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An Interval Type-2 Fuzzy-Markov Model for Prediction of Urban Air Pollution

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Abstract

Prediction is a very important problem that appears in many disciplines. Better weather forecasts can save lives in the event of a catastrophic hurricane; better financial forecasts can improve the return on an investment. The increasing rate of industrial development and urbanization, especially in developing countries, has led to increased levels of air pollution along with increased concern about air pollution effect on human health. This has taken about a diversity of strategies for air quality management, prediction and pollution control. Today's applications of fuzzy systems are emerging in uncertain environments such as air quality assessments. A fuzzy system that accounts for all of the uncertainties that are present, namely, rule uncertainties due to training with noisy data and measurement uncertainties due to noisy measurements that are used during actual forecasting. The performance results on real data set show the superiority of the fuzzy-markov model in the prediction process with an average accuracy of 94.79% compared to other related works. These results are promising for early prediction of the natural disasters and prevention of its side effects.

Keywords: Fuzzy Logic, Markov Chain, Hybrid Intelligent System, Air Pollution Prediction

1.Introduction

Urban air pollution once thought of as entirely a localized issue, and now is recognized as a complex and force major problem that is also subject to regional and global influences. This disaster is a worldwide challenge that may harm humans or other living creatures in our environment. Prediction of air pollution is a common important way because that the prediction of critical events should guide decision making the polluted weather is affecting public health and ecosystem. The motivation of this research is to assist accurate and reliable prediction of air quality index to improve public health and to manage one of dangerous humanity crisis. On the other hand, Markov chains are usually used in modeling many practical problems. It's also effective in modeling time series. In this paper, we apply the Markov chains model to a fuzzy inference system and make reliable prediction of air quality indexes inn different time series. Some series can be expressed by a first-order discrete-time Markov chain and others must be expressed by a higher-order Markov chain model. Numerical examples are given. The results show that the performance and effectiveness of the Markov chain model to predict the time series is very well. Inverse modeling is a powerful tool for the investigation of complex systems in various fields of application. If models derived from first principles are either very complicated or just non-existing, inverse modeling-constructing models from available data can be an interesting alternative. A typical situation where inverse modeling can be very useful is the case when a complex system yields relatively simple macroscopic behavior that may be captured with

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low-order models, but where the derivation of such low-order models from first principles is very difficult or impossible. Observed time series analysis and modeling has been deviating, over the last decades or so, from the linear paradigm with the aim of incorporating nonlinear features. Indeed, there are many cases when subject-matter, theory or data suggests that a time series is generated by a nonlinear stochastic process.

2.Research Background

This section presents an overview of computational intelligence models applied to natural disaster prediction problems [1]. presented a prediction model for natural crisis using an Adaptive Neuro-Fuzzy Inference System (ANFIS) model and compared it with two other conventional models. The first approach was Artificial Neural Networks (ANN), and the second one was Multiple Regression (MLR). They collected and used dataset is observed in three years (from 2009 to 2012) [2,3] and applied as a training dataset. The inputs of their models are important elements to improve prediction accuracy. They applied step by step regression analysis to choose the appropriate features as the input of the representations in their model. Moreover, the selected features were related to: air pressure, temperature, humidity, wind speed, and wind direction. In [4] the authors shows that the powers of a fuzzy matrix exhibit a stable behavior if the operator used is the max-min. Moreover, where [5] used these results to obtain the powers of a fuzzy matrix using the max-archimedean operator. For further information about powers of a fuzzy matrix [6-8]. In this way, the following theorem is useful to find the stationary distribution of a fuzzy matrix by using a time convergence criterion.

An automatic hybrid retrieval model for a natural disaster as well as dust storm classification. Their proposed method consists of two scales [9]. First scale is an ANN model for near real-time detection of dust storms at a wider provincial scale and the second scale was a ANN model for the detailed dust storm. Dust storm areas are first known in the near real-time detection ANN model based on Multi-Functional Transport Satellite (MTSAT) interpretations and numerical weather approximating models. Once the positions of dust storms are pin-pointed, the ANN method for detailed dust storm mapping at local scale are triggered to save more detailed material about dust aerosols. Their classification accuracy of the NN method was evaluated using a confusion matrix that describes the probabilities of each class being appropriately recognized with 89% accuracy evaluated by ROC curve.

In [10] a combined Synthetic Minority Over-Sampling Technique (SMOTE) algorithm with Adaboost technique as a random forest algorithm and propose a combination machine learning method appropriate for the study of intermittent classes proportions. In their research, the first step is balancing the samples of different classes according to the idea of SMOTE algorithm, and then they make predictions using random forest, according to the adaboost technique. They claimed that their combination algorithm possesses given a total predictive accuracy which reaches 90% respectfully. The proposed SMOTE system has been applied to rebalance the dataset and escalation the performance of multi-rare-class classification while random forest is utilized as a weak learner of adaboost collaborative learning procedure. The authors in [11, 12] extends the concept of linguistic uncertainty through type-2 fuzzy sets and its Footprint of Uncertainty. In this way, an uncertain FM can be defined with uncertain type-1 fuzzy sets, in other words, an uncertain FM can be defined with type-2 fuzzy sets. Type-1 fuzzy sets are measures of imprecision based on the perception about a variable through its linguistic label. Uncertain-based models use multiple perceptions about the same linguistic variable, where uncertainty can be treated in two ways: Linguistic and Random uncertainty.

2.1.Literature Review

The FTS model is first introduced by Song and Chissom [13,14] based on a fuzzy set theory proposed by Zadeh [15]. Chen [16] developed the FTS model of Song and Chissom based on fuzzy logic group relations tables for reducing the computational complexity in the model. Huarng [17,18] developed Chen's [19] model by determining the effective length of intervals. Yolcu et al. [20] developed the ratio-based method based on a constrained optimization to select the length of intervals. Yu [21] improved a predicting model based on weighted fuzzy relations, which produced better forecasting results than the Chen [22] model. Cheng et al. [23] introduced the trend weighted FTS model for TAIEX forecasting by assign proper weights to individual fuzzy relationships. in [24] the authors modified a weighted FTS model for enrollment forecasting. They adopted the weighted model by adding the difference between the observed dataset across a midpoint of intervals. Tsaur [25] proposed the FTS model based on Markov chain, which is used for obtaining the largest probability using the transition probability matrix. He also used a random length of interval for the universe of discourse, which leads to a negative effect by abnormal observations and outliers. Sadaei et al. [26] developed a refined exponentially weighted FTS for forecasting the load data, which is developed prediction preciseness. More specifically, the effective interval length has been investigated by several studies based on different methods.

Table 1
Summary of Literature reviewed

Method	Advantages	Input	Output	Feature
Type-1 Fuzzy	Reliable and interpretable.	10	2	6
ANFIS	Determine the optimum number of fuzzy	18	8	7
Evolutionary ANFIS	Acceptable performance	7	2	7
PLSR, MPR	Capture the nonlinearity in the data	5	2	5
Neural Network	Tried basic methods	8	2	7
Adaptive Neural Network	Accurate in complex time series	2	5	5
Fuzzy GA	Evolutionary optimization	1	5	6

3. Method and Materials

3.1.Finite Markov Chain

A finite Markov chain is a process which moves among the elements of a finite set Ω in the following manner: when at ∈ , the next position is chosen according to a fixed probability distribution $P(x. \cdot)$. More precisely, a sequence of random variables $(X_0. X_1 \dots . X_n)$ is a Markov chain with state space and transition matrix P if for all $x. y \in \Omega$, all t ≥ 1, and all events $Ht-1 = Tt-1\, s = 0\{Xs = xs\}$ satisfying $P(Ht-1 \cap \{Xt = x\}) > 0,$ we have [13]:

$$P\{Xt+1 = y \mid Ht-1 \cap \{Xt = x\}\} = P\{Xt+1 = y \mid Xt = x\} = P(x.y) \quad (1)$$

Equation (1), often called the Markov property, means that the conditional probability of proceeding from state x to state y is the same, no matter what sequence $x0. x1. \dots . xt-1$ of states precedes the current state x. This is exactly why the $|\Omega| \times |\Omega|\; matrix\; P$ suffices to describe the transitions. The $x-th$ row of P is the distribution $P(x. \cdot)$. Thus P is stochastic, that is, its entries are all non-negative and,

$$\sum_{y\epsilon\Omega} \mathrm{P(x.y)} = 1 \text{ for all x } \in . \Omega \quad (2)$$

3.2.Interval Type-2 Fuzzy Markov Chain

Uncertainties in fuzzy Markov chains can be treated in different ways. The use of interval type-2 fuzzy sets (IT2FS) allows describing the distributional behavior of an uncertain discrete-time Markov process through infinite type-1 fuzzy sets embedded in its Footprint of Uncertainty. In this way, a finite state fuzzy Markov chain process is defined in an interval type- 2 fuzzy environment. Uncertainties in fuzzy Markov chains can be treated in different ways. A Type-1 Fuzzy Markov chain is an approach which uses Type-1 Fuzzy Sets (T1 FS) to describe the distributional behavior of a Discrete-Time Markov process, while the IT2 FS approach is an extension of its scope that allows to embed several T1 FS inside its Footprint of Uncertainty. The use of interval type-2 fuzzy sets (IT2FS) allows describing the distributional behavior of an uncertain discrete-time Markov process through infinite type-1 fuzzy sets embedded in its Footprint of Uncertainty. In this way, a finite state fuzzy Markov chain process is defined in an interval type-2 fuzzy environment.

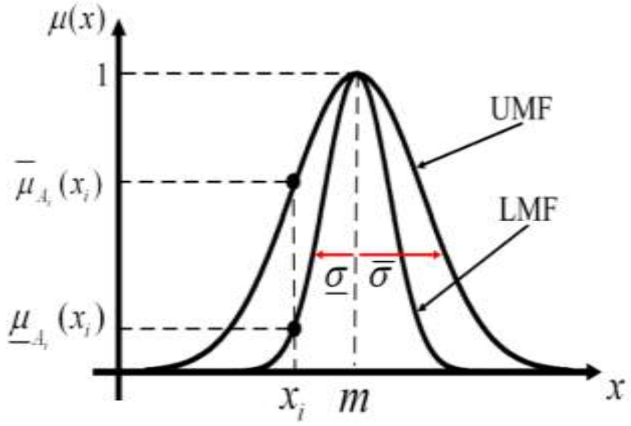

Fig.1.Type-2 Fuzzy Gaussian Membership Functions [14]

Type-1 fuzzy sets are measures of imprecision based on the perception about a variable through its linguistic label. Uncertain-based models use multiple perceptions about the same linguistic variable, where uncertainty can be treated in two ways: Linguistic and Random uncertainty. An uncertain FM can be defined with uncertain type-1 fuzzy sets, in other words, an uncertain FM can be defined with type-2 fuzzy sets. As in classical Markov processes analysis, the definition of a fuzzy Markov chain is based on a square relational matrix that represents the conditional possibility that a discrete state at an instant t changes into any state at the next instant t+1. The concept of fuzzy Markov chains has been defined, which are shown as follow:

Definition 3.1 : Let $S = \{1.2.3. \cdots . n\}$. A finite fuzzy set for a fuzzy distribution on S is defined by a mapping x from S to $[0.1]$ represented by a vector $x = \{x1. x2. \dots xn\}$. where $0 \leq Xi \leq 1. i \in S$. In this way, xi is the membership degree that a state i has regarding a fuzzy set $S. S \in i$ with cardinality $m. \ell(S) = m$. In this method, all operations and relations are defined for fuzzy sets, so their properties and computations are preserved. Now, a fuzzy relational matrix P is defined in a metric space by:

$$S \times S \text{ matrix } \{P_{ij}\}_{ij=1}^{m} \text{ where } 0 \leq P_{ij} \leq 1. ij \in S \quad (3)$$

The complete set of all fuzzy sets is denoted by:

$$\mathcal{F}(\mathrm{S}) \text{ where } . \ell(\mathrm{S}) = \mathrm{m} \quad (4)$$

The total variation distance between two probability distributions μ and ν is defined by:

$$\mathrm{k}\mu - \nu\mathrm{kTV} = \max \mathrm{A} \subset |\mu(\mathrm{A}) - \nu(\mathrm{A})| \quad (5)$$

This definition is explicitly probabilistic: the distance between μ and ν is the maximum difference between the probabilities assigned to a single event by the two distributions.

Definition 3.2 (IT2 fuzzy conditional state): Let ~P be an Interval Type-2 fuzzy relational matrix defined in $l(s) \times l(s) with\ elements \{P_{i.j}\} = l. composed\ by\ n_a\ embedded\ values\ of\ p_{ij}^{j_x}$ in the closed intervals $\left[\overline{p_{ij.}}\,\underline{p}_{ij}\right]$ characterized by a secondary membership function:

$$\frac{fx(u)}{u} = \frac{l}{u}. j_x \subseteq [0.1] \forall\ x \in S. j \in S$$
(6)

Denote the conditional state $\{x^t = j \mid x^{t-1} = i\}\ as\ x_{ij.}$ When we have:

$$S_{i=} \sum_{x_{i.j}}^{m} \frac{\left[\sum_{u \in j}^{i} \frac{1}{u}\right]}{x_{ij} \forall\ i \in S} \quad (7)$$

and consequently:

$$j_{x_{i.j}=} \frac{\left[\sum_{k=1}^{m_j} \frac{1}{u_{jk}}\right]}{x_{ij} \forall\ i \in S} \quad (8)$$

Note that each S_i is composed by an infinite number of fuzzy sets, n_a. The union of all those n_a embedded fuzzy sets namely $e(i)$ is:

$$S_{i=} \sum_{l=1}^{n_a} S_{e(i)}^{l} \tag{9}$$

Now, an IT2FS called $\tilde{p}$ can be composed by m individual IT2FS S_i, obtaining the following result:

$$S_i = \{x_{i.j}.\mu_{S_i}(x_{i.j}) \mid x_{i.j} = i\} \; i.j \in S \tag{10}$$

3.3.Study Area and Period

In this study, five major air pollutants (CO, SO_2, PM_{10}, $PM_{2.5}$, and NO_2) were considered. Their concentrations are classified into five different categories according to frequency breakpoints. Table 3 shows the five main classes of AQI for input variables. Tehran covers a large area of over 613 km2 and is divided into 22 administrative districts. It is located at 35_410 of North and 51_250 of East, with the Alborz Mountains in the north, a desert in the south, and the populated areas ranging from 1000 m to 1800 m above sea level. Tehran is the most populous city in Iran, with approximately 12 million urban residents, and a daytime population of more than 10 million people due to commuters from the outlying.

Table 2
Classification levels of AQI of Inputs [15]

Feature	Low	Mid	High	V-High	E-High
NO2	0-0.105	0.10-0.21	0.21-0.31	0.31-0.42	>0.42
SO2	0-0.065	0.06-0.13	0.13-0.19	0.19-0.26	>0.26
CO	0-5.50	5.51-11	11-16.50	16-22	> 22
PM10	0-60	61-120	121-220	221-320	>320
PM2.5	0-15.4	15.5-40.4	40.5-65.4	65-150	> 150

Table 3
Major selected features for AQI prediction [16]

Features	Description
Sulfur Dioxide (SO2)	This is one of the sources for anxiety over the ecological influence of the use of fuels as power sources.
Nitrogen Dioxide (NO2)	Inhalation of such particles may cause or worsen respiratory illnesses such as emphysema, bronchitis it may also aggravate existing heart disease.
Carbon Monoxide (CO)	The health threat from CO at low levels is important for those who hurt from cardiovascular diseases like angina pectoris.
Particulate Matter (PM)	EPA grouped particle matter pollution into two classes: particles smaller than 10 µm and 2 .5 µm (PM10 and PM25).

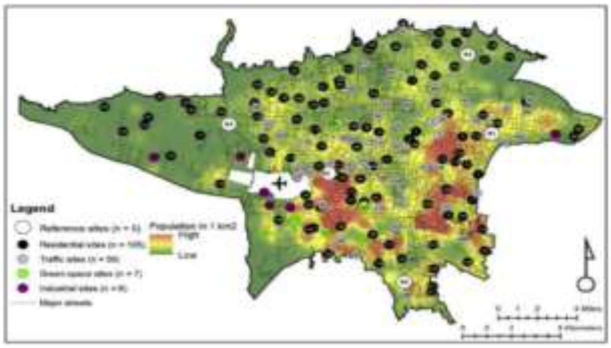

Fig.2.The study area and locations of 179 measurement sites in Tehran mega-city, Iran [17]

4. Performance Evaluation

Statistical evaluation of analytic performance in general and specifically ROC curve analysis was conducted for calculating the performance of predictive proposed model. The confusion matrix was calculated to define the performance of the suggested approaches. The confusion matrix describes all possible results of forecasting results in the table structure.

Specificity: The prospect of the test finding the correct class among all classes [18-21]:

$$\frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \tag{11}$$

Accuracy: The fraction of test results those are correct:

$$\frac{TP + TN}{TP + FN + TN + FP} \quad (12)$$

Precision: Precision or positive predictive value:

$$\frac{TP}{TP + FP} \quad (13)$$

Sensitivity (Recall): Hit rate

$$\frac{TP}{TP + FN} \quad (14)$$

The sensitivity analysis has been usen in the current version of the manuscript (Equation 14) to understand the impact a range of variables has on a given outcome for ROC analysis (which includes both benefit and costs). The sensitivity analysis is based on the variables that affect valuation, which a predictive model can depict using the variables' AQI. The sensitivity analysis isolates these variables and then records the range of possible outcomes. The simulation results of sensitivity for Type-1 fuzzy markov and type-2 fuzzy markov model calculated as following:

Table 4
Performance comparison for IT2FLSTM model applied to Tehran AQI time-series

Method	95% CI	Sensitivity	Precision
T1-Markov	[88-91]	89%	90%
T2-Markov	[91-95]	93%	94%

In order to evaluate the performance of the proposed model for AQI index prediction, a ROC curve analysis was conducted. The AQI problem is a multi-class classification, because of high dimension and massive complexity of surface under the curve (SUC) is used binaries technique (One Vs. One) to report the average of five class as a ROC curve. In order to evaluate the precision of the passive samplers, we used duplicates and blanks for 15% of the serial 10-years samples taken at the reference sites throughout the decade. In addition, this research deployed duplicates and blanks at 15% of the 324 non-reference sites during the five campaigns. These quality assurance/quality control (QAQC) procedures show the performance or ROC curve for the proposed method, where $\mu_{(i)}$ AND $\mu_{(J)}$ are the means ROC curve accuracy of the 10-fold cross-validation as follow as:

$$\mu_i = \frac{1}{10}\sum_{k=1}^{10} AUCj$$
(15)

Table 5
Estimation of the FOU Parameters with 10-Fold Cross Validation

Fold	Type-1 Fuzzy Markov	Type-2 Fuzzy Markov
1	90.63%	94.19%
2	91.39%	95.23%
3	94.58%	96.59%
4	90.88%	95.09%
5	91.23%	94.61%
6	92.46%	91.71%
7	93.91%	93.48%
8	91.58%	97.41%
9	95.08%	94.84%
10	93.28%	93.94%
Average	**92.60%**	**94.79%**

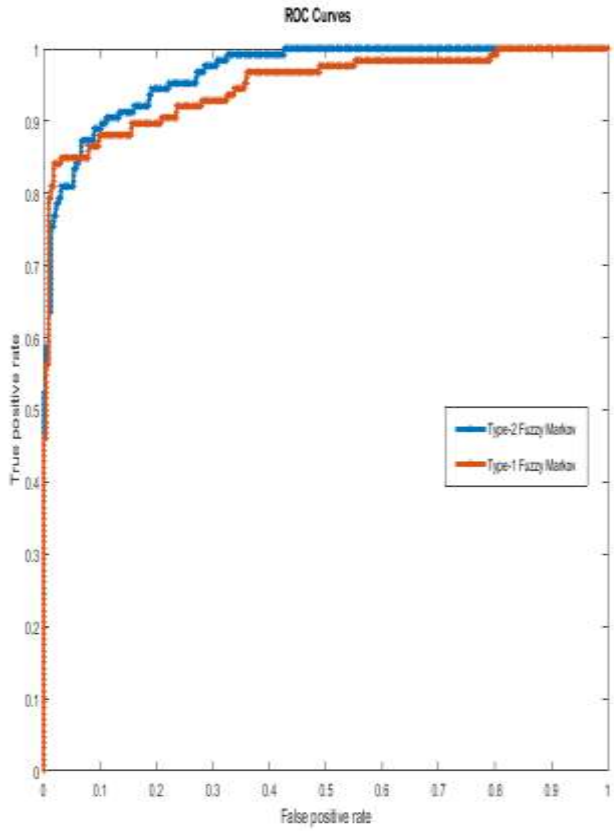

Fig.3.The ROC curves for the proposed approach (Type-1 and Type-2 Fuzzy Markov)

Table 6
A comparison of the performance of related works with proposed model

Method	AUC%	Inputs	Outputs
Markov Chain [25]	91	7	5
Fuzzy Neural Networks [26]	89	11	2
fuzzy overlay, and Dempster-Shafer theory [27]	92	6	4
DT2FTW [28]	93	7	5
IT2-Fuzzy LSTM [29]	93	7	3
Type-1 Fuzzy Markov (Counterpart)	90	6	5
Type-2 Fuzzy Markov (This work)	**94**	6	5

Table 7
Complexity Comparison of proposed model and counterparts

Model	Order	Time
Markov	O(1) + O(N)	0:01:03
Fuzzy	O(N) + O(M*N)	0:01:17
T1-Fuzzy-Markov	O(1) + O(M*N)	0:01:41
Proposed Model	O(1) + O(log(M*N))	0:01:53

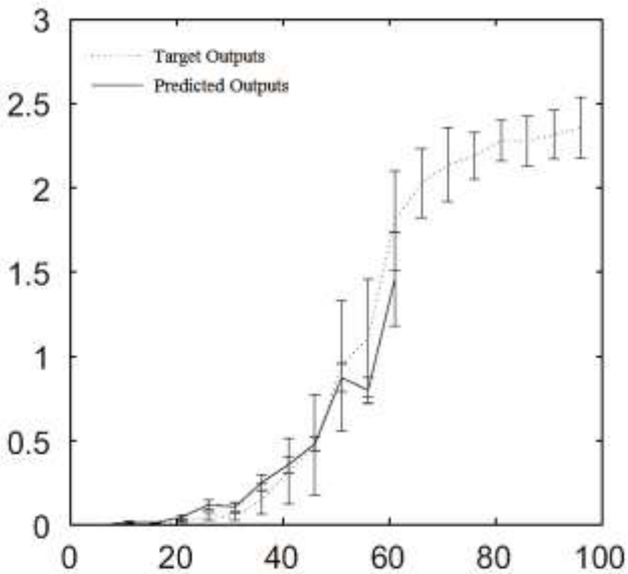

Fig.4.Multi-step NMSE values and the corresponding confidence intervals for the proposed method

5. Conclusions

This article presented Markov-Fuzzy inference model to estimate the AQI factors over an urban area such as Tehran. The proposed approach is capable enough to predicting other uncertain and imprecise conditions such as natural phenomena environment. To evaluate the methodology, the ROC curve is applied to the Tehran standard AQI data set for the last decade (2012-2022). The average accuracy of proposed model which using five input variables and after applying a 10-fold cross-validation was 94.89% with a 95% confidence interval, which is comparative the average outcome of the earlier methods. Furthermore, the suggested Markov-fuzzy model has shown a good trade-off between accuracy and interpretability in a high dimensional phenomenon and it has the competence to accomplish more uncertainties in all part of prediction system and is appropriate for pattern classification problems when are have noisy training and imprecise data set or lack of expert’s knowledge. Our future work is to design an automatic Deep Markov-Fuzzy network for AQI prediction problem to reduce the increase the accuracy measure and improve the training procedure.

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