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METHOD AND APPLICATION FOR URBAN GAS DEMAND PREDICTION BASED ON THE INTEGRATED ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

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Accurate urban gas demand forecasting can significantly assist managers in developing efficient natural gas supply plans. This study, based on the Adaptive Neuro-Fuzzy Inference System (ANFIS), innovatively integrates neural networks with fuzzy logic principles to construct a daily urban gas demand prediction model. Experimental results demonstrate that the hybrid forecasting algorithm based on ANFIS achieves superior performance in daily urban gas demand prediction compared to Artificial Neural Networks (ANNs), Fuzzy Cognitive Maps (FCM), and their combined models. The Mean Absolute Percentage Error (MAPE) on the test set is less than 20%, significantly improving prediction accuracy. Validation results indicate that the ANFIS prediction algorithm effectively enhances the accuracy of neural network models, providing a scientific basis for emergency supply planning in gas companies and exhibiting promising application prospects.

Keywords: Neuro-fuzzy; neural networks; soft computing; fuzzy cognitive maps; urban gas prediction

1. Introduction

With the increasing emphasis on transitioning to a sustainable and environmentally friendly economy, natural gas, celebrated for its cleaner-burning properties, is securing a growing share in global energy consumption. A report from the China Petroleum Economic and Technological Research Institute revealed that in 2023, China consumed a total of 391.7 billion cubic meters of natural gas, marking a 6.6% increase compared to the previous year. This highlights the vast growth potential of the country's natural gas market [1]. The consumption of natural gas in China is mainly allocated to four major sectors: urban use, industrial fuel, power generation, and chemical production, contributing 32.6%, 39.0%, 18.1%, and 9.9% respectively to the overall demand. This highlights that urban gas (UG) represents a major share of China's natural gas consumption. For government and

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natural gas industry policy-makers, accurately forecasting urban gas demand, especially during winter, is crucial for formulating and implementing effective policies. Additionally, for urban gas providers, accurately forecasting short-term demand is vital for efficient production planning and gas supply management. This guarantees the secure provision of urban gas, improves the balance between supply and demand, and optimizes resource utilization [2].

Owing to a multitude of unpredictable elements, short-term urban gas demand experiences nonlinear effects. Currently, models for forecasting short-term gas demand in urban areas are generally divided into three main categories. The initial group encompasses traditional statistical forecasting models, including those that rely on time series analysis and multivariate regression techniques [3,4]. The second category encompasses models that utilize artificial intelligence, including grey prediction models, Artificial Neural Networks (ANN), and Support Vector Machines (SVM) [5,6]. For instance, reference [7] developed a FARX (function autoregressive with exogenous variables) model to predict gas demand for the following day. In references [8,9], the adaptive intelligent grey model was used for forecasting urban gas (UG) demand. Various methods have been explored regarding neural network algorithms, including the training and testing of multilayer perceptrons with different activation functions and radial basis function networks. In the third category, hybrid forecasting techniques are delineated, which include the amalgamation of genetic algorithms with Back Propagation (BP) neural networks [10,11], the synthesis of adaptive networks and fuzzy mathematics [12], as well as the integration of neural networks [13] and multivariate time series methodologies [14-16].

A review of existing literature highlights certain limitations in next-day urban gas demand predictions using Artificial Neural Networks (ANN) and hybrid methods [17]. Specifically, since neural network models follow the principle of minimizing empirical risk, they may be affected by overfitting. Furthermore, the complexity associated with the multi-tiered architecture of network systems may impart a consequential impact on the stability of the predictive outcomes. Moreover, as the sample size grows, the complexity of training neural network models also increases, resulting in a lack of model simplicity and flexibility, along with a diminished capacity for generalization within the modeling process. The ability to handle inherent data fuzziness is also somewhat lacking. Most forecasting methods require large datasets for training and relatively many features for accurate predictions [18]. In addition, the model structure is complex, time-consuming, and difficult for non-experienced AI users to apply. Currently, there is little research on how to apply ANFIS technology to urban gas (UG) demand forecasting, especially with a lack of in-depth exploration in determining the optimal model configuration.

Based on the research gap outlined above, this paper aims to develop an easy-to-use and highly generalized integrated forecasting model for urban gas demand prediction. The main innovations are as follows:

First, a simple, fast, and robust integrated ANFIS forecasting model is constructed. The proposed model exhibits high flexibility, making it particularly suitable for large datasets. It is user-friendly and demands short running time.

Second, a meticulous optimization process is applied to ANFIS to determine the output structure that best enhances forecasting performance.

2. Basic Method

2.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) [19] is an integrated intelligent system that merges the adaptive properties of neural networks with the capacity of fuzzy logic to manage ambiguity and process linguistic expressions. It can be described using Takagi-Sugeno (TS) type fuzzy "IF-THEN" rules. The TSK-ANFIS framework refers to the Adaptive Neuro-Fuzzy Inference System (ANFIS) built on Takagi-Sugeno-Kang (TSK) type fuzzy inference rules. In this framework, the fuzzy rules are in TSK form, where "T" stands for "Fuzzification", "S" for "Solution" (or "System"), and "K" for "Knowledge" (or "Rules").

TSK fuzzy rules are expressed in the IF-THEN form, with each rule consisting of a fuzzified antecedent variable and an output result. The antecedent variable is fuzzified based on input variables, and the output is computed through the solving part. The ANFIS framework combines TSK fuzzy rules with neural networks, enabling adaptive learning and parameter adjustment of the fuzzy rules, thereby improving the accuracy and robustness of the system.

$$\begin{gathered} R_i\colon if\ x_1 = A_{i,1}\ and \ldots and\ x_k = A_{i,k} \\ then\ y_i = b_{i,0} + b_{i,1}x_1 + \cdots + b_{i,k}x_k \end{gathered} \tag{1}$$

In the equation: R_i represents the fuzzy rule number; x_k is the input variable; $A_{i,k}$ represents the membership function that corresponds to the input variable x_k; y_i is the output variable; $b_{i,k}$ is the linear coefficient term.

A typical ANFIS network structure includes five layers (Fig. 1).

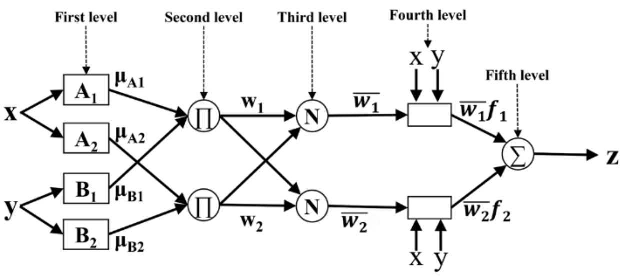


Fig. 1: TSK ANFIS basic frame diagram.

In the first layer, each node i is associated with a linguistic label and defined by the membership function in equation (2).

$$w_i = \prod_{k=1}^{n} A_{i,k}(x_k) \tag{2}$$

In the equation, w_i represents the activation strength of the i-th rule; n is the number of input variables; x_k is the input variable; and $A_{i,k}(x_k)$ denotes the membership degree of x_k associated with the membership function $A_{i,k}$.

In the third layer, the i-th node calculates the proportion of its activation relative to the total activation of all rules. This layer serves as a normalization step, balancing the intensities across the rules. The output from each node is given by equation (3).

$$\overline{w}_i = \frac{w_i}{\sum_{i=1} w_i} \tag{3}$$

In the equation: $\overline{w}_i$ is the normalized activation strength of the i-th rule; w_i is the original activation strength of the i-th rule.

Within the fourth layer, each node operates as a dynamic component, with its activities regulated by equation (4). At this layer, each node conducts a linear computation, with the coefficients being iteratively refined based on the error feedback from the interconnected layers of the feedforward neural network.

$$\bar{y}_i = \overline{w}_i(p_i x + q_i y + r_i) \tag{4}$$

In the equation, $\bar{y}_i$ represents the weighted output of the i-th rule, $\overline{w}_i$ denotes the normalized activation of the i-th rule, and (p_i, q_i, r_i) is the set of conclusion parameters.

In the fifth layer, there exists a single fixed node, which embodies the cumulative net outputs from the nodes of the preceding layer. This node determines the aggregate output by aggregating all incoming signals, as illustrated in the equation (5).

$$z = \sum_i \bar{y}_i \tag{5}$$

In the equation, z represents the final system output, and $\bar{y}_i$ denotes the weighted output of the i-th rule.

ANFIS employs a composite learning strategy for model training. The parameters of the initial layer are honed through the backpropagation method, whereas the parameters of the penultimate layer are refined using either a least squares estimation technique or an adaptation of the backpropagation approach.

2.2 The Fuzzy C-Means (FCM) clustering algorithm

The Fuzzy C-Means (FCM) clustering algorithm is based on fuzzy set theory, allowing data points to have varying levels of membership across multiple clusters. In FCM, every datum is assigned a level of affiliation to each cluster centroid, rather than being exclusively allocated to one particular cluster. The membership degree is computed by optimizing an objective function, which aims to minimize the distance between data points and their corresponding cluster centers while maximizing the consistency of their membership degrees. The procedure of the FCM algorithm (Fig. 2) is as follows:

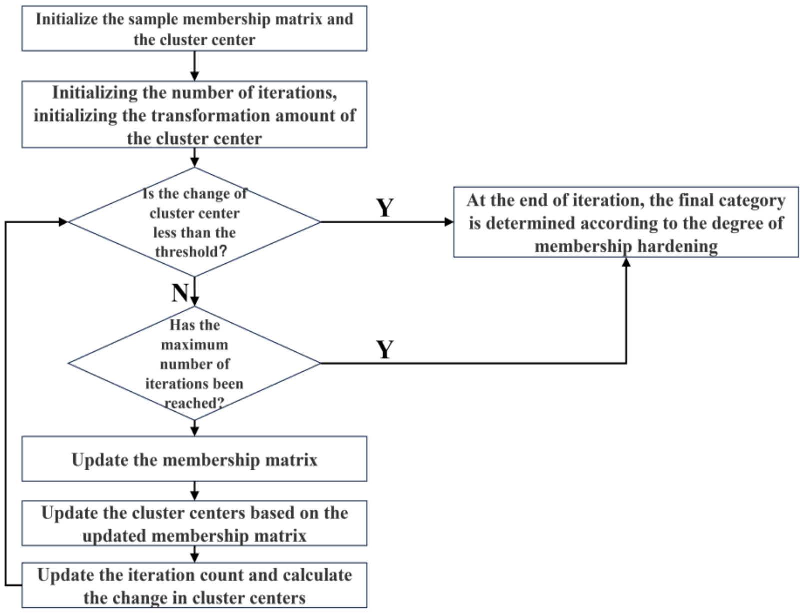


Fig. 2: FCM algorithm flow chart

Step 1: Initialize Cluster Centers: Select initial cluster centers, which can be chosen randomly or determined based on prior knowledge.

Step 2: Compute Membership Degrees: For each data point, calculate its degree of membership with respect to each cluster center, typically using Euclidean distance or other distance metrics.

Step 3: Refine Cluster Hubs: Reassess the coordinates of the cluster hubs according to the determined membership magnitudes.

Step 4: Repeat Steps 2 and 3: Keep cycling through steps 2 and 3 until the termination conditions are satisfied, such as achieving the predetermined maximum iterations or observing no further alterations in the cluster centers.

3. GA-FCM-ANFIS Urban Gas Demand Prediction Model

The Genetic Algorithm, Fuzzy C-Means clustering, and Adaptive Neuro-Fuzzy Inference System are integrated to form the GA–ANFIS-FCM hybrid method. The process is as follows:

Step 1: Initialize and generate the initial population.

Step 2: Assess the viability of each individual within the population, choose a duo of individuals for replication, and arrange them based on their viability.

Step 3: Integrate the separated individuals and a subset of the current population into the existing group, forming a new one.

Step 4: Stop the algorithm and adjust the ANFIS parameters. This process is repeated until the predefined endpoint is reached.

Fig. 3 illustrates the algorithm flow for urban gas demand prediction.

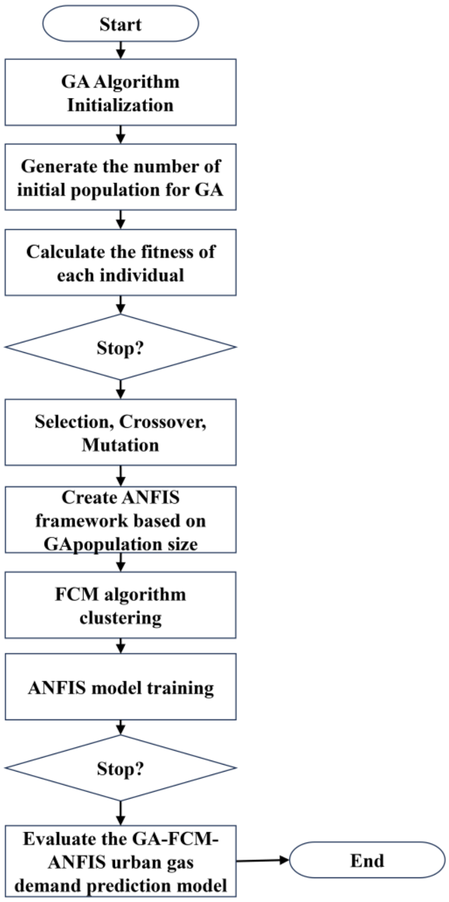


Fig. 3: Flow chart of GA-FCM-ANFIS prediction model

To ensure that the ANFIS model is efficiently applied to urban gas demand prediction, a structured process must be followed, with the correct configuration of the model's inputs and training parameters. The steps are as follows:

1.**Select the Fuzzy Inference System (FIS) Model**: Given the need for interpretability and computational efficiency, this paper selects the Sugeno fuzzy model.

2. **Partition the Input Space**: There are two approaches: grid partitioning and subtractive clustering. The grid partitioning approach compartmentalizes the

input space into a mesh pattern devoid of overlaps, which is well-suited for contexts with a limited quantity of input variables.

3. **Choose the Partition Method**: This paper opts for the grid partitioning method since it is simple and effective, especially when investigating the types and forms of membership functions, particularly for a small number of input variables.

4. **Input Variables and Membership Functions (MFs)**: Five variables have been chosen as inputs for the model: month, day, temperature, gas consumption from the previous day, and the current day's gas demand. The grid partitioning approach is used to determine the quantity and types of membership functions for each input, along with the corresponding fuzzy rules and their parameter values.

5. **Consider the Limitations of the ANFIS Architecture**: As the count of input variables surpasses five, ANFIS encounters constraints stemming from heightened computational intricacy and extended training durations.

6. **Explore Configurations to Improve Efficiency**: To enhance the model's accuracy and reduce errors, five configurations are considered:

- Number of membership functions (MFs)
- Type of membership functions (triangular, trapezoidal, bell-shaped, Gaussian, S-shaped)
- Output membership function type (constant or linear)
- Optimization method (hybrid or backpropagation)
- Number of training epochs

Given the complexity of the model architecture and the need to explore various parameters to optimize performance, this paper aims to construct an effective ANFIS model for urban gas demand (UG) prediction by following this structured approach.

In the revised manuscript, we have clarified that all experiments were carried out in MATLAB R2024a using the Fuzzy Logic Toolbox (v2.6) and Global Optimization Toolbox (v3.5). Specifically, FCM clustering was executed with the built-in *fcm* function, the initial Sugeno-type FIS structure was generated via *genfis1*, and ANFIS training employed the *anfis* function under the hybrid learning scheme. Genetic-algorithm operations—including population initialization, fitness evaluation, selection, crossover, and mutation—were conducted using the *ga* function, with each individual's fitness computed as the RMSE of the trained ANFIS model. We also detail the key training parameters: the number and type of membership functions per input (triangular, trapezoidal, bell-shaped, Gaussian, or S-shaped), the use of a Hybrid optimizer, a maximum of 200 training epochs, and convergence criteria based on negligible change in the training error.

4. Experimental Preparation

4.1 Experimental Data

The dataset covers historical data on urban gas demand from ten different cities across Italy (Rome, Milan, Napoli, Turin, Palermo, Genoa, Bologna, Firenze, Bari, and Catania), spanning a total of 8 years. Notably, the time periods for each dataset (city) differ. Table 1 describes the years covered by each dataset. The data was initially provided by the Italian Gas Pipeline Company, which operates, manages, develops, and interconnects Italy's gas system. After comparing outliers and the total sample size, this study selected data from the following ten cities. In the preprocessing stage, a minor number of outliers were eliminated, and missing data points were imputed using the mean value of the two preceding days. The dataset was divided into training and test sets for ANFIS modeling and performance evaluation. For every city, the dataset from the final year, covering November 2017 to October 2018, was allocated for validation purposes, while data from the preceding years were used to train the developed GA-FCM-ANFIS hybrid forecasting model, as depicted in Table 1.

Table 1

The time period involved in the time series data set of each city

City	Data Time Dimension	City	Data Time Dimension
Rome	2/2013-10/2018	Genoa	3/2010-10/2018
Milan	3/2013-10/2018	Bologna	6/2013-10/2018
Napoli	9/2011-10/2018	Firenze	3/2012-10/2018
Turin	5/2014-10/2018	Bari	9/2012-10/2018
Palermo	3/2010-10/2018	Catania	3/2010-10/2018

Accurate forecasting of urban gas demand in Italy requires selecting the appropriate quantity and category of input parameters. Consequently, five variables were meticulously selected to serve as input parameters, with the urban gas consumption demand at each distribution point from the previous day being the output parameter. This forecasting model is grounded in historical urban gas consumption data, meteorological information, and calendar-related indicators. These factors are the core input variables for predicting urban gas demand. More specifically, the dataset includes the following components: historical urban gas demand data for each city's gas supply station, the average daily temperature (in Celsius), and indicators for the month and date. Among these, historical urban gas demand data is associated with two distinct input variables: the gas consumption of the previous day and the current day. Temperature data is obtained from the meteorological station closest to the delivery point. As for the calendar indicators (month and date), some data formatting preprocessing is required. Specifically, each variable needs to consider two different input indicators. Let $k = 1, 2, \ldots, 12$ define the month indicator (January to December), and $l = 1, 2, \ldots, 7$ define the date indicator (Monday to Sunday). According to the encoding program, the month index is mapped to the range [1/12, 1], with January to December corresponding to consecutive scaled values within this range. That is to say, the parameter for January is set to 1/12, while for December it is set to 1. In a similar fashion, the days of the week are scaled to fall within the interval [1/7, 1], with Monday being assigned the value of 1/7 and Sunday the value of 1. These parameters are detailed in Table 2.

Table 2

Model input and output parameters

Type	Parameter	Unit
Input	Previous day's gas demand	MWh
	Current day's gas demand	MWh
	Daily average temperature	°C
	Month indicator	K=1/12, 2/12,…,1
Output	Next day's gas demand	I=1/7,2/7,…, 1

To ensure that all data entries have the same finite value range, each variable is normalized to the [0,1] range using Min-Max normalization. However, during the testing phase, the normalized variables will be restored to their original values. The data normalization follows the equation (6):

$$x_i^{\mathrm{new}} = \frac{x_i - x^{min}}{x^{max} - x^{min}}, \forall i = 1,2,\ldots,N \tag{6}$$

In the equation, x_i^{new} represents the normalized value of the i-th variable x; x_i denotes the i-th input variable; and x^{min} and x^{max} indicate its minimum and maximum values, respectively.

4.2 Evaluation function

This study evaluates the predictive performance of different models using Mean-Square Error (MSE), Root Mean-Square Error (RMSE), and Mean Absolute Error (MAE) as criteria. The specific equations are as follows:

$$\mathrm{MSE} = \frac{1}{T}\sum_{t=1}^{T}(Z(t) - X(t))^2 \tag{7}$$

$$\mathrm{MAE} = \frac{1}{T}\sum_{t=1}^{T}|Z(t) - X(t)| \tag{8}$$

$$RMSE = \sqrt{MSE} \tag{9}$$

In the equation: T represents the number of samples; Z(t) denotes the true value, and X(t) denotes the predicted value of the t-th sample.

5. Results Analysis

5.1 Prediction Using the Integrated ANFIS Model

Modeling and simulation were carried out based on the integrated ANFIS prediction framework proposed in Section 3. Different configurations of ANFIS models were constructed according to the characteristics of datasets from various cities. The next-day NG demand (i.e., T+1 prediction) was calculated using the generated fuzzy inference systems.

Table 3 presents the optimal ANFIS configurations for each city in the Italian sample dataset. The results were ordered according to the smallest MAPE, MSE, and RMSE values. The findings indicate that the three ANFIS configurations—trimf 2-2-2-2-2, trimf 3-3-3-2-2, and gaussmf 3-3-3-2-2—performed best. Among these, triangular membership functions (trimfs) generally demonstrated superior performance when used as input variables. Specifically, for the input variables *month*, *day of the week*, and *average temperature*, the number of MFs was set to 3. For the input variables *current-day gas demand* and *previous-day gas demand*, the number of MFs was set to 2 or 3 in most cases. Notably, the output membership-function type is *"Constant"* and the optimizer is *"Hybrid"*.

Table 3

Optimal ANFIS Architecture of Sample Cities in Italy (epochs=10)

City	ANFIS Run	Input MF Type	Number of MFs	MSE	RMSE	MAPE
Rome	22	gaussmf	3-3-2-2-2	0.0031	0.0430	9.1031
Milan	15	trimf	3-3-3-2-2	0.0025	0.0502	20.1432
Napoli	3	trimf	3-2-2-2-2	0.0017	0.0534	5.4434
Turin	3	trimf	2-2-2-2-2	0.0020	0.0432	12.0043
Palermo	22	gaussmf	3-2-2-2-2	0.0008	0.0298	11.5244
Genoa	2	trimf	2-2-2-2-2	0.0089	0.0865	24.4294
Bologna	5	gaussmf	2-2-2-2-2	0.0009	0.0287	10.2824
Firenze	22	gaussmf	3-3-3-2-2	0.0008	0.0343	13.0023
Bari	3	gaussmf	2-2-2-2-2	0.0018	0.0399	10.5800
Catania	3	gaussmf	2-2-2-2-2	0.0019	0.0500	11.0343

5.2 Comparison Between the Integrated ANFIS Model and Other Prediction Models

With the aim of delve deeper into the efficacy of the proposed ANFIS-based architecture, this research undertakes a comparative analysis of the integrated ANFIS model against Artificial Neural Networks (ANNs), Fuzzy Cognitive Maps (FCMs), and hybrid models that amalgamate FCMs with ANNs in terms of their predictive accuracy.

The ANN architecture is a three-layer feedforward neural network model. The architecture of the model includes an initial layer with five distinct input parameters (month, day, temperature, yesterday's gas consumption, and today's demand), a subsequent layer furnished with a decade of processing units, and a terminal layer configured to predict the demand for the upcoming day. In this ANN structure, an S-shaped activation function is applied, and training is performed using the Levenberg-Marquardt algorithm.

The Fuzzy Cognitive Map (FCM) approach, a subset of soft computing techniques, possesses adaptive learning attributes, exemplified by the Real-Coded Genetic Algorithm tailored for FCM (RCGA-FCM) and the Structure Optimization Genetic Algorithm tailored for FCM (SOGA-FCM). These methodologies are frequently implemented within the energy domain for the purposes of time series analysis and predictive modeling of demand. Consequently, this segment will embrace the application of RCGA-FCM and SOGA-FCM. [19]

The composite FCMs-ANNs model [20] encompasses an initial layer that includes five inputs curated by SOGA-FCM, a subsequent layer housing a decade of neurons, and a final output layer. The model uses a sigmoid activation function and trains with the Levenberg-Marquardt backpropagation algorithm.

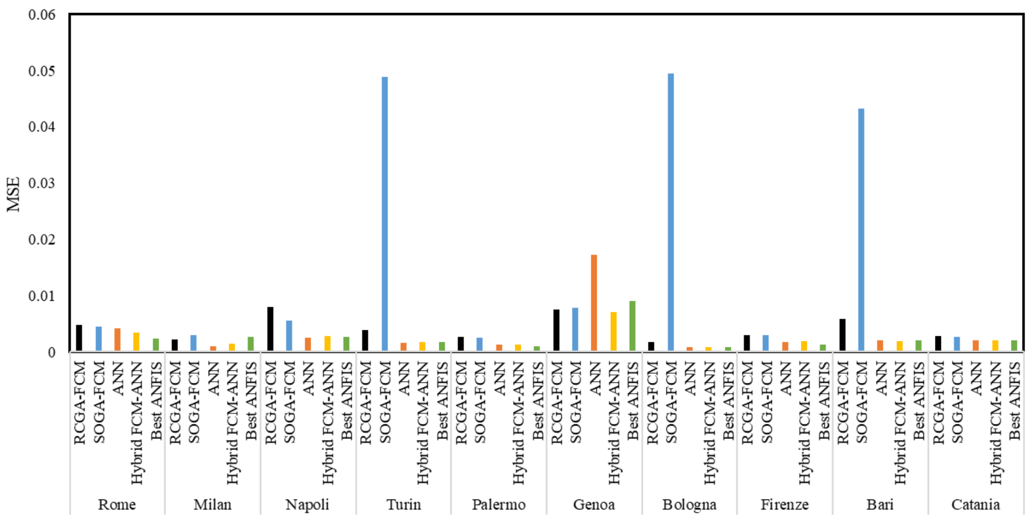
Table 4

Parameters and mean execution time for models

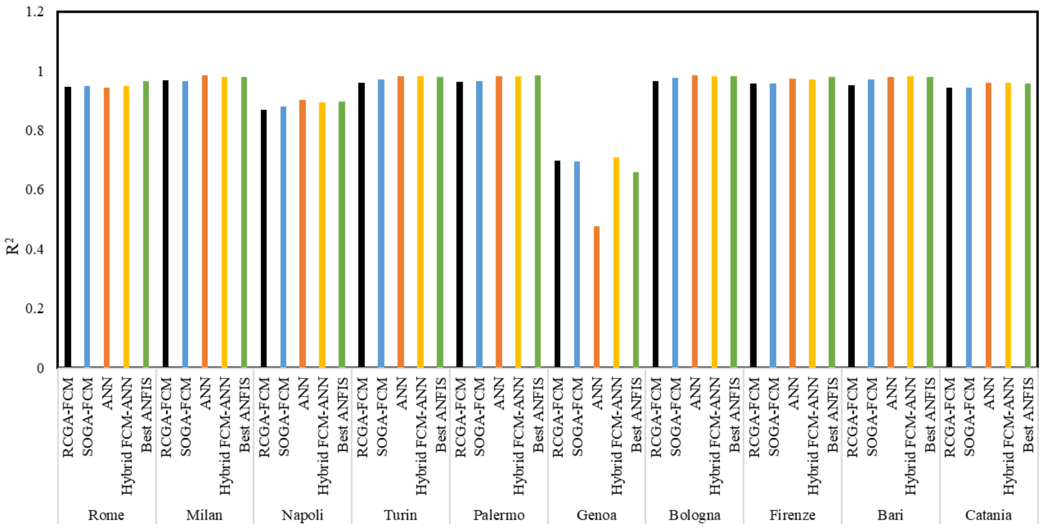
Architectures	Parameters for cities Average Running Time	Average Running Time
ANN	The model is a multilayer feedforward network that incorporates six input variables, consists of a layer with 12 neurons, and produces a single output. It utilizes a sigmoidal activation function for processing, employs the Levenberg-Marquardt learning algorithm for training, and is set to run for 70 epochs.	22-28s
RCGA-FCM	The genetic algorithm parameters include uniform crossover at a probability of 0.3, Mühlenbein's mutation at a probability of 0.3, ranking-based selection, an elitism strategy, a population size of 250 individuals, and a maximum of 500 generations.	1203s
SOGA-FCM	The genetic algorithm is configured with uniform crossover at a probability of 0.3, Mühlenbein's mutation at a probability of 0.3, and employs a ranking selection process. It adopts an elitism strategy, maintains a population size of 250, and is set to evolve for a maximum of 500 generations. Additionally, the learning parameters are set with b1 and b2 both equal to 0.01.	900s
Hybrid FCM-ANN	The model is a multilayer feedforward network that includes four inputs determined by the SOGA-FCM method, encompassing month, temperature, consumption from the previous day, and current consumption. This network contains a single hidden layer composed of 12 neurons and generates a solitary output. A sigmoidal activation function is employed within the network. It is trained via the Levenberg-Marquardt learning algorithm and is configured to	762s

	operate for 25 epochs.	
Best ANFIS	The model employs a triangular membership function (mf) with two different architectures: 2-2-2-2-2 or 3-3-3-2-2. It features a constant output layer and utilizes a hybrid optimization strategy. The training process is set to run for 15 epochs, with b1 and b2 learning parameters both set to 0.01.	25s

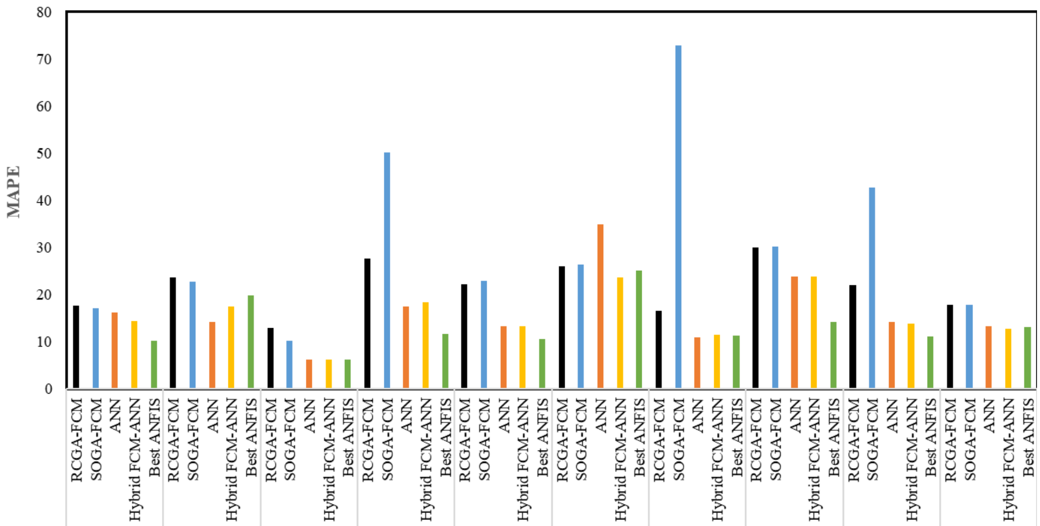
Fig. 4 shows the comparison of prediction performance between the optimal ANFIS architecture and the aforementioned models for sample cities. The outcomes demonstrate that the ANFIS model surpasses other models by a significant margin in regard to prediction performance for the sample data. For instance, in the case of urban gas demand prediction for Rome, Italy, the MAPE values for ANFIS models is 9.89%, which is lower than other comparable models.



(a) MSE


R2
1.2
1
0.8
0.6
0.4
0.2
0
RCGA-FCM
SOGA-FCM
ANN
Hybrid FCM-ANN
Best ANFIS
Rome
Milan
Napoli
Turin
Palermo
Genoa
Bologna
Firenze
Bari
Catania

(b) R2


MAPE
80
70
60
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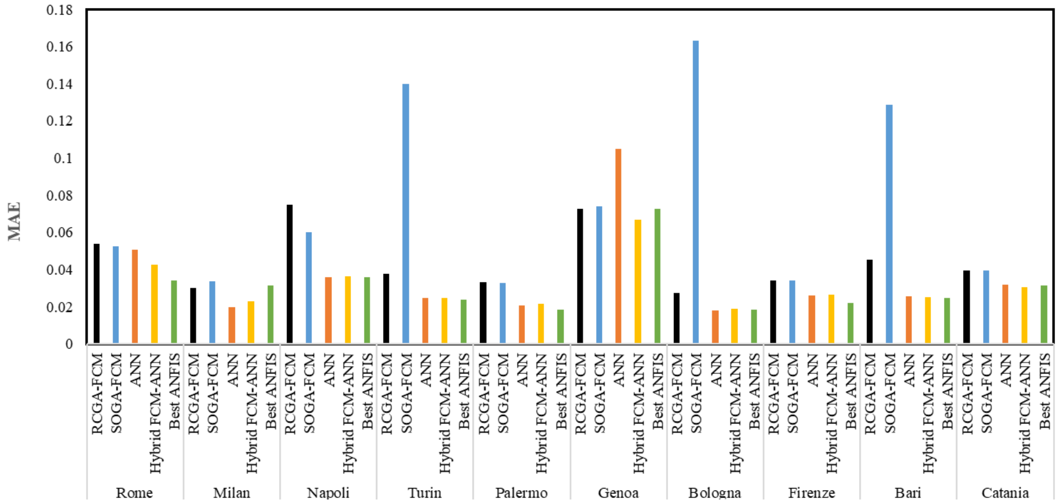
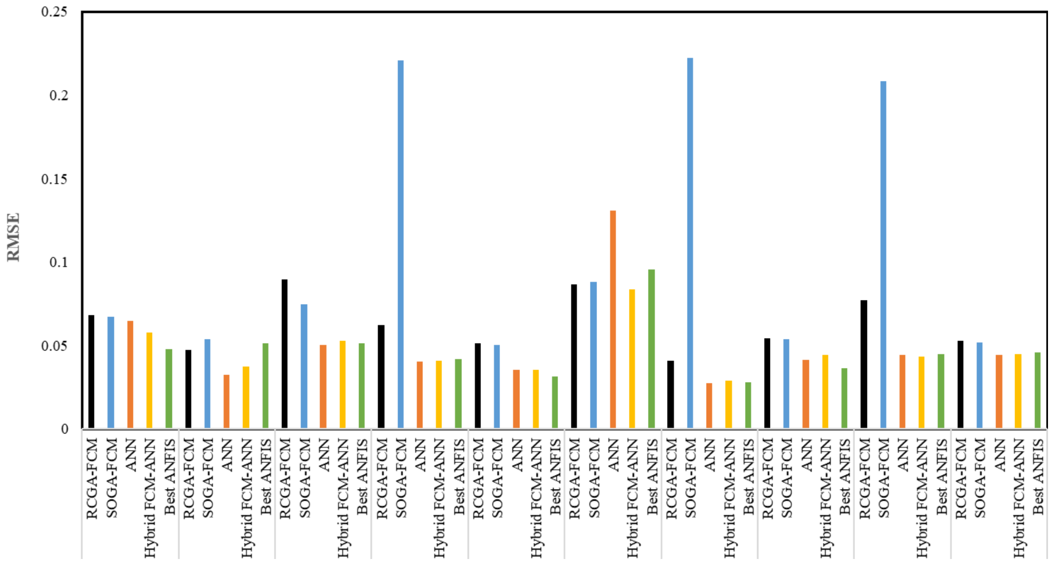
RCGA-FCM
SOGA-FCM
ANN
Hybrid FCM-ANN
Best ANFIS

(c) MAPE



(d) MAE



(e) RMSE

Fig. 4: Comparison of Prediction Performance of Sample Cities under Different Models

6. Conclusion

The paper proposes an integrated method based on the ANFIS framework for predicting urban gas demand. By simulating data sets from 10 cities in Italy, the optimal ANFIS integrated model for each city was identified and compared with ANNs and other soft computing models. The following conclusions were drawn:

(1) The hybrid ANFIS model exhibits markedly enhanced performance in energy demand forecasting when juxtaposed with conventional ANN and FCM frameworks.

(2) The integrated ANFIS model has a much shorter runtime than the other comparison models, making it the optimal choice for next-day urban gas demand prediction.

(3) When most cities use the same model configuration, the integrated ANFIS model demonstrates superior prediction accuracy, highlighting its generalization ability.

The results indicate that the proposed integrated ANFIS model is efficient, fast, and robust, making it suitable for gas demand forecasting in cities similar to those in Italy. Predicting urban gas requirements in the short term is crucial for the immediate scheduling of gas transportation, improving the efficiency of storage facilities, making prompt purchases, and managing resource distribution. Therefore, this method is crucial for energy regulation and management authorities in Italy and surrounding regions.

Upcoming studies will prioritize the creation of more sophisticated neuro-fuzzy frameworks that provide clarity and openness, thereby evaluating the method's capacity to generalize. Additionally, research will explore applications in energy sector time series modeling and forecasting, through a profound exploration of efficient deep learning and integrated models based on regularized recurrent neural networks.

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