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Rainfall events prediction using rule-based fuzzy inference system

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ABSTRACT

We are interested in rainfall events prediction by applying rule-based reasoning and fuzzy logic. Five parameters: relative humidity, total cloud cover, wind direction, temperature and surface pressure are the input variables for our model, each has three membership functions. The data used is twenty years METAR data for Cairo airport station (HECA) [1972–1992] 30° 3′ 29″ N, 31° 13′ 44″ E. and five years METAR data for Mersa Matruh station (HEMM) 31° 20′ 0″ N, 27° 13′ 0″ E. Different models for each station were constructed depending on the available data sets. Among the overall 243 possibilities we have based our models on one hundred eighteen fuzzy IF–THEN rules and fuzzy reasoning. The output variable which has four membership functions, takes values from zero to one hundred corresponding to the percentage for rainfall events given for every hourly data. We used two skill scores to verify our results, the Brier score and the Friction score. The results are in high agreements with the recorded data for the stations with increasing in output values towards the real time rain events. All implementation are done with MATLAB 7.9.

1. Introduction

The meteorological phenomenon chosen here to demonstrate fuzzy method is rainfall events. Information on rain forecast has great importance in agricultural areas specially at the northwest of Egypt where many crops irrigation mainly on the rain water, also at Cairo airport station due to the effect of rain in visibility and in turn in the airport; so an expert system models based on fuzzy logic will be introduced to forecast rainfall events in Mersa Matruh (HEMM) station and Cairo airport (HECA) station (Fig. 1). For the area under investigation statistical and synoptic studies show that the probability for rain to be event increase in winter and spring time more than in autumn and occasionally happened in summer; because the rainfall happened usually when passing the fronts associated with the Mediterranean depressions.

Rainfall forecast is an essential and vital process nowadays; each year hundreds died and were displaced by rains and floods. Rainfall events can be predicted using different models, Arnaud et al. (2007) built rainfall model based on the use of independent variables describing rainfall events and on the assumption that the process under study is a stationary one. Manel et al. (2009) investigated rainfall variability in southern Tunisia by analyzing monthly and annual rainfall data. Melani et al. (2010) use satellite images to study rainfall variability associated with the summer African monsoon. Charabi and Al-Hatrushi (2010) study the observed relation between winter rainfall in Oman and the large-scale circulation and synoptic activity was examined on a monthly basis. Bookhagen (2010) presented a study for appearance of extreme monsoonal rainfall events in the Himalaya. However weather forecasting is one of the most imperative and demanding operational responsibilities carried out by meteorological services all over the world. It is a complicated procedure that includes numerous specialized fields of know-how (Guhathakurta, 2006). The task is complicated since in the field of meteorology all decisions are

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Fig. 1. Mersa Matruh and Cairo cities on the Egypt map.
Source: http://www.maptown.com/geos/egypt.html"www.maptown.com/geos/egypt.html

to be taken in the uncertainty. Several authors (i.e. Brown and Murphy, 1988; Elsner and Tsonis, 1992 and many others) have discussed the uncertainty associated with the weather systems. Chaotic features associated with the atmospheric phenomena also have attracted the attention of the modern scientists (Sivakumar, 2000, 2001; Sivakumar et al., 1999; Men et al., 2004). Different scientists over the globe have developed stochastic weather models which are basically statistical models that can be used as random number generators whose output resembles the weather data to which they have been fit (Wilks, 1999). Statistical models have the drawback that in most of the cases they depend upon several tacit assumptions regarding the system. But, a chaotic system like atmosphere cannot be bound by any postulation. However, several studies have shown that NWP models and their forecasts are subject to errors and biases because of the complex atmospheric uncertainties and the currently limited knowledge of the mathematical formulation of the atmospheric physics and dynamics (Idowu and Rautenbach, 2009). The numerical models are based on the scheme of nonlinear operator equations which prevail in the atmospheric system. But in the absence of any analog solution of this system of operator equations, numerical solutions based on different assumptions are the only alternative. Furthermore, the chaotic behaviors of these nonlinear equations sensitive to initial conditions make it more intricate to solve these equations (Guhathakurta, 2006). As a result, flawed forecast comes out. Artificial intelligence has been later investigated in weather forecasting owing to their ability to deal with uncertainty, vagueness, incomplete and inexact specifications, intuition and qualitative information.The ability of fuzzy logic to handle imprecise and inconsistent real-world data made it suitable for wide variety of application.

Artificial intelligence (AI) is a term, in its broadest sense, means the ability of a machine or artifact to perform functions similar to those that characterize human thought. The term Artificial Intelligence (AI) has been applied to computer systems and programs that can perform tasks which are more complex than straight forward programming, although still far from the realm of actual thought. AI consists of many branches such as, Expert Systems (ESs), Artificial Neural Networks (ANNs), Genetic Algorithms (Gas) and Fuzzy Logic (FL) and various Hybrid Systems (HSs), which are combinations of two or more of the branches mentioned previously (Medske, 1996). AI technologies have a natural synergy that can be exploited to produce powerful computing systems. A theme that can be found in these alternatives is the attempt to make up for deficiencies in the conventional approaches. In some cases, the goal is to produce better, more efficient and effective computing systems. AI has also been applied for modeling, identification, optimization, prediction, forecasting, and control of complex systems (Mellit, 2008). But, this requires adding features associated with human intelligence such as learning and the ability to interpolate from current knowledge. The appropriate use of intelligent technologies leads to useful systems with improved performance or other characteristics that cannot be achieved through traditional methods (Rich and Knight, 1996).

Fuzzy logic are a clever way to deal with vagueness that often faced in meteorological forecast fields it can easily incorporate expert knowledge into standard mathematical models in the form of a fuzzy inference system (FIS). A FIS is a nonlinear mapping of a given input vector to a scalar output vector by using fuzzy logic. A FIS simulates the process of human reasoning by allowing the computer to behave less precisely than conventional computing. It is suitable for approximate reasoning by using a collection of membership functions and rules and is very powerful for modeling systems that are difficult to represent by an accurate mathematical model (Shu and Ouarda, 2008; Hansen, 2007). The field of meteorology commonly involves a system of concepts, principles, and methods for dealing with modes of reasoning that are approximate rather than exact. The capability of dealing with imprecision gives fuzzy logic great potential for weather forecast. In the recent years, fuzzy technique has drawn considerable attention towards handling this kind of complex and non-linear problems. The technique has been widely applied to many meteorological problems such as long term rainfall forecasting, Abraham et al. (2001), climate classification by McBratney and Moore (1985), classification of atmospheric circulation pattern, Bardossy et al. (1995), forecasting of temperature-humidity index using fuzzy logic approach by Mitra et al. (2006) and fog forecasting using rule based fuzzy inference system Mitra et al. (2008).

Rainfall forecast is one of the most complex elements in such fields since rainfall is a stochastic process, whose upcoming event depends on some precursors from other parameters such as the sea surface temperature (SST) for monthly to seasonal time scales, the surface pressure (SP) for weekly to longer than daily time scale and other atmospheric parameters for daily to hourly time scale. The latter atmospheric parameters could be temperature, relative humidity and wind. Variability of weather and climatic factors, especially those atmospheric parameters will be the major forcing for precipitation event. If we could recognize such a variability pattern and use it for future trajectory, rainfall prediction is very much feasible. Wong et al. (2003) constructed fuzzy rule bases with the aid of back propagation neural networks and by the help of rule base developed predictive model for rainfall. Shao (2000) used fuzzy membership functions for cloud amount, cloud type, wind speed and relative humidity to compose a fuzzy function of weather categorization for thermal mapping. Hansen (2003) presented a fuzzy case based prediction of cloud ceiling and its visibility. Hansen (2007) applied fuzzy k-nn weather prediction system to improve the technique of persistence climatology by using past and present cases. Suwardi et al. (2006) used a neuro-fuzzy system for modeling wet season tropical rainfall. Fallah-Ghalhary et al. (2009) has used fuzzy inference system for predicting rainfall time series depending on the rainfall data corresponding to a certain period in the past. Hasan et al. (2009) improved the primary fuzzy model for predicting rainfall by fuzzifying the wind speed, relative humidity and temperature differences from the days before rainfall data. In this study, we apply fuzzy logic and rule-based reasoning to predict rainfall events for every given hourly data for two stations in Egypt Mersa Matruh (HEMM) and Cairo Air Port station (HECA) by generating membership functions for each input parameter (relative humidity, total cloud cover, wind direction temperature and surface pressure) and the output gives the percentage for rainfall event.

2. Data used in the models

The data used in building our models are twenty years METAR data for Cairo airport station [1972–1992] and five years Metar data for Mersa Matruh station [2003–2007], first we separate the inputs parameters with their corresponding present weather data; separated set of data for training process. After building the models we selected the rainfall event cases and six previous hours to study the behavior of the models.

3. Method

3.1. Fuzzy logic

Our attempt is to forecast rainfall with the help of fuzzy logic based approximate reasoning. This process uses the concept of a pure fuzzy logic system where the fuzzy rule base consists of a collection of fuzzy IF–THEN rules. The fuzzy inference engine uses these fuzzy IF–THEN rules to determine a mapping from fuzzy sets in the input universe of discourse to fuzzy sets in the output universe of discourse based on fuzzy logic principles. In order to build our models we defined the fuzzy sets consist of five parameters: relative humidity, total cloud cover, wind direction, temperature and surface pressure are the input variables for our model; each has three membership functions with single output which is rain event percentage.

Under the fuzzy set theory, elements of a fuzzy set are mapped to a universe of membership values using a function-theoretic form belonging to the closed interval from 0 to 1 (Mellit, 2008).

FL is very useful in modeling complex and imprecise systems, and fuzzy set theory is a powerful tool and its applications have rapidly increased with establishing its utility in numerous areas of the scientific world. Any system consisting of vague and ambiguous input variables may contribute to an ultimate effect. The fuzzy logic possibility and its degree of effect due to the ambiguous input variables are considered by some as being generated in the human mind and is often referred to as expert knowledge. This expert knowledge is the accumulation of knowledge and ideas as a result of the expert's experience in a particular system; hence, decision-making processes may be considered as fuzzy expressions perceived by the expert (Hasan et al., 2009).

The fuzzy theory first proposed by L.A. Zadeh (1965), operated through three main steps.

1. *Fuzzification:* The first step is to determine the definition domain of each variable based on the ranges of input and output variables in actual conditions.
2. *Fuzzy rules determination and fuzzy inference:* Based on the experience and knowledge of experts, the language rules of determination were transferred into the executable fuzzy syntax for inference.

3. *Defuzzification:* The fuzzy inference outputs are finally transformed back into crisp values (Sivanandam et al., 2007).

Fuzzy inference is the process of mapping functions from a given input to an output using fuzzy logic. Fuzzy inference systems (FIS) are used to explain the specific methods of fuzzy inference (Matlab, 2009). Fuzzy inference systems (FISs) are also known as fuzzy rule-based systems, fuzzy model, fuzzy expert system, and fuzzy associative memory. A fuzzy inference system consists of inputs and their membership functions; output and its membership functions; and rules for the memberships.

The steps of *fuzzy reasoning* (inference operations upon fuzzy IF–THEN Rules) performed by FISs are:

1. Compare the input variables with the membership functions on the antecedent part to obtain the membership values of each linguistic label (this step is often called *fuzzification*).
2. Combine (through a specific *t*-norm operator, usually multiplication or Min) the membership values on the premise part to get *firing strength* (*weight*)of each rule.
3. Generate the qualified consequents (either fuzzy or crisp) or each rule depending on the firing strength.
4. Aggregate the qualified consequents to produce a crisp output.

A membership function (MF) is a curve that defines how each value in the input space is mapped to a membership value between 0 and 1. Thus, it specifies the degree to which a given input belongs to a set or is related to a concept. Depending on the methods for the fuzzy rules, FIS type is selected. The most common FIS types are Mamdani type and Sugeno-type. Mamdani type is used widely by fuzzy system designers in which the fuzzy sets from the consequent of each rule are combined through the aggregation operator and the resulting fuzzy set is defuzzified to yield the output of the system (Mamdani and Assilian, 1975; Ozkok, 2005).

3.2. Why use this method to our Met. data?

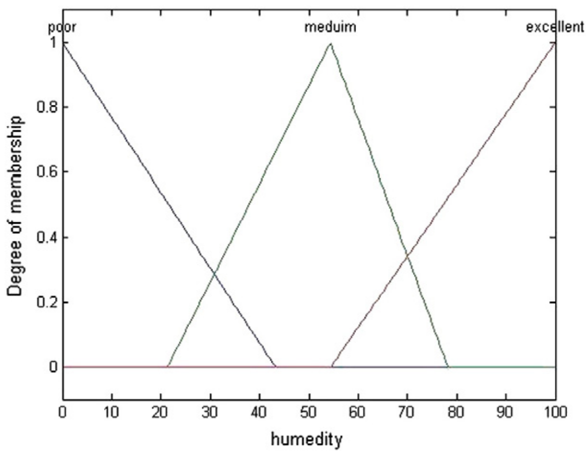

Fig. 2. Membership functions associated with the relative humidity are referred to as “poor”, “medium” and “excellent.”

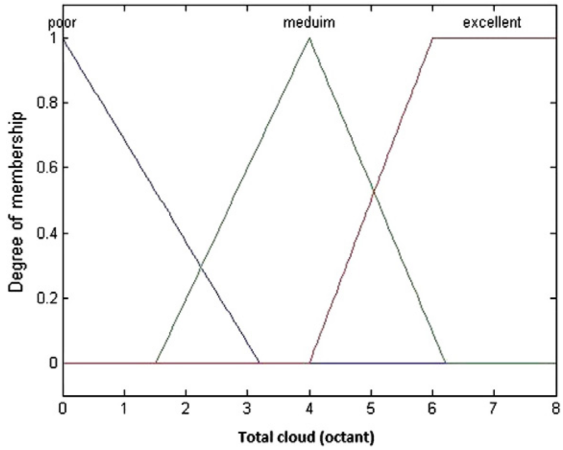

Fig. 3. Membership functions associated with the total cloud are referred to as “poor”, “medium” and “excellent.”

- Very fast, easy calculated and near optimum.
- It is intuitive.
- It has widespread acceptance.
- It is well suited to human input.

The fuzzy set we defined consists of five variables: pressure, temperature, relative humidity, wind direction, and total cloud cover. The inputs were fuzzified by building the membership function for each input. We chose two types of membership function in this work: trapezoidal and triangular membership functions for fuzzifying the system variables after trying many other types until we get the appropriate results.

a. The trapezoidal curve is a function of a vector, x, and four scalar parameters *a*, *b*, *c*, and *d*, has been chosen depends on our experts in the meteorological field and statistical background of data this function is given by:

$$f(x, a, b, c, d) = max\left(min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right).$$

b. By the same manner triangular curve is a function of a vector, x, and depends on three scalar parameters *a*, *b*, and *c*, as given by

$$f(x, a, b, c) = max\left(min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right).$$

The scalar parameter values chosen due to theoretical, statistical and locality conditions for the two stations the following figures are the system variables membership functions, we define and built the membership functions to our model parameters by use the MATLAB fuzzy toolbox. Five inputs for our system (relative humidity, total cloud cover, wind direction, pressure and temperature) since they are the major weather parameters mostly affect the rainfall events, with the output variable are considered the fuzzy sets. Relative humidity ranging from 0 to 100% has three membership functions poor, medium and excellent all are well-known triangular membership function as shown in

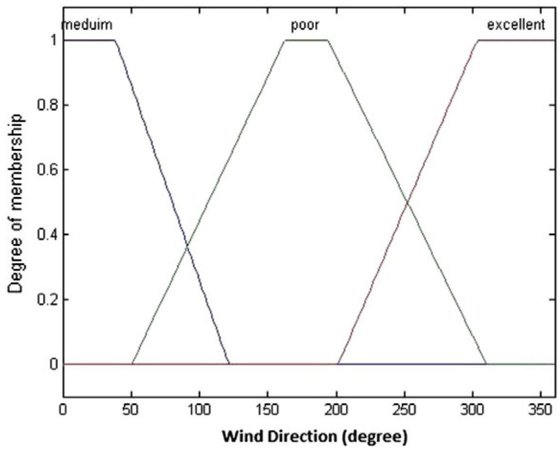

Fig. 4. Membership functions associated with the wind direction are referred to as "poor", "medium" and "excellent."

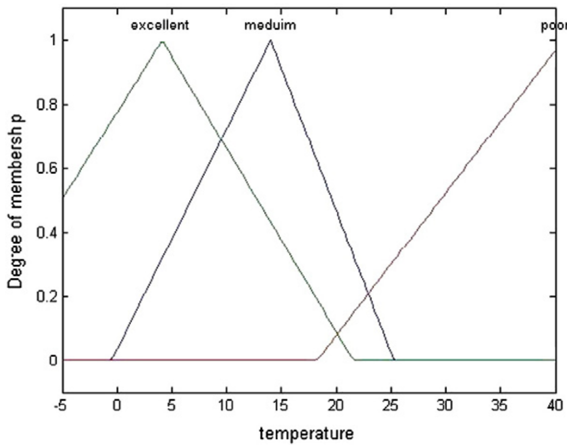

Fig. 6. Membership functions associated with the temperature are referred to as "excellent", "medium" and "poor."

Fig. 2. Total cloud cover- ranging from 0 to 8 octants has three membership functions poor, medium, and high the first two membership function are triangular whereas the excellent one is trapezoidal as shown in Fig. 3.

Wind direction ranging from 0 to 360° has three membership functions medium excellent and poor all well-known trapezoidal membership functions as shown in Fig. 4. Surface pressure ranging from 996 to 1030 hPa has three membership functions low, medium, and high all are triangular as in Fig. 5. The latest input variable is the temperature ranging from −5 to 40°C has three membership functions excellent, medium and poor all are triangular as in Fig. 6. The values mentioned above are sample values from one model of the 24th models we built.

The output variable is the percentage of rain to event ranging from 0 to 100 has four membership functions poor, low, medium, and high all triangular as in Fig. 7. The output membership functions aid in determining a final value of the system output. All membership function types and numbers for our models were chosen depending on statistical study for our training data sets, synoptic and climate study of the area.

Slight changes in weather parameters forced us to build 12 models for every station by doing corresponding change in the input parameters membership functions.

3.3. The rule base

The rule base is a set of rules of the IF–THEN form. The IF portion of a rule refers to the degree of membership in one of fuzzy sets. The THEN portion refers to the consequence, or the associated system output fuzzy set. We edit the rules using training data set until we give the suitable output using the fuzzy inference rule editor and tested against checking data set. We edit 118 rules for every model guided by training data set, synoptic, climate and statistical studies for the area.

The properties for the sets of rules are:

- Completeness,
- Consistency,
- Continuity and
- Interaction.

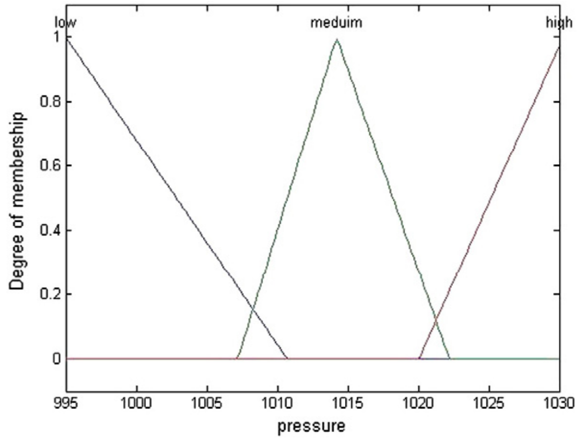

Fig. 5. Membership functions associated with the pressure are referred to as "low", "medium" and "high."

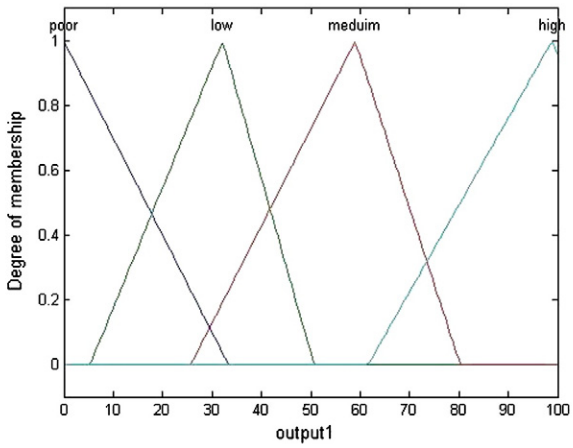

Fig. 7. Membership functions associated with the output are referred to as "poor", "low", "medium" and "high."FIS Output compared with observed rain events.

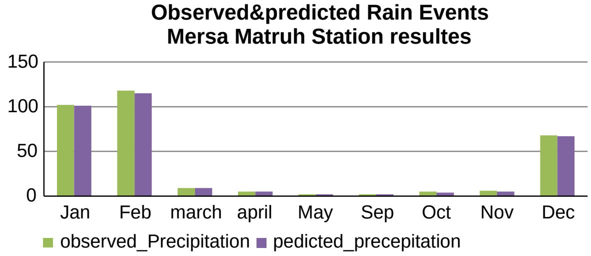

Fig. 8. FIS Output compared with observed rain events for Mersa Matruh station.

1. (Completeness) A set of IF–THEN rules is complete if any combination of input values result in an appropriate output value.
2. (Consistency) A set of IF–THEN rules is inconsistent if there are two rules with the same rules-antecedent but different rule-consequents.
3. (Continuity) A set of IF–THEN rules is continuous if it does not have neighboring rules with output fuzzy sets that have empty intersection.
4. (Interaction) In the interaction property, suppose that is a rule, "IF x is A THEN y is B," this meaning is represented by a fuzzy relation $R2$, then the composition of A and R does not deliver.

$$\underset{\sim}{A} \circ \underset{\sim}{B} = \underset{\sim}{B}$$

Examples from the rules we edit are:

a. IF humidity is excellent AND IF total cloud is excellent AND IF wind direction is excellent AND IF pressure is low AND IF temperature is excellent THEN rain percentage is high.
b. IF humidity is poor AND IF total cloud is poor AND IF wind direction is poor AND IF pressure is high AND IF temperature is poor THEN rain percentage is low.

The output is then obtained from the FIS after defuzzification. In many instances, defuzzification is desired to come up with a single crisp output from an FIS.

The center of mass method is used for defuzzifying; Center of mass is a technique that takes the output distribution and finds its center of mass to come up with one crisp number.

Table 1
Twenty years tested rainfall events for Cairo airport station (HECA).

Month	No. of rain events	No. of success forecasts
Jan.	388	301
Feb.	337	316
March	285	279
April	116	100
May	38	32
June	21	12
July	41	32
Aug.	47	45
Sep.	42	37
Oct	70	62
Nov	134	105
Dec	313	275

Table 2
Five years tested rainfall events for Mersa Matruh station (HEMM).

Month	No. of rain events	No. of success forecasts
Jan.	102	101
Feb.	118	115
March	9	9
April	5	5
May	2	2
June	–	–
July	–	–
Aug.	–	–
Sep.	2	2
Oct	5	4
Nov	6	6
Dec	68	67

This is computed as follows:

$$Z = \frac{\sum_j^q z_j u_c(zj)}{\sum_j^q u_c(z_j)}$$

where z is the center of mass and u_c is the membership in class c at value z_j.

4. Results and discussion

After filtering and correcting the data we made file contained the rain phenomena and 6 previous hours before every each one of them. The calculation was done by our system to evaluate the percentage for rainfall events using (FIS) that gives increase in this percentage as being more close to the rain events than the observed rain event take 0, or 1 where our calculated result takes value from 0 to 1 after we divided the values by 100 to be able to compare them by the real one. Our results was built by dividing twenty years METAR data for Cairo airport station (1972–1992) and five years METAR data for Mersa Matruh station (2003–2007) for every station into two sets one for training and the other for testing. Complete statistical results for the two stations are given in Tables 1 and 2. The output percentage approximately around eighty percent is considered as success forecast, it is clear that this means that we still have a degree of uncertainty associated with the models output for the rainfall events and more verification skills will be introduced in the following section that all give high agreement with the recorded rainfall.

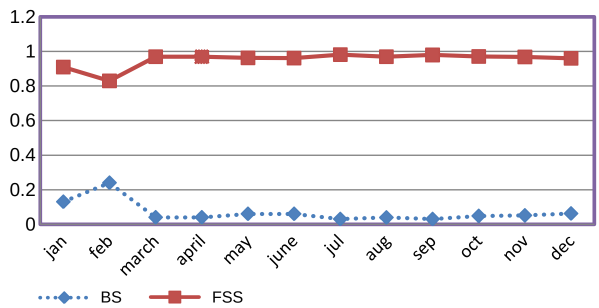

Fig. 9. Brier and Friction skill score for Cairo station (HECA).

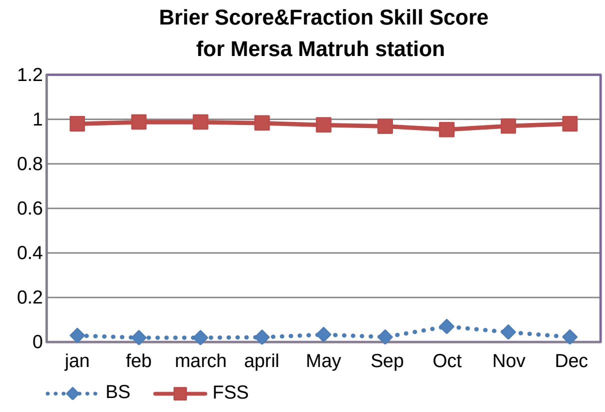

Fig. 10. Brier and Friction skill score for Mersa Matruh station.

By the same manner the (FIS) was applied to predict the rainfall events for Mersa Matruh station after adapt the system membership functions to be suitable for the station topography – Marine station – and the results are given in Table 2.

The results of total tested rain events for Mersa Matruh station is closed to be perfect due (Fig. 8) to the topography of the station since it is coastal station and the condition for rainfall events can be totally controlled by rules and the limitation of its data sets deduced the fuzzy sets and rules. Figs. 9 and 10 present the statistics for observed rainfall events and forecasted one by our models as mentioned before it considered the percentage for the event by more than eighty percent as success forecast.

5. Forecast verification

While variables such as pressure, temperature, humidity and wind speed are traditionally forecast as a point forecast, precipitation has historically been forecast as a probability (Pocernich, 2010; Berrocal et al., 2008).

A probabilistic forecast gives a *probability* of an event occurring, with a value between 0 and 1 (or 0 and 100%) as our system did. In general, it is difficult to verify a single probabilistic forecast. Instead, a set of probabilistic forecasts, p_i, is verified using observations that those events either occurred ($o_i=1$) or did not occur ($o_i=0$) (Laio and Tamea, 2006). A commonly adopted verification suited to this case is Brier score (BS) which is the mean-squared error of the probability forecasts (Zacharov and Rezacova, 2009). The reference forecast is the observed rain events and take the form.

$$BS = \frac{1}{N}\sum_{i=1}^{N}(p_i - o_i)^2.$$

Range: 0 to 1. Perfect score: 0.

Another skill score we also did which is the fraction score take the form

$$FSS = 1 - \frac{1}{N}\sum_{i=1}^{N}(p_i - o_i)^2.$$

Range: 0 to 1. Perfect score: 1

Applying BS and FSS scores in case of ones (i.e. rain events observed yes) for the two stations give the results in Tables 3 and 4.

The results for two arbitrary picked cases show clearly how our models succeeded in rainfall events prediction; for zero cases (i.e. observed no rainfall) our models present novel opportunities for those cases (Figs. 11 and 12). The conditions for rain to be event increase towards this event, this was a general perception, but it is amazing that the fuzzy models can *measure* this change by gathering all variable membership functions to give clear percentage for rainfall event every hour. Pressure sometimes can give indication about vertical

Table 3
BS and FSS for Cairo airport station (HECA).

Month	BS	FSS
Jan.	0.13	0.91
Feb.	0.24	0.83
March	0.04	0.97
April	0.04	0.97
May	0.06	0.963
June	0.06	0.9625
July	0.03	0.9819
Aug.	0.039	0.97
Sep.	0.03	0.98
Oct	0.048	0.9714
Nov	0.051	0.969
Dec	0.062	0.961

Table 4
BS and FSS Mersa Matruh station (HEMM).

Month	BS	FSS
Jan.	0.03	0.98
Feb.	0.02	0.988
March	0.02	0.988
April	0.022	0.984
May	0.034	0.975
June	0.0228	0.969
July	0.07	0.954
Aug.	0.045	0.97
Sep.	0.023	0.98

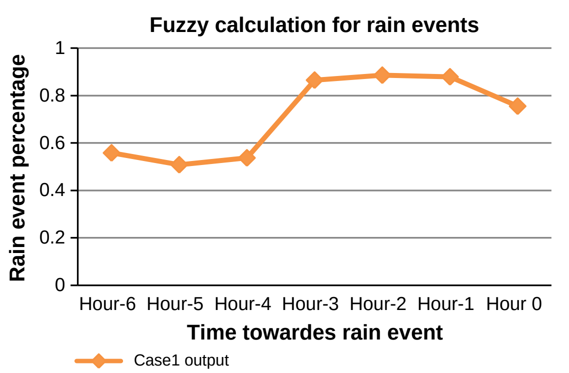

Fig. 11. Output values towards rain event for first case.

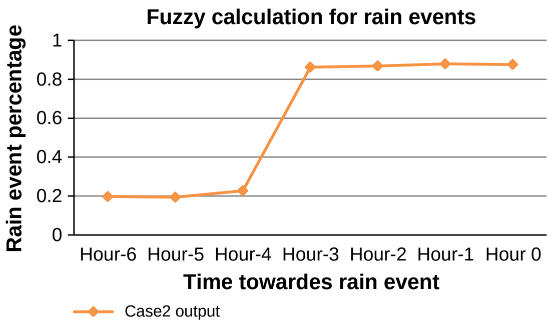

Fig. 12. Output values towards rain event for second case.

motion with increasing in total cloud cover and relative humidity accompanied by change in wind directions to be northwest to north direction due to passing of the Mediterranean depressions, also the temperature change, towards the rainfall events made the fuzzy inference output preceded the recorded rain data by time varying from 2 to 6 h. Two case studies from our results can explain the idea as shown in Table 5.

The calculated percentage values for the two picked cases increase with time towards the record rain at hour 0 (the time at which the rain fall happened) and six previous hours and have maximum value in almost all our results before the rain happening.

6. Conclusion and suggestions

We introduced intelligent models for rainfall events prediction for two Egyptian meteorological stations based on fuzzy inference system. We have proven that when using such technique it is desirable to merge the experiences of forecasters and theoretical studies with efficiency and the accuracy of the computer systems by procedure based on algorithm. In this algorithm we define the appropriate membership functions for all parameters and put efficient rules gathering the membership functions to give methodology easy to be driven and implement, unlike the complexity associated with other forecasting techniques as N.W.P., and gave results in a high agreement with the actual data. The models presented can further improve by increasing the set of input parameters; adjusting the set of rules to get multiple weather phenomena forecast e.g. fog and/or thunderstorms. Since the set of rules is mainly responsible for the accuracy of the model highly dependent on the experience of the one who puts the rules and the length of training data set; this reflects the limitation ability of fuzzy inference systems to learn.

For future work, the use of hybrid intelligent approach by merge the fuzzy inference system with neural networker may give the ability to learn and reduce the need for the experts.

Table 5
The FIS calculation toward rainfall events for two picked cases.

Time	Case 1	Case 2
Hour 0	0.75478	0.87601
Hour-1	0.87876	0.87913
Hour-2	0.88559	0.86868
Hour-3	0.8648	0.8625
Hour-4	0.5365	0.22773
Hour-5	0.50759	0.19428
Hour-6	0.55751	0.1977

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