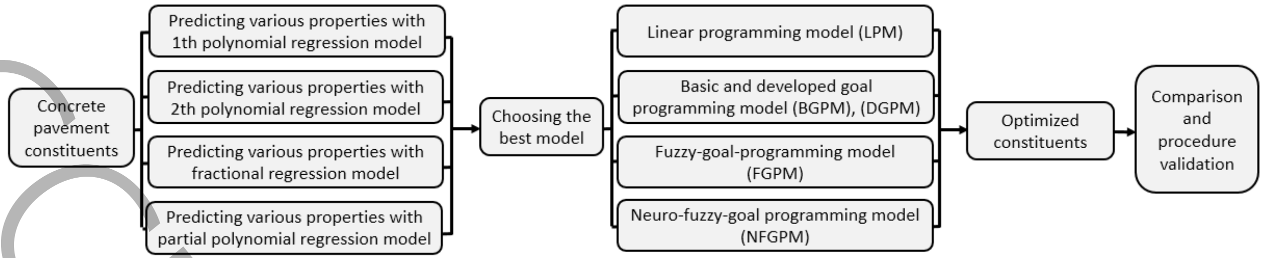

Fig. 1. The schematic structure of applied optimization models in this study

2.1. Regression

Regression analysis is employed to characterize the relationship between one or more independent variables and dependent variable. The regression equation is is derived from statistical data and it can be used to estimate the targeted parameter. Linear regression is one of the regression methods, defined by a relationship among independent variables that is additive and subtractive (i.e., linear in parameters). [20]

2.2. Linear programming

Linear programming models are a mathematical optimization methods widely employed in structural design problems [21]. A key characteristic of this approach is that all constraints and the objective function are expressed as linear functions of the design variables. The objective function can be either maximized or minimized depending to the problem, and the constraints may take the form of equalities or inequalities.

2.3. Goal programming model (GPM)

Goal programming is a multi-objective decision making method. Unlike other approaches, in this method goals are treated as desirable targets and attaining them exactly is not mandatory. In fact, the presented solution approaches all goals acceptably, and the model may violate some of the goals.

For each goal, the deviations di- and di+ are defined from the respective sides, and the smaller the deviation, the closer the target is to being achieved. A key advantage of this modelling approach is that certain goals may be in conflict; in such cases, the optimal solution lies at a point within the feasible region often referred to as the "utopia" point. This method enables multi-objective optimization by converting all targets into a single aggregated goal and subsequently minimizing the sum of distances to single-objective, which can be solved using the LINGO software [22]. The GPM model for the mix-proportion optimization problem can be developed through the following analysis: If the target values for each concrete specification are taken as b_i then the model can considered as equation (1):

$$G_i(x_j) = \sum_{j=1}^{m} w_{ij} x_j \cong b_i \quad (For\ i = 1,\ldots,n) \tag{1}$$

Using two nonnegative values, for example, d_i^- and d_i^+, equation 8 can be converted into an equation 2:

$$\sum_{j=1}^{m} w_{ij} x_j + d_i^- - d_i^+ = b_i \quad (d_i^- \geq 0, d_i^+ \geq 0) \quad (For\ i = 1,\ldots,n) \tag{2}$$

d_i^+ means approaching from the positive side to the target; in other words, more values than the desired value are checked; Thus, the negative sign is introduced into the equation to achieve the goal. Similarly, since d_i^- approaches the target from lower values, it must be introduced with the positive sign in the equation. With these interpretations, if one of these two values takes a number, the other becomes zero. Consequently, goal programming approach defines the optimal solution by minimizing this gap across all goals. A goal programming formulation is presented in Equations 3-5.

$$Z = \text{Minimum} \sum_{i=1}^{n} (d_i^- + d_i^+) \tag{3}$$

Subject to:

$$\sum_{i=1}^{m} w_{ij} x_j + d_i^- - d_i^+ = b_i \quad (4)$$

$$d_i^-, d_i^+, b_i, p_i, w_{ij}, x_j \geq 0 \quad (5)$$

In Equations (1) to (5), $G_i(x_j)$ represents the value of the i-th goal function. The parameter w_{ij} denotes the coefficient (weight) of decision variable x_j in the i-th goal, while x_j represents the j-th decision variable of the model. The parameter b_i is the target value associated with the i-th goal. The variables d_i^+ and d_i^- are non-negative deviation variables representing the positive and negative deviations from the target value, respectively. The objective function Z denotes the minimization of the sum of deviation variables for all goals. All deviation variables and decision variables are constrained to be non-negative.

3. Prediction of Concrete Properties from Mix Design

The structure of the regression modelling systems including inputs and outputs for predicting concrete properties from mix design, were schematically shown in Fig. 2. The input parameters were (I) cement (II) water, (III) silica fume, (IV) aggregates, (V) plasticizer, (VI) fiber and (VII) air-entraining admixture (AEA) by the weight per unit volume of concrete. Also, Table 1 presents the ranges of input and output of data used for regression modelling object. These ranges are based on the previous researches [23-28].

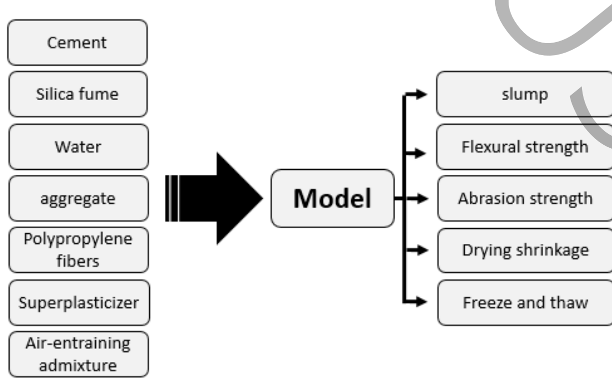

Fig. 2. The schematic structure of the regression modeler systems

Table 1. Input and output of data used for regression modelling

Inputs		Range	
		Minimum	Maximum
Cement (kg/m^3)	C	331.2	420
Silica fume (kg/m^3)	SF	0	33.6
Water (kg/m^3)	W	140.4	180.6
aggregate (kg/m^3)	AG	1683.9	1845.8
Polypropylene fibers (kg/m^3)	PPF	0	1.5
Superplasticizer (kg/m^3)	SP	0	3.57
Air-entraining admixture (kg/m^3)	AE	0	0.252

In the present study, using the regression model, with the real data and Minitab software, we aim to obtain equations to determine concrete properties, including slump, flexural strength, abrasion resistance, drying shrinkage and freezing thawing, considering cement, aggregates, water, a variety of chemical and mineral admixtures and fibers. Experimental data include 24 ordinary concrete samples prepared with different amounts of cement, silica fume, water, aggregates, fibers, super-plasticizer and air entraining additives. The mix proportions of these samples are presented in Table 2. Then each sample was prepared in the laboratory, and various experiments were conducted on them at different ages, with the results from each experiment used to determine the model. Results of slump tests, flexural strength, drying shrinkage and freezing-thawing are presented in Table 3. To make the model's precision, reduce the error rate, and prevent overfitting during training, a scaling operations is applied to all the data before the regression, with all data ranging from between 0.1 to 0.9 [11]. This operation is performed according to the following formula:

$$i = 0.1 + 0.8 \times \left(\frac{X - X_{min}}{X_{max} - X_{min}} \right) \quad (6)$$

Where *i* is the scaled input, *X* is the not-scaled input, *Xmin* and *Xmax* are the minimum and maximum not-scaled input values respectively.

Table 2. Proportions of mixtures used as actual data in regression model

Mixture	w/c	Cement (kg/m3)	Silica fume (kg/m3)	Water (kg/m3)	Aggregate (kg/m3)	fiber (kg/m3)	Super-plasticizer (kg/m3)	Air-entraining (kg/m3)
NC-1	0.39	380	0	148.2	1809.5	0	1.71	0
NC-2	0.41	380	0	155.8	1790.6	0	1.52	0
NC-3	0.37	380	0	140.6	1828.0	0	2.09	0
NC-4	0.39	360	0	140.4	1845.8	0	1.62	0
NC-5	0.39	400	0	156	1773.2	0	1.8	0
NC-6	0.39	380	0	148.2	1808.9	0	1.71	0.114
NC-7	0.39	380	0	148.2	1804.4	1.5	2.09	0
NC-8	0.39	380	0	148.2	1804.8	1.5	1.71	0.228
NC-9	0.45	380	0	171	1755.3	0	0	0
NC-10	0.41	420	0	172.2	1715.7	0	1.68	0.126
NC-11	0.37	386.4	33.6	155.4	1744.7	0	2.73	0
NC-12	0.43	380	0	163.4	1774.7	0	0	0
NC-13	0.45	331.2	28.8	162	1779.7	1.5	0	0.216
NC-14	0.43	420	0	180.6	1697.9	0	0	0.252
NC-15	0.37	403.2	16.8	155.4	1744.4	1.5	3.57	0
NC-16	0.45	400	0	180	1712.8	1	0	0.24
NC-17	0.39	349.6	30.4	148.2	1798.6	0	1.71	0.114

NC-18	0.45	349.6	30.4	171	1740.2	1.5	0	0.114
NC-19	0.43	386.4	33.6	180.6	1683.9	1	0	0
NC-20	0.41	386.4	33.6	172.2	1699.1	1.5	2.1	0
NC-21	0.39	345.6	14.4	140.4	1837.1	1	1.98	0
NC-22	0.39	384	16	156	1767.1	0	1.8	0.24
NC-23	0.45	380	0	171	1750.9	1.5	0	0.114
NC-24	0.41	380	0	155.8	1785.8	1.5	1.52	0.228

Table 3. Values of test results of experimental mixtures

Mixture	**slump**	**Flexural strength**	**Abrasion strength**	**Drying shrinkage**	**Freeze and thaw**
	mm	**MPa**	**Weight loss (%)**	**µm/m**	**Relative dynamic modulus of elasticity (%)**
NC-1	40	6.333	7.13	398	76
NC-2	45	6.318	8.03	491	73
NC-3	45	6.770	6.68	342	81
NC-4	35	6.314	7.10	310	76
NC-5	50	6.469	7.09	436	77
NC-6	55	6.192	7.43	423	81
NC-7	40	6.593	6.70	281	70
NC-8	50	6.044	8.43	408	78
NC-9	70	5.623	9.87	760	62
NC-10	60	6.032	8.58	640	79
NC-11	45	6.982	6.54	405	84
NC-12	60	5.912	8.59	674	65
NC-13	70	5.498	9.65	740	75
NC-14	75	5.600	8.12	790	76
NC-15	55	6.650	6.58	388	76
NC-16	75	5.398	10.23	794	68
NC-17	45	6.298	7.10	544	81
NC-18	70	5.732	9.12	612	64
NC-19	55	6.280	7.60	690	67

NC-20	40	6.490	7.98	542	72
NC-21	50	6.342	6.84	384	76
NC-22	60	5.980	7.34	584	84
NC-23	75	5.540	9.75	644	65
NC-24	50	5.890	8.64	452	83

To evaluate and compare the proposed regression models, two, two metrics, RMSE and R^2, were used to compare model results with experimental (actual) results. The RMSE parameter indicates the amount of error between the predicted results and the actual results, in the form of the following equation, with lower values corresponding to higher model accuracy [20, 29]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i\,(\text{actual}) - Y_i\,(\text{predicted}))^2} \qquad (7)$$

Where $Y_i\,(\text{actual})$ and $Y_i\,(\text{predicted})$ are the experimental and predicted values, respectively, and N is the number of data samples.

Moreover, the value of R^2 is between 0 and 100 that in case it is closer to 100, indicates the accuracy and power of the model. To predict the properties of concrete, several regression models are presented in Table 4 based on the results of slump, shrinkage, flexural strength, abrasion resistance, and freezing-thawing. In Figures 3 and 4, comparing the values of RMSE and R^2, it is found that 2th Polynomial is the best model for all properties. The Relationships for slump, shrinkage, freezing-thawing, abrasion resistance and flexural strength are given in equations 8-12, respectively.

$$G_{\text{Slump}} = 128.8 - 70.9W - 49.1C - 25.1\text{SF} - 3.05\text{PPF} - 0.136\text{AE} - 6.59\text{SP} - 106.6\text{AG} + 2.019W^2 + 0.547C^2 - 1.338\text{SF}^2 + 0.215\text{PPF}^2 - 0.232\text{AE}^2 + 0.704\text{SP}^2 - 2.83\text{AG}^2 \quad (8)$$

$$G_{\text{Shrinkage}} = -22.1 + 13.3W + 7.7C + 4.8\text{SF} + 0.68\text{PPF} + 0.156\text{AE} + 0.58\text{SP} + 19.3\text{AG} - 0.22W^2 + 0.221C^2 - 0.337\text{SF}^2 - 0.413\text{PPF}^2 + 0.098\text{AE}^2 + 0.423\text{SP}^2 - 0.15\text{AG}^2 \quad (9)$$

$$G_{\text{Freez \& Thaw}} = 0.9 + 0.4\text{W} - 0.3\text{C} - 0.5\text{SF} + 0.4\text{PPF} + 0.447\text{AE} + 0.33\text{SP} - 1.6\text{AG} - 1.41\text{W}^2 + 0.647\text{C}^2 + 0.744\text{SF}^2 - 0.595\text{PPF}^2 + 0.05\text{AE}^2 - 0.059\text{SP}^2 + 1.33\text{AG}^2 \quad (10)$$

$$G_{\text{Abrasion}} = -94.1 + 53.4W + 34.4C + 17.5\text{SF} + 2.67\text{PPF} + 0.973\text{AE} + 4.24\text{SP} + 80.2\text{AG} - 0.75W^2 - 0.5C^2 + 1.095\text{SF}^2 - 0.706\text{PPF}^2 - 0.352\text{AE}^2 + 0.933\text{SP}^2 + 0.31\text{AG}^2 \quad (11)$$

$$G_{\text{flexural}} = 18.9 - 11.4W - 6.3C - 3.92\text{SF} - 0.33\text{PPF} - 0.593\text{AE} - 0.51\text{SP} - 15\text{AG} + 0.564W^2 + 0.206C^2 + 0.6148\text{SF}^2 - 0.001\text{PPF}^2 + 0.231\text{AE}^2 - 0.432\text{SP}^2 - 0.2736\text{AG}^2 \quad (12)$$

Where G_{slump}, $G_{shrinkage}$, $G_{freeze\ \&\ thaw}$, $G_{abrasion}$ and $G_{flexural}$ are the values of slump, shrinkage, freezing-thawing, abrasion resistance and flexural strength that estimated by regression model. Also, W, C, SF, PPF, SP and AG are values of water, cement, silica fume, and polypropylene fiber, air entraining admixture, super plasticizer and aggregates respectively.

Table 4. Various regression models usable in the study (Sobhani et al., 2010)

Model	Type	Regression model
1	1nd Polynomial	$a_0 + a_1W + a_2C + a_3\text{SF} + a_4\text{PPF} + a_5\text{AE} + a_6\text{SP} + a_7\text{AG}$
2	2nd Polynomial	$a_0 + a_1W + a_2C + a_3\text{SF} + a_4\text{PPF} + a_5\text{AE} + a_6\text{SP} + a_7\text{AG} + a_8W^2 + a_9C^2 + a_{10}\text{SF}^2 + a_{11}\text{PPF}^2 + a_{12}\text{AE}^2 + a_{13}\text{SP}^2 + a_{14}\text{AG}$
3	Fractional	$a_0 + a_1\dfrac{W}{C + \text{SF}} + a_2\dfrac{W + \text{SP} + \text{AE}}{\text{AG} + \text{PPF}}$

4	Partial polynomial –fractional Type 2	$a_0 + a_1\left(\frac{W + \text{SP} + \text{AE}}{C + \text{SF}}\right) + a_2\left(\frac{\text{AG} + \text{PPF}}{C + \text{SF}}\right) + a_3\left(\frac{W + \text{SP} + \text{AE}}{C + \text{SF}}\right)^2 + a_4\left(\frac{\text{AG} + \text{PPF}}{C + \text{SF}}\right)^2$

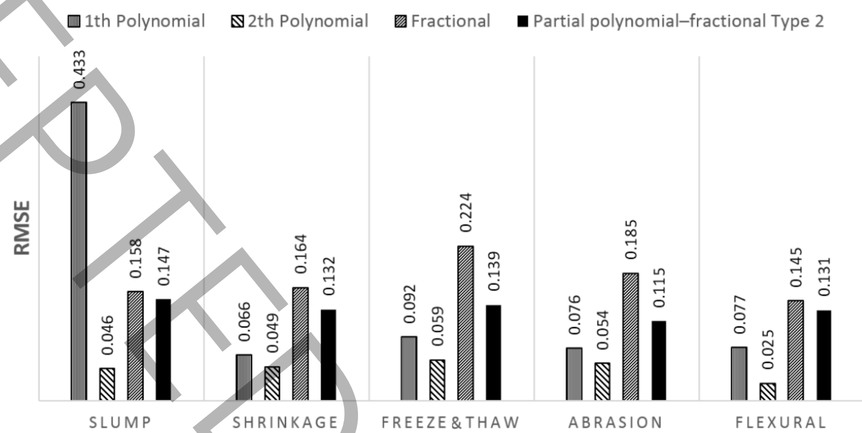

Fig. 3. RMSE values of model for the prediction of concrete pavement properties

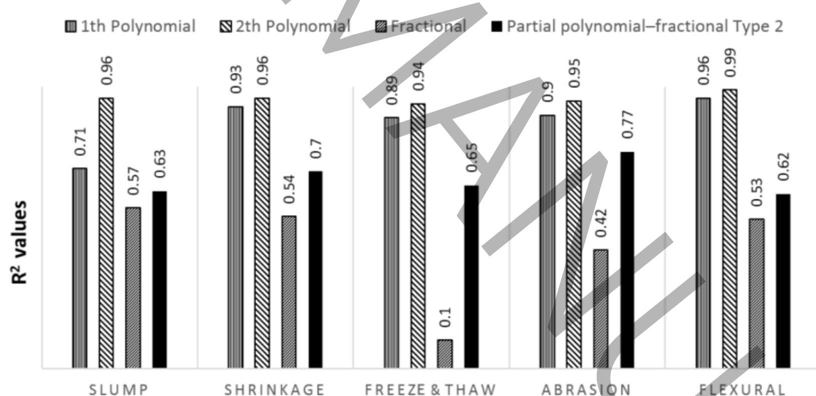

Fig. 4. R^2 values of model for the prediction of concrete pavement properties

4. Description of problem and object

In this study, the optimization of the mixture proportions for a concrete pavement as a highway road with a length of 10 km, a width of 25.9 m and a thickness of 0.4 m is considered. The batching of site is located midway through the project at kilometer 5. The cost of materials is calculated according to the distance from batching site to the factory and the purchase and transportation costs, based on the currency of Iran (IRR), and it is shown in Table 5. The cost of silica fume, fibers, air-entraining agents and superplasticizer depends on the purchase quantity according to the supplier's pricing policy; up to a certain quantity, the price is at the first step, and with the increase in the purchase, the price decreases, hence, in the next step or steps, the cost is reduced.

Table 5. Cost of materials (IRR/kg) for 1 cubic meter

Cement	Water	Aggregate	Silica fume			fiber		Air-entraining		Super-plasticizer	
			$x \leq 1000$	$1000 \leq x \leq 2000$	$x \geq 2000$	$x \leq 100$	$x > 100$	$x \leq 10$	$x > 10$	$x \leq 150$	$x > 150$
			IRR/kg								
1122.25	**124.25**	**143.5**	**7000**	**6000**	**5000**	**35000**	**28000**	**70000**	**60000**	**50000**	**40000**

5. Proposed optimization models

5.1. Linear programming model (LPM)

In the linear programming method used in this article, the purpose of the model is to minimize costs while achieving accurate results for the desired concrete properties. In fact, there is only one objective function, while the remaining goals are encoded as fixed definitions that the model must satisfy and cannot violate. The main issues and limitations of the linear programming method are discussed in this section. It is noteworthy that the model cannot solve a single-objective problem when multiple constraints are considered, and cannot satisfy all the requirements to determine the optimal mixture proportions. The following message is obtained when the proposed linear programming model model is implemented:

"The model is locally infeasible."

The reason is that some of the constraints and objectives are in conflict with one another, and since in linear programming models all the constraints must be satisfied, the model cannot find the optimal solution.

5.2. Basic goal programming model (BGPM)

The flexural strength, abrasion resistance, freezing and thawing, slump and shrinkage are described by equations 8-12 as presented previously. The cost function is also given in accordance with equation (13) as bellow:

$$Cost = Cost_{Water} + Cost_{Cement} + Cost_{Fiber} + Cost_{AirEntrainment} + Cost_{SuperPlasticizer} + Cost_{Aggregate} \quad (13)$$

Where $Cost_{water}$, $Cost_{cement}$, $cost_{fiber}$, $Cost_{air\text{-}entraining}$, $Cost_{superplasticizer}$ and $Cost_{aggregate}$ are cost of water, cement, fiber, air entraining admixture, super plasticizer and aggregate respectively per 1 cubic meter volume of concrete.

All model inputs and outputs were normalized within the range of 0.1–0.9 to ensure numerical consistency among different objectives. The cost target was set to 0.1 as the ideal minimum value in the normalized space, while the slump target was selected as the midpoint of its allowable range to represent balanced workability. Since the objective of the study is to achieve an overall optimal compromise solution, all goals were assigned equal weights in the goal programming formulation. However, the cost function must be expressed in kilograms based on the use of coefficients (kilogram per rial). To link the relationships, equation (14), is used to convert the mixture components from their normal form (Equation (1)) to ordinary values suitable for inclusion in the cost function. This cost is ultimately scaled by the maximum and minimum cost values and incorporated into the constraints in Equation (21).

$$X = (i - 0.1) \times \frac{X_{max} - X_{min}}{0.8} + X_{min} \quad (14)$$

By solving equation 15 in the LINGO software, the minimized values of the distance to the optimal concrete specifications are obtained according to the model's objectives. In Equation (15), the standard deviations for concrete specifications are scaled and numerically are less than 0.9, whereas the cost term lies in the higher range. Consequently, considering the maximum and minimum costs of the 24 mix designs presented in Table 2 and in Equation (1), the standard deviation of the cost is scaled in the same manner as the other standard deviations to combine them coherently.

$$Z = \text{Minimum}(d^{-}_{\text{Slump}} + d^{+}_{\text{Shrinkage}} + d^{-}_{\text{Freez \& Thaw}} + \text{d}^{+}_{\text{Abrasion}} + \text{d}^{-}_{\text{Flexural}} + \text{d}^{+}_{\text{Cost}}) \quad (15)$$

Subject to:

$$G_{\text{Slump}} + d^{-}_{\text{Slump}} = 0.5 \quad (16)$$

$$G_{\text{Shrinkage}} - d^{+}_{\text{Shrinkage}} = 0.1 \quad (17)$$

$$G_{\text{Freez \& Thaw}} + \text{d}^{-}_{\text{Freez \& Thaw}} = 0.9 \quad (18)$$

$$G_{\text{Abrasion}} - d^{+}_{\text{Abrasion}} = 0.1 \quad (19)$$

$$G_{\text{flexural}} + d^{-}_{\text{Flexural}} = 0.9 \quad (20)$$

$$\left(0.1 + 0.8 \times \frac{G_{\text{cost}} - \text{Cost}_{min}}{\text{Cost}_{max} - \text{Cost}_{min}}\right) - d^{+}_{\text{Cost}} = 0.1 \quad (21)$$

In Equations (15) to (21), the following symbols and parameters are used. Z represents the overall objective function of the basic goal programming model, which is minimized. d^{-}_{Slump}, $d^{+}_{\text{Shrinkage}}$, $d^{-}_{\text{Freez \& Thaw}}$, d^{+}_{Abrasion}, and d^{-}_{Flexural} represent the deviation values related to slump, shrinkage, abrasion resistance, freezing–thawing resistance, and flexural strength, respectively. d^{+}_{Cost} denotes the deviation associated with the total cost of the concrete mixture. G_{Slump} represents the predicted value of concrete slump obtained from the regression model. $G_{\text{Shrinkage}}$ denotes the predicted value of concrete shrinkage estimated by the regression model. $G_{\text{Freez \& Thaw}}$ indicates the predicted freezing–thawing resistance of concrete obtained from the regression model. G_{Abrasion} represents the predicted abrasion resistance of concrete estimated by the regression model G_{flexural} denotes the predicted flexural strength of concrete obtained from the regression model. G_{cost} represents the total cost of the concrete mixture, calculated based on the unit costs and quantities of the materials used. Cost_{min} denotes the minimum total cost among the 24 concrete mix designs presented in Table 2. Cost_{max} denotes the maximum total cost among the 24 concrete mix designs presented in Table 2.

For the results of shrinkage and abrasion resistance, since the minimum feasible value was considered for them, it is necessary for the model to move from the larger numbers toward the target to reach the optimal point. Hence, the standard deviation values for these parameters are positive, and the expression d^{+} is used. Similarly, for the freezing-thawing values and the flexural strength due to their maximum orientation, the d^{-} term is used. Furthermore, the desired value for the maximum slump is taken as the average of the scaled range.

The ideal amount of cost is also presented to the model as 0.1 with a minimization goal so that the model will find the least amount of cost to achieve the desired concrete profile. To provide the outputs of the model based on the actual conditions, some constraints should be added to the model. The first constrain which should be taken into account is limiting the volume of the mixture proportions to 1 m^3.

Another constrain is considered so that the water-to-cement ratio is at least 0.37 for the model. Moreover, all inputs and outputs of the model must be lie within specified ranges (between 0.1 and 0.9). The necessary constraint for stepping the cost of silica fume, fibers, air entraining and super plasticizer are based on the study of [30] to meet the seller's conditions. This constraint for silica fume is provided, for example, in the relationships, and its schematic figure is shown in Fig. 5. For this purpose, the binary parameters (zero or one) are used. For example, equations 22 to 30 can be used to step silica fume cost. In these equations the parameters B1 and B2 are binary. If both are equal to 0, the cost is placed in the first step. By entering the second step, the parameter B1 is 1 and B2 is zero, and entering the third step B1 is 0 and B2 is equal to 1. Also, by equation 30, the amount of 1 is prevented for two parameters simultaneously.

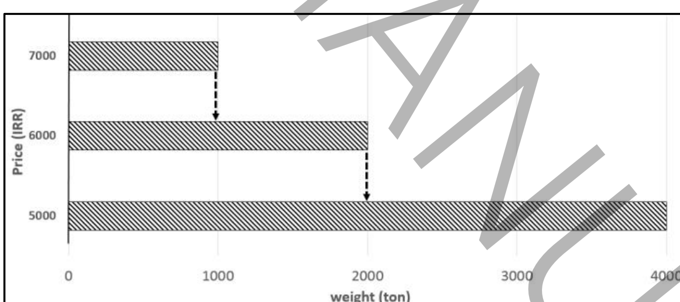

Fig. 5. Stepping consideration of the silica fume cost

$$B_1, B_2 \in \{0,1\} \tag{22}$$

$$\text{cost} = 7000x_1 + 6000x_2 + 5000x_3 + 1000x_1B_1 + [1000x_1 + 1000x_2]B_2 \tag{23}$$

$$x_1 \leq 1000 \tag{24}$$

$$x_1 \geq 1000(B_1 + B_2) \tag{25}$$

$$x_2 \leq 1000(B_1 + B_2) \tag{26}$$

$$x_2 \geq 1000B_2 \tag{27}$$

$$x_3 \leq 1000B_2 \tag{28}$$

$$x_3 \geq 0 \tag{29}$$

$$B_1 + B_2 \leq 1 \tag{30}$$

In Equations (22) to (30), B_1 and B_2 are binary variables that take values of 0 or 1 and are used to define the active cost step of silica fume. The variables 1, x_2, and x_3 represent the quantities of silica fume allocated to the first, second, and third cost steps, respectively. The parameter *cost* denotes the total cost of silica fume, which is calculated based on different unit prices assigned to each step. The numerical values 7000, 6000, and 5000 represent the unit cost of silica fume (IRR/kg) in the first, second, and third purchasing steps, respectively. The constant value 1000 indicates the upper limit of silica fume quantity for each step. The constraints ensure that only one cost step can be active at a time and that the silica fume quantity remains non-negative and within the defined step limits.

5.3. Developed goal programming model (DGPM)

To upgrade the basic goal programming model and bring its results closer to the actual situation, the minimum silica fume content in concrete is set at 4% of the cement weight. In other words, silica fume must be either zero or at least 4% of the cement content, if it is used. Moreover, for fibers, the amount is more than 0.9 kg/ m^3, if it is used. The necessary constraint for considering the minimum use of silica fume and fibers using two binary parameters is presented in the form of the equation 31 in LINGO software.

The parameters A_{1sf} and A_{2sf} are binary parameters, with values either zero or one. If these two binary parameters are equal (both 0 and both 1), the state in which one is 0 and the other is 1 is eliminated; In other words, they (A_{1sf} and A_{2sf}) are either 0 or 1. If both are zero, the amount of silica fume on one side is minor (0) and the other side is major (o), resulting in the amount of silica fume being considered 0. However, if both are 1, its amount is larger on one side and equal to 4% of the cement, and on the other side, while on the other side it is smaller and equal to 8% of the cement material. Similarly, it should not be used or its amount should not exceed 0.9 kg/m^3.

$$A_{1SF}, A_{2SF} \in \{0,1\} \tag{31}$$

$$A_{1SF} = A_{2SF} \tag{32}$$

$$\mathrm{SF} \geq A_{1SF} \times 0.04 \times (C + \mathrm{SF}) \tag{33}$$

$$\mathrm{SF} \leq A_{2SF} \times 0.08 \times (C + \mathrm{SF}) \tag{34}$$

$$A_{1PPF}, A_{2PPF} \in \{0,1\} \tag{35}$$

$$A_{1PPF} = A_{2PPF} \tag{36}$$

$$\mathrm{PPF} \geq A_{1PPF} \times 0.9 \tag{37}$$

$$x > 150 \tag{38}$$

In Equations (31) to (38), A_{1SF} and A_{2SF} are binary variables that take values of 0 or 1 and are used to activate the lower and upper limits of silica fume content. The parameter SF represents the amount of silica fume (kg/m³), while C denotes the cement content (kg/m³). These constraints ensure that the silica fume content remains within 4% to 8% of the total cementitious materials (C+SF)(C + SF)(C+SF). Similarly, A_{1PPF} and A_{2PPF} are binary variables used to control the allowable range of polypropylene fiber content. The parameter PPF represents the amount of polypropylene fibers (kg/m³), and $\max_{PPF}$ denotes the maximum allowable fiber content. These constraints ensure that the fiber content remains within acceptable practical limits and is properly activated using binary decision variables.

The output of the optimal mixture proportions for the both of models (Basic Goal programming Model (BGPM) and Developed Goal Programming model (DGPM) is presented in Table 6. As observed, when the minimum constraints for silica fume and fibers are considered, the DGPM eliminates fiber from the mixture design, because BGPM provides a lower fiber content than the specified minimum.

Table 6. The output of optimal mixture proportions of DGPM model

Mixture	w/c	Cement	Silica fume	Water	Aggregate	fiber	Air-entraining	Super-plasticizer	Cost
		(kg/m³)							(IRR/m³)
DGPM output	0.37	349.10	30.36	140.40	1813.8	1.267	0.124	2.390	1049212

5.4. Fuzzy-goal-programming model (FGPM)

In the previous modeling framework (BGPM and DGPM model), cost is considered as a goal with the objective of attaining a zero value. This approach did not account for the influence of concrete properties on cost. However, cost is a function of concrete specifications, Accordingly, recognizing the relationship between concrete properties and cost, as well as the inherent uncertainty and ambiguity of these values, a fuzzy logic approach was employed to estimate costs [31].

Using Matlab software, a fuzzy system was created whose inputs are flexural strength, shrinkage, abrasion resistance, slump and freezing and thawing, with costs considered as its output. To define membership functions and rules, several experts with 10 to 20 years of experience in this field contributed. Ultimately, based on the optimal concrete specifications, the cost is predicted by the fuzzy system, and this cost is added as a constraint to the goal programming model, replacing the deterministic cost goal value. Figure 6 presents schematic diagram of the fuzzy system used in this study.

Table 7 compares the results of developed goal programming model (DGPM) and Fuzzy-goal programming model (FGPM). As it is clear, FGPM suggested mixture with higher content of fiber, cement, air entraining admixture and superplasticizer than DGPM and consequently a higher cost. Having more fiber and air entraining admixture reduces shrinkage cracking potential and improves durability against freezing and thawing cycles. Therefore, performance of mixtures designed by FGPM is better than mixture optimized by DGPM. However, its cost is higher.

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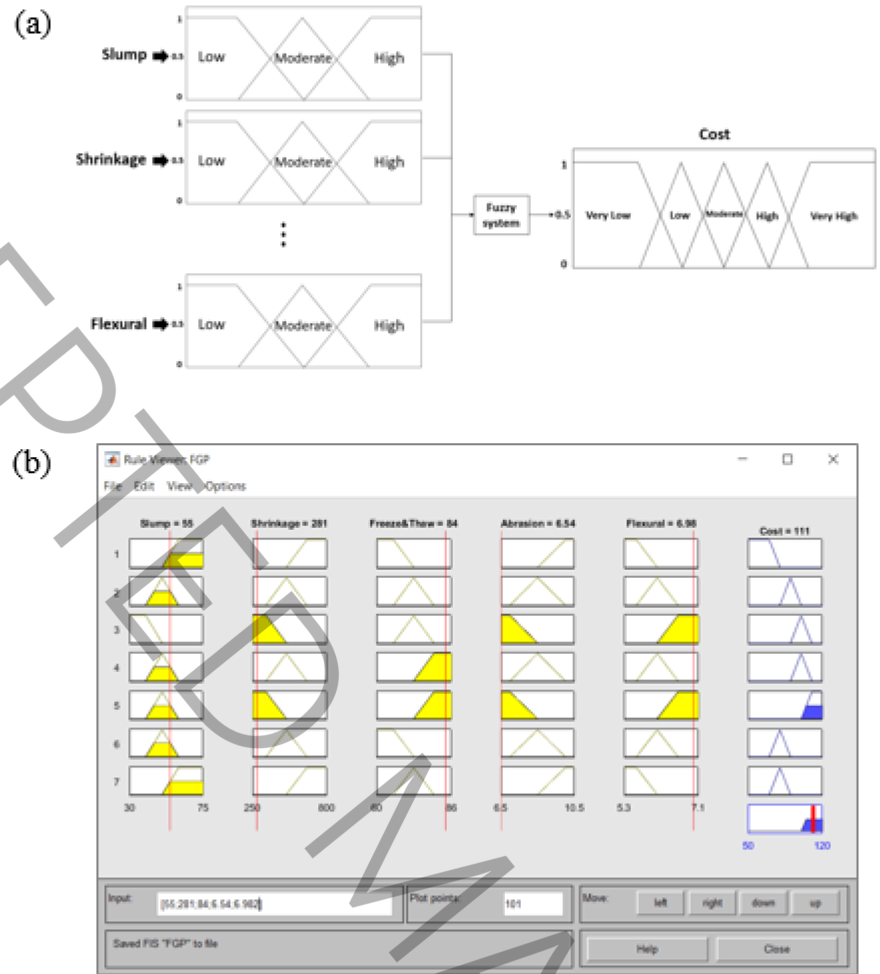

Fig. 6. Schematic figure of fuzzy system used in this study

Table 7. Comparing outputs of DGPM and FGPM

Mixture	w/c	Cement	Silica fume	Water	Aggregate	fiber	Air-entraining	Super-plasticizer	Cost
		(kg/m^3)							(IRR/m^3)
DGPM output	0.37	349.10	30.36	140.40	1813.8	1.267	0.124	2.390	1049212
FGPM output	0.37	388.2	28.7	154.3	1747	1.5	0.148	2.8	1110000

5.5. Adaptive neuro-fuzzy inference system goal programming model (NFGPM)

Due to the difficulty of formulating rules and membership functions, instead of employing traditional fuzzy system, an integration of artificial neural network and fuzzy logic (adaptive neuro-fuzzy inference system, ANFIS) was used so that the software can drive membership functions and rules from data [32-34]. To this end v, regression relationships derived from the concrete properties (Equations 8-12), were used to generate 200 hypothetical mixture proportions, and the cost for each was computed. Then, using the data, an ANFIS-based system was constructed. This cost, like the cost obtained from the fuzzy system, is eventually incorporated into the goal programming framework. The 200 hypothetical concrete mix designs used for training the ANFIS model were generated using uniform random (Monte Carlo–based) sampling within predefined practical bounds of each mixture component, ensuring that all input variables remained within realistic and experimentally validated ranges. Figure 7 illustrates the ANFIS structure designed in this study.

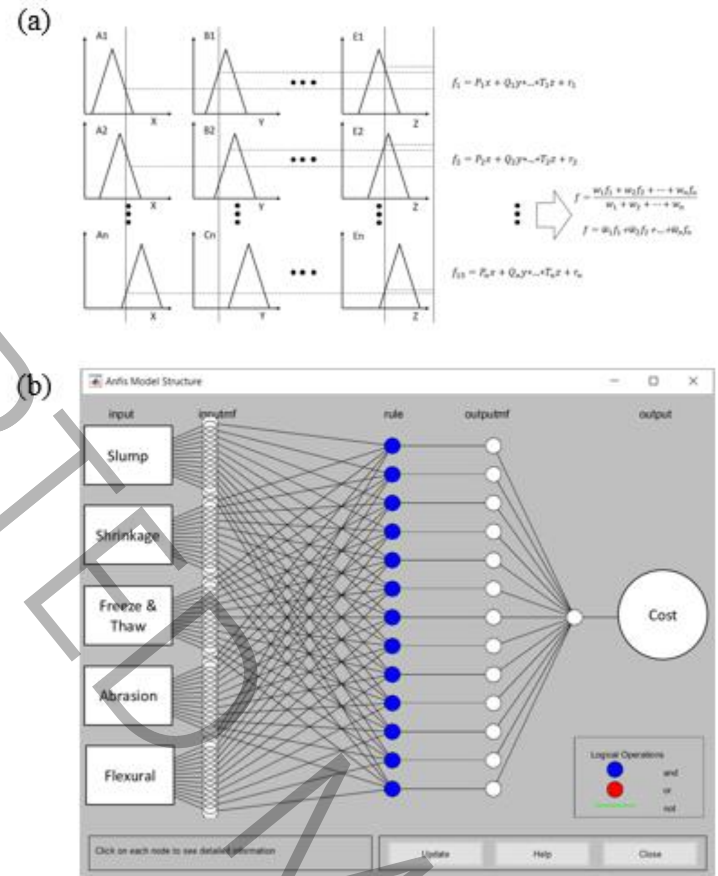

Fig. 7. The structure of artificial neural fuzzy inference system (ANFIS) designed in this study (a) ANFIS description (b) Schematic of ANFIS architecture

6. Comparison

Table 8 presents the optimal mixture proportions presented by all three models examined in this study. As noted, the lowest mixture cost is achieved by the neuro-fuzzy model, exhibiting a substantial difference from the costs associated with the DGPM and FGPM models. Table 9 presents the calculated the fresh and hardened concrete properties corresponding to the optimal mixture proportions from each model. The results show that slump, freezing-thawing, abrasion resistance, and flexural strength values are closely aligned across models. The shrinkage predicted by the fuzzy-goal-programming and neuro-fuzzy-goal programming models exceeds that of the developed basic goal programming. This issue is also illustrated in Figure 8. However, despite the close relationship among the properties of fresh and hardened concrete and the durability of the mixtures proportions proposed by all three models, the neuro-fuzzy model achieves a substantially lower cost than the other two models.

Table 8. The outputs of optimal mixture proportions designed by all three models

Mixture	w/c	Cement (kg/m^3)	Silica fume (kg/m^3)	Water (kg/m^3)	Aggregate (kg/m^3)	fiber (kg/m^3)	Air-entraining (kg/m^3)	Super-plasticizer (kg/m^3)	Cost (IRR/m^3)
DGPM output	**0.37**	**349.10**	**30.36**	**140.40**	**1813.8**	**1.267**	**0.124**	**2.390**	**1049212**
FGPM output	**0.37**	**388.20**	**28.70**	**154.30**	**1747.00**	**1.500**	**0.148**	**2.800**	**1110000**
NFGPM output	**0.37**	**389.38**	**0**	**145.78**	**1806.3**	**0.965**	**0.161**	**1.137**	**837044**

Table 9. The calculated values of concrete properties through the optimal mixture proportions presented by each model

Concrete properties	DGPM	FGPM	NFGPM
Slump (mm)	**54.3**	**55**	**55**
Shrinkage (μm/m)	**299**	**343**	**341**
Freeze and thaw (%)	**84**	**84**	**84**
Abrasion (%)	**6.540**	**6.540**	**6.540**
Flexural (MPa)	**6.785**	**6.685**	**6.535**
Cost (IRR)	**1049212**	**111000**	**837014**

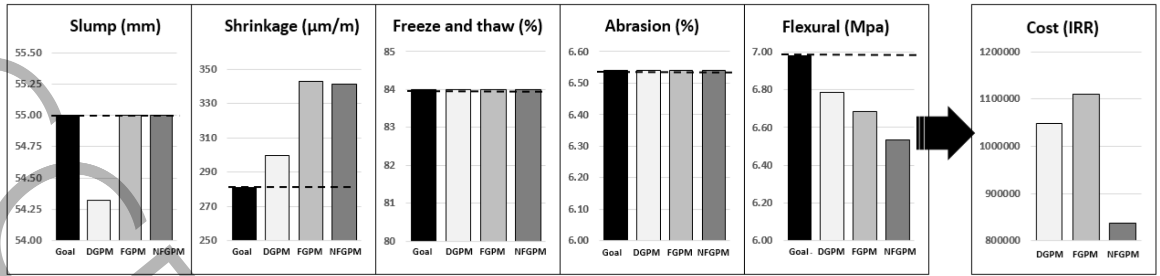

Figure 8. The outputs of optimal mixture proportions designed by all three models

The differences among DGPM, FGPM, and NFGPM results can be explained by their distinct cost treatment strategies. While DGPM minimizes deterministic cost and therefore suppresses the use of high-cost materials such as fibers, FGPM allows improved durability and mechanical performance at the expense of higher cost through fuzzy cost estimation. The proposed NFGPM effectively balances this trade-off by learning nonlinear cost–performance relationships, achieving comparable performance with significantly lower cost.

The differences among DGPM, FGPM, and NFGPM results can be explained by their distinct cost treatment strategies (can be seen in Table 10 and Fig. 9). While DGPM minimizes deterministic cost and therefore suppresses the use of high-cost materials such as fibers, FGPM allows improved durability and mechanical performance at the expense of higher cost through fuzzy cost estimation. The proposed NFGPM effectively balances this trade-off by learning nonlinear cost–performance relationships, achieving comparable performance with significantly lower cost.

Table 10. The differences among DGPM, FGPM, and NFGPM Models

Model	Cost (IRR/m³)	Flexural (MPa)	Shrinkage (μm/m)
DGPM	1,049,212	6.785	299
FGPM	1,110,000	6.685	343
NFGPM	837,044	6.535	341

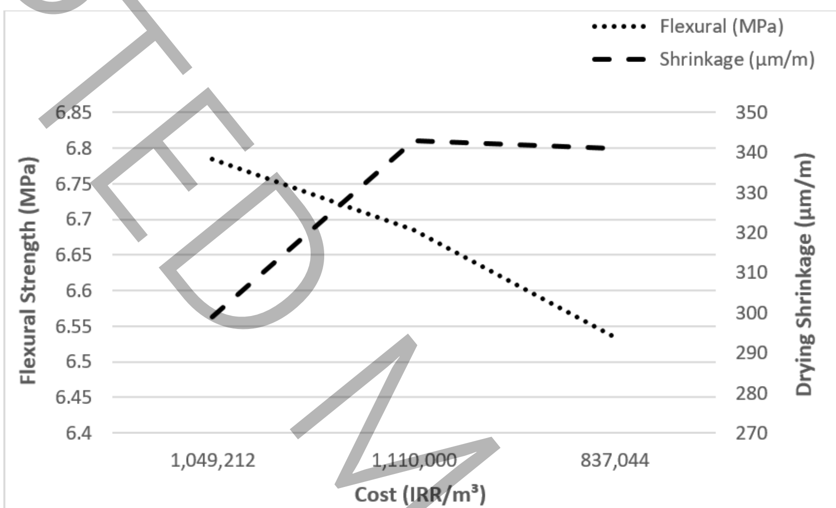

Figure 9. Cost–performance trade-off of optimized mixtures

7. Validation

Given the better efficiency of the adaptive neuro-fuzzy inference system goal programming model compared to the other two models,, it is necessary to check the reliability and accuracy of the results of this model. To ensure the correct performance of the adaptive neuro-fuzzy inference system model, the most optimal mixture proportions provided by the model, as presented in the previous sections, were prepared in the laboratory in real conditions and tested in various ways. Although cross-validation was not applied due to the limited size of the experimental dataset, the reliability of the proposed ANFIS-goal programming model was verified through independent laboratory testing of the optimal mixture proportions, providing external experimental validation of the model predictions. Table 11 and Fig. 10 compare the actual test values with the values predicted by the NFGPM model. As it is evident, model's predictions are very close to the actual values. This confirms that the neuro-fuzzy-goal programming model proposed in this study is capable of providing the most optimal concrete pavement mixture proportions with the lowest cost and optimal concrete properties.

Table 11. Comparing of neuro-fuzzy-goal programming model prediction with the actual experimental values

Concrete properties	NFGPM output	Experimental results
Slump (mm)	55	65
Shrinkage (μm/m)	341	363
Freeze and thaw (%)	84	82
Abrasion (%)	6.540	6.68
Flexural (MPa)	6.535	6.77

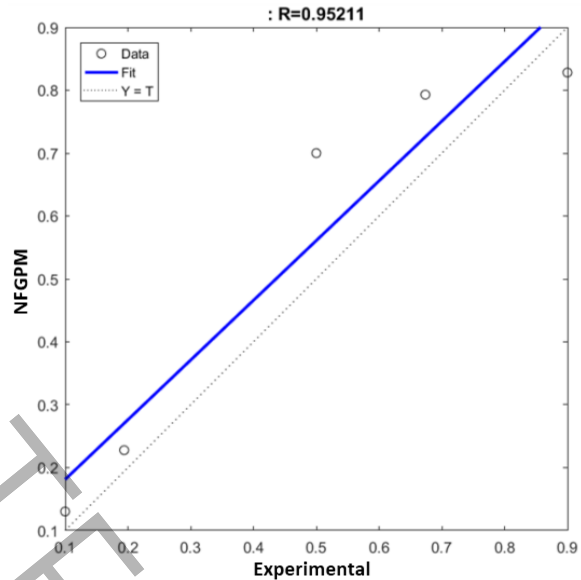

Fig 10. Comparing of adaptive neuro-fuzzy inference system goal programming model prediction with the actual experimental values

8. Conclusions

In this research, an adaptive neuro-fuzzy inference system with a goal-planning has been developed for optimizing the concrete mixture ratio of sidewalk. This approach is based on using artificial neural networks to predict the best cost and integrating it into the fuzzy-goal-programming model. The proposed model has the capability to consider multiple goals and objectives. The results of this study lead to the following conclusions:

- The linear programming model with multiple constraints and cannot meet all the requirements and find the optimal mixture proportions consequently.
- Goal programming, though, is capable of optimizing several goals but with disadvantages. Including that a definitive cost should be given as a number.

- Blends designed with the fuzzy-goal-programming Method (FGPM) perform better than those optimized with the developed-goal-programming model (DGPM). However, the production cost of these blends is slightly higher.
- Although an explicit parameter sensitivity analysis was not conducted, uncertainty is inherently considered through the fuzzy and neuro-fuzzy modeling frameworks, and the robustness of the proposed approach is supported by consistent optimization results across different models and independent experimental validation.
- The values predicted by the model are very close to the actual values. This confirms that the neuro-fuzzy-goal programming model with neural capabilities can provide optimal ratios for concrete mix with minimum cost and best concrete properties.

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