Advanced of Mathematics-Statistics Methods to Radar Calibration for Rainfall Estimation; A Review

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Abstract— Ground-based radar is known as one of the most important systems for precipitation measurement at high spatial and temporal resolutions. Radar data are recorded in digital manner and readily ingested to any statistical analyses. These measurements are subjected to specific calibration to eliminate systematic errors as well as minimizing the random errors, respectively. Since statistical methods are based on mathematics, they offer more precise results and easy interpretation with lower data detail. Although they have challenge to interpret due to their mathematical structure, but the accuracy of the conclusions and the interpretation of the output are appropriate. This article reviews the advanced methods in using the calibration of ground-based radar for forecasting meteorological events include two aspects: statistical techniques and data mining. Statistical techniques refer to empirical analyses such as regression, while data mining includes the Artificial Neural Network (ANN), data Kriging, Nearest Neighbour (NN), Decision Tree (DT) and fuzzy logic. The results show that Kriging is more applicable for interpolation. Regression methods are simple to use and data mining based on Artificial Intelligence is very precise. Thus, this review explores the characteristics of the statistical parameters in the field of radar applications and shows which parameters give the best results for undefined cases.

Keywords- *radar, statistical techniques, data mining, rainfall Stimation*

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I. Introduction

Measuring rainfall accurately, in both space and time is very difficult due to the high variability of the rainfall characteristics [1]. Therefore, hydrometeorologists have been seeking ways to measure rainfall quantity using different statistical techniques or mathematical methods. Weather radars are known as one of the best prediction tools in the hydrometeorological field, and weather forecasting is based on statistical sciences [2]. The statistical techniques and modeling methods are created for a more accurate assessment of the data. The statistical models are combined with reliable mathematical models to predict weather and climate data [3]. Two approaches are used for radar data processing: data mining and statistical techniques. These techniques can be mentioned for classical data mining includes; Neural Networks, Kriging, Nearest Neighbor and Decision Tree. All types of regression methods can be stated for statistical techniques. In many radar field studies, the forecasting methods are based on statistical techniques [4]. Recent studies in weather radar based on data mining are associated with AI [5][6]. In the synthetic methods such as machine learning and statistics based on data distribution, usually it is assumed that the distribution is normal. In many engineering sciences, data mining and statistical techniques are used together to solve problems.

Data mining creates a multi-scale approximation method (MAME) that can have low computational complexity and can approximate the ultimate optimal solution with high precision [7]. In many machine learning techniques, at least a few statistical results are employed to build data set models. This is particularly seen with neural networks [8]. The statistical methods are generally older techniques that are related to probability modes. Data mining is a newer approach, which is related to machine learning, artificial intelligence, management information systems (MIS) and the dataset methodology.

The statistical methods are used when the number of data is less than normal, and more information about the data can be obtained. In other words, these methods deal with the slight data collection, (unlike data mining techniques, which are opaque) this method uses a limited range of input data. Reasons for using large data sets are to increase the likelihood of error, because the noise in the data is more than trial and error procedure. Statistical techniques usually decrease noise, and the accuracy of the error controls is so high that this results in more radar data uncertainty [9][10]. The quite satisfactory results can be achieved by applying statistical techniques too. Actually, it is necessary to know the distribution of the data by means of some statistical techniques. Since statistical methods are based on mathematics, they offer more precise results than other existing methods but using mathematical relationships require more information about the data. Another advantage of statistical methods is the interpretation of data. Although they are more challenging to interpret due to their mathematical structure, the accuracy of the conclusions and the interpretation of the output are more accurate.

In general, when data interpretation is difficult with other methods, the statistical methods present a useful solution [11]. Data mining is frequently based on overlapping data not on probability. This is for gaining familiarity with all basic types. In majority of studies in order to rainfall estimation, is used several data mining algorithms together [12] Moreover, statistical inference is often thought to be the result of a partnership and is not related to the causes. A machine technique is interpreted easily. However neural network approach is founded on a simple model based on the human, but output of them is a mathematical structure equation that is more difficult to interpret. Although, data mining techniques and statistical methods are usually analyzed separately, this article highlights the most widely used illustrations, in both data mining and statistical techniques for ground-based radar data analysis.

This paper discusses practical mathematics methods and refers to the most common models based on a variety of artificial intelligence approaches, such as genetic algorithms, neural networks and Kriging. We also illustrate the fuzzy logic method as applied to ground-based radar data. We provide a complete explanation of regression; section four on ‘Artificial intelligence’ describes all application methods and models dependent of intelligent machine. This section consists of five subsections reviewing the experimental methods that are more widely used nowadays. Furthermore, we discuss unique statistical methods such as fuzzy logic and special data mining methods such as Kriging and co-Kriging. The final part of this review provides some conclusions as well as giving an outlook on research directions and trends.

II. Research Periods

The ground-based radar is employed in hydrometeorology after second world war[13]. From 1943 to 2000 has been focused on radar-rainfall measurement validation by ground based radar[14]. The relationship between radar reflectivity (Z) and rainfall amount (R) that is known Z-R relationship has been found in that period. Regression was the unique method to find this relationship in that time. Several methods based on mathematical-statistics have been applied since 2001. The research period and used methods is presented in table 1.

Table 1. Performed topics and findings in different time periods based on mathematical -statistics methods

Year	**second world war - 2000**	**2001-2008**	**2009- now**
Topics	Radar-rainfall measurement validation	Use of data from other measurement system ; satellite, disdrometer, clouds physics, hydrograph, etc.	Identification of uncertainty resources
Mathematical - statistics methods	Regression	New algorithm and methods; ANN, AI, Fuzzy Logic, Kriging, etc.	
Findings	Defaults of Z-R relationship	Radar calibration by using data from other measurement system	Identification of uncertainty and calibration by errors reduction

However, just regression methodes are used in first time but there are agreat jump in recent decade. So that, in addition the data mining and statistical technique, the new algorithms being used in majority of radar-hydrology field[15][16]. More founding due to use of mathematics methods are identification uncertainty sources[17]–[19]and calibration by errors reduction[20]–[22]. Of course, the use of advanced models in recent years does not mean that the simpler models such as regression do not using now. Usually regression due to simplicity is a common method for radar-rainfall calibration.

III. Types of Regression

Regression is a statistical parameter that can forecast the performance of a variable relatively to another variable. In depth study of the relationships between variables is done through regression analysis. The primary goal of regression is to discover and provide a detailed description of the relationships between variables. To perform a regression analysis in radar calibration, the analyst first assumes that a relationship exists between two variables (amount of rainfall and the radar data). In fact, one assumes that there is a linear relationship between variables[23]. These data are plotted as points in a two-dimensional graph. The regression technique has an important place in data analysis. Several methods, such as simple linear regression, multiple linear regression, logarithmic regression, fuzzy regression, logistic regression are commonly used. Although most regression equations that are used in radar calibration follow the general equation as proposed by Marshal and Palmer (1948) is power regression, there is another type of regression used for special methods for radar or rainfall forecasting[25]. The Z-R relationship is not a complete linear (Isolinear) but is more matched by the power regression that Marshal-Palmer (1947) and later by professor Battan in 1973 proposed and determined[26]. The Z-R may match another type of regression in special cases, of course, if the ratio between the electromagnetic echoes and the rainfall amount matches another regression type, and if it can be confirmed by the great number of experiments in the radar accuracy field. Many researchers argue that power regression best fits accuracy radar forecasting[27] and shows good results for radar data calibration[28].

A. Applications of the regression approach

Regression models are very suitable for radar data forecasting and the relationship between them. Some studies used a regression model to show related flood stage and certain discharge. Simple regression estimation is proposed for radar and backscatter and radiometric emission from vegetative terrain. In weighted regression, the task regulator for this equation is a factor named an adjusting factor (AF) that is affected by the distance between the radar, and the rain gauges [29]. Multiple linear regression models describe the relationship between the dependent variables in each pixel at each stage of the precipitation radar-rainfall have been shown by Sokol (2003) to be very appropriate. In a study, by [30], the authors have shown the use of all kinds of regression models which they evaluated the cumulative rainfall amounts using a network of three radars from the western Alps. Furthermore, investigation of several regressions method types (with slight changes) includes: ordinary least square method (OLS), semi-parametric linear model (SLM), bootstrapping regression (BR) and multilevel normal linear model (MNLM) to estimate radar rainfall according to the scaling properties. This showed about ±15% uncertainties. Here, is named parameter (q) moment order, and K (q) is the scaling function [31]. The relationship between discrepancies of the methods is shown in figure 1.

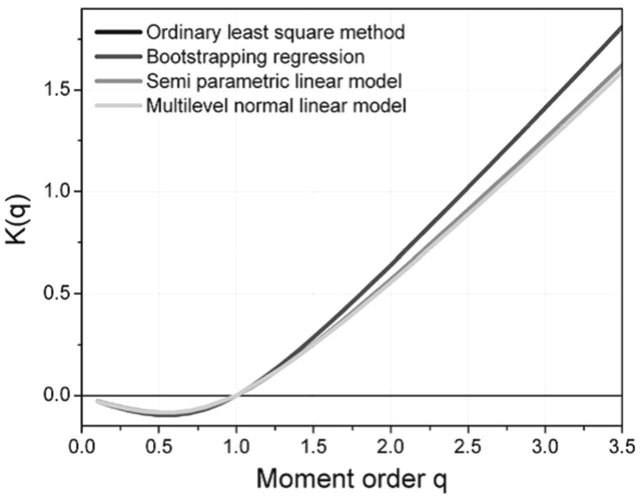

Figure1. Comparison of four different regression methods (OLS, BR, SLM, and MNLM) based on scaling properties (Villarini et al., 2007).

Estimation of hail with s-band radar using logistic regression showed the amounts of intermediate points between independent and dependent variables, It also has a very strong performance to show nonlinear effects. A study of high-frequency radar (HF) on the Keum river in South Korea, using a simple regression analysis (y=1.7x-0.061) showed good results, the high correlation coefficient (R=0.91) was used to demonstrate the efficiency of the method. In comparisons between radar measurements and Lidar, simple regression also shows a good fit [32]. For calibration of polarimetric radar by rain gauge and Disdrometer based on daily time, power regression showed the best fit according to Lee and Zawadzki (2006). Moreover, other types of regression models to compare other rainfall measurement instruments such as variety of Disderometer showed acceptable results [34]. The comparison of Ku-band space borne and two ground-based C-band radars during the winter precipitation field, demonstrated that the relationship between dependent and independent variable can be interpreted using logarithmic regression. Scott and Ryzhkov, (2005)applied multiple linear regressions to show the connection between horizontal reflectivity(Zh), different reflectivity(ZDR) and different phase shift(KDP) coefficients to calibrate dual radar. The polynomial regression algorithm was applied to investigate the discrepancy of micro physics clouds and rain regime by ground-based microwave remote sensors and showed acceptable fitness. Inspired by the variability in the Z–R relationships and different types of precipitation, multiple linear regression analysis has been successfully used to evaluate and understand which variables are more significant in the calibration process[36]. In determining radar-rainfall error adjustment effect on radar calibration, different types of regression methods have also been used by Chumchean et al.,(2003)and Bechini et al.,(2008). Regression models have several capabilities in the collection of scientific information such as description of data, calculation of parameters, simulation data, forecasting and control. However, in the radar calibration field, there has not beensuch a large number of publications, but from the ones existing, many have used regression methods[38].Usually in some of these studies the goals of using regression methods in the radar field are forecasting, simulation or both subjects together[39]. The Correlation Coefficient has a supplementary role in cases where an applied regression method shows the accuracy of the relevant variables. It means the results are scientific when the correlation coefficient (R2) between variable data (reflectivity and precipitation) is at an ideal level. Indeed, this statistical technique is very simple, available and a very economical method for rainfall forecasting and data adjustment by ground-based radars.

IV. ARTIFICIAL INTELLIGENCE

In the simple mode, Artificial intelligence in the meteorology science is the machine learning based on systematic learning. However, AI is a computational model of human behavior but it solves the problems based on mathematic system.In radar calibration, a mathematical algorithm can learn some process during the first step and apply it after that. Although artificial intelligence is a part of computer science, is often used to solve some problem in other fields using an AI algorithm. Artificial intelligence methods have been used in radar-rainfall estimation [40] and in radar-hydrology field [22], [41]. The AI shows itself in the form of Decision Tree (DT), Support Vector Machine (SVM)[42], Nearest Neighbor(NN)and Artificial Neural Network (ANN) structures[22] that can each cover a part of the data analysis in radar operation(Islam et al., 2012a). The aforementioned methods are very detailed and sensitive. The majority parameters of polarimetric radar, such as differential propagation phase (QDP) and cross-correlation coefficient (ρHV) are determined in the calibration process by artificial intelligence. This is so, as other methods are not very precise to data estimation.

A. Support vector machine (SVM)

The SVM is a novel artificial intelligence system, the performance of which is founded on a statistical learning concept and maintenance vectors. It is used to resolve the arrangement problem as “perfect learning” to organizational threat minimization standards. The SVM is categorized based on the data line and in the dividing line data; it tries to select the line to be more confident than the margin. Performance of SVM in solving the radar equation is non-probabilistic binary linear classification that is based on the concept of statistical learning for pattern recognition [44]. The SVM methods to ground clutter identification showed a suitable result in polarimetric radar signatures [45].

B. Decision tree (DT)

A DT is a decision maintenance system that services a tree like diagram or classical of choices and their prospective magnitudes, such as unplanned event products, source values, and effectiveness. The decision tree is one way to demonstrate a procedure. It is frequently used in process research, specifically, in conclusion examination, to support and identify a scheme most possibly to complete a certain aim. If preparation decisions need to be made online with no recall using insufficient information, a DT will parallel a chance model as a perfect another model or online range model procedure. Another way it can be used is as an expressive device for calculating provisional prospects.

The DT technique contains the constant separating of the teaching data by using directions in line with characteristic values. It is being drawn an outline of the classification of radar data and shown that radar data in the calculation by DT methods are independent of the present values. The study of the signal classification from ground clutter used through this technique has been well described by Islam et al. (2012a).Also, decision tree based on mathematical algorithms for robotic credit and rejection of undesired radar signals has been proposed. DT can offer a better solution and offer more possibilities than the designer of Electronic Support Measure (ESM) systems “the systems have been used to passively detect electromagnetic emission from airborne, ship borne, and land borne platforms”(Matuszewski, 2010). It is to combine different and classifiers together and demonstrated which of methods is more appropriate for radar signal’s recognition.

The DT method has been successfully used in data classification and data forecasting in radar data analysis [47]. Thus, DT is a very suitable statistical technique to select the right direction to reach the best result in primary radar data. In an overall comparison between DT and classification regression we find that the relationship between the constant radar data is determined more accurately and the effectiveness of displays are most pronounced.

C. Nearest neighbor (NN)

The NN is a type of machine learning that is named “lazy learning” and is based on training according to the nearest variable. The NN has a systematic account and mathematical formulations based on classification is provided by Lopez and Armengol, (1998) and Cooper et al., (1997). The classification is due to the majority existence of nearest neighbors variables performed in multidimensional space. Comparison between different types of NN algorithm and support vector machine experiments to forecast radar data, demonstrated that the kernel NN algorithm is more powerful than a straight NN algorithm[50].

Data fusion is a key technique in radar target recognition by which multiple features can represent the characteristics of a target more comprehensively. It uses the fuzzy membership function to process different types of features. Also, the problem arises from different data types and scales are solved. The nearest neighbor fuzzy can effectively process the combined features with different data types and scales in radar target recognition[51]. In some cases the nearest neighbor used to show the similarity of radar pixel data[52]. Definitely, NN is the successful statistical technique to find appropriate result and very near the real outcomes, in radar final data.

D. Genetic Algorithm (GA)

In artificial intelligence, the genetic algorithm (GA) is an exploratory tool that copies the natural advancement procedure. This exploratory tool is generally used to produce fit consequences to complications regarding optimization and examination. Genetic algorithms are appropriate to the larger group of evolutionary procedures or evolutionary Algorithm (EA), which make answers to optimization complications using methods encouraged by natural evolution. GNU/Linux is an interesting open-source software for calculation and optimization of multi-layered radar, this software package united the electromagnetic parameter's database and an optimization engine based on genetic algorithms.

The genetic algorithm is an optimizer that helps to improve the performance of the recognizer efficiently. The GA has been strongly proposed by Yang et al., (2009)for the extraction of target characteristics and image recognition, especially for synthetic aperture radar (SAR). Furthermore, for the purposes of radar image modeling, genetic algorithm (GA) is very common for the GPO (Geometric Parameter Optimization) of the radar target. To conclude, GA gives good results, but outcomes are very sensitive because it is based on artificial intelligence. Obviously, results from AI itself are very subtle and complex, especially in Interpretation.

E. Artificial neural network

A novel approach for radar calibration is the artificial neural network (ANN). Most authors have proposed ANN to be used for spatial data analysis. Extensive series of abilities of the ANN such as simplification, organization, noise saving and calculation have made that applicable for answering difficulties in numerous fields of skill and technology. Use of remote sensing and rain gauge data and combination of artificial neural network (ANN) has been recently highlighted byChiang et al., (2007). The Radial Basis Functions (RBF) network and Multilayer Perceptron's (MLP) network have been used for solving radar field issues [5]. Use of ANN in radar forecasting is probably a new solution because of radar data characteristics. The ANN technique can learn the processes of calculating data, especially for continuity and extremes in the data. Many studies have applied a neural network approach in the radar forecasting field[55]. Use of remote sensing and rain gauge data and combination of artificial neural network (ANN) has been recently highlighted byChiang et al., (2007). He used a dynamic ANN model attitude for quantitative precipitation estimation (QPE) in real time about the one-hour impact on quantitative precipitation forecasting (QPF) by using a 3-dimensional ground radar data. No then developed a Z-R relationship and ANN method. He has also used ANN and remote sensing data very successfully in QPE and QPF predicting.

One of the essential elements of a neural network is back-propagation. The learning methods in multi-layers use the back-propagation (BP) algorithm. This means it uses gradient descent, thatthe square of output error and the objective function are minimized. The learning methods in a multi-players environment are based on the back-propagation (BP) algorithm.This also uses of gradient descent by whichthe square of the output error and the objective function are minimized. Xiaorui and Changchuan (2011)showedthree estimating parameters governing DSD from X-band dual polarized radar parameters. In their paper, they present a non-parametric approach using a regularized ANN.

The result of research from a large dataset (WSR-88D radar) in Tulsa, Oklahoma demonstrated that there are no important changes among ANN procedures and simple convective systems. Using the ANN method in a watershed modeling by weather radar data showed that the ANN methods gave better results than regression-multi-parameter model, and can also be used in flood forecasting cases[57]. Simulations using *Matlab* software have demonstrated the algorithm's effectiveness. It was found that the MSE = 0.0001, under the condition of nine hidden layer nodes[56].

The ANN is a new tool in quantitative precipitation estimation and quantitative precipitation forecasting (QPE) / (QPF), in using radar data, which is capable of learning complex nonlinear relationships. Research in dynamic ANN for rainfall approximation and forecasting from radar explanations have shown that RNN produces better hourly precipitation evaluations than those obtained from Z–R relations, with smaller RMSE in both appraisal parts[39]. Another, major benefit is that small errors are not amplified because the processing is distributed.

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F. Kriging and co-Kriging

The Kriging is a statistical technique for interpolating data. This method is particularly used in geographic information systems. The Kriging technique can interpolate values of the same parameter [58]such as elevation, landscape as a function of the geographic location of the unseen position at adjacent locations.In standard cases, Kriging is a geostatistical interpolation method that estimates the significance of an endogenous variable at a point. The radar data processing, Kriging can estimate a linear least squares. The goal of Kriging technique is to evaluate the rate of an unknown real-valued function[20], [22]. The Kriging estimator accomplishment is created on weighted moving average logic. Depending on the stochastic properties of the random field, different types of Kriging are used. Depending on the condition, different types of Kriging have been applied.The linear constraint on the weight and the method for calculating the weights can be divided in several ways. The classical methods of Kriging are:Simple Kriging, Universal Kriging, Ordinary Kriging, Indicator Kriging (uses an indicator factor instead indicator function) (IRFK-Kriging), Multiple Indicator Kriging, Disjunctive Kriging (is a nonlinear generalization of the Kriging) and LognormalKriging.

The aim of all types of Krigingis is the interpolation from time and location of radar data[59]. The more common application types of Kriging that are used in the radar calibration field are Simple Kriging, Ordinary and Co-Kriging. Kriging is the simplest form of a mathematical function that has random background and a performance based on covariance functions, the simplest of them is ordinary Kriging[32], it is based on two assumptions: a) Intrinsic stationary (technically a time series) or the extensive intelligence stationary of the playing field and b) sufficient explanations to approximate the variogram. It usesCo-Krigingifare allowed samples of an auxiliary variable or co-variable besides the target value of interest, to be used when predicting the target value at the sample locations.

KrigingExternal Drift method for interpolation of extreme hourly precipitation in large scale by ground-based radar showed successful results [60] . Recent research shows that to estimate the time and location of precipitation Kriging is very convenient [61].Furthermore, to predict real-time flash flood with radar data on road inundation counsel system it was found that Kriging is the best method among other methods for radar forecasting[62]. In rainfall estimation using radar and rain gauge data together, between exponential, spherical and Gaussian models the Co-Kriging is used for identifying the variogram model. The results showed that Kriging External Drift (KED) is the most accurate method compare to other estimators (Velasco-Forero et al., 2009)

In The NEXRAD data project are used several types of Kriging includingRegressing Kriging (RK), Bias Adjustment method (BA) and Simple Kriging with varying Local Means (SKLM). The results showed that SKLM is performing best amount of these techniques. The correlation coefficient of SKLM reached 0.96 and the mean absolute error showed about 22.8% (Zhang and Srinivasan, 2010).Without a doubt, Kriging is a unique method to interpolate data in radar data forecasting. It can be applied to low frequency or huge amount of data. The results are very close to the real data. Moreover, the most common application of Co-Kriging is because the Co-variable is cheaper to measure, and therefore has been more densely sampled than the target variable.

G. Fuzzy logic

Recently, there has been a rapid growth in the number and variety of applications of FL techniques in recent works. FL has widely been used in image processing, image-understanding and other applications such as detection of edges, clustering, classification and feature extraction. Many studies have been carried out to reach these objectives in the radar data field (Gader et al., 2000; Ryzhkov et al., 2005; Bringi and Chandrasekar, 2001; Islam et al. 2012b). Previously, all traditional computing was based on vigor, precision and certainty. Surely, precision depends on the degree of certainty in all of the cases, which carries high costs. We can use FL to solve many problems in the field of words and numbers in low cost.

Fuzzy logic has been developed as partial truth, where the result value can range between completely true or completely false (Diodato and Bellocchi, 2007). This technique can mimic the human mind so that modes of reasoning can be done. It is approximation rather than an exact mapping. It is a form of probabilistic logic or much value logic. The function of FL is related to human role. Gaining approximate results and interpretations as well as ambiguous statistics (fuzzy data) largely hang on crisp data (binary yes/no choices). Another basic concept in FL is the fuzzy “if-then rule”. In this function, the FL solution is a translation of the human solution. In these cases, FL can model nonlinear functions of arbitrary complexity to a desired degree of accuracy. It is based on reasoning and the result is approximatic, not fixed or exact. Unlike the traditional mathematical methods, in which binary sets have the just two-value/two-answer, true or false, fuzzy logic variables may have a true value in the range of 0,1.

In radar calibration models, researchers are trying to find a multi input, and multi output. The FL is one of the tools

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used to model a multi input, multi output system [67]. Furthermore, radar outputs have a variety of features and numbers. FL can offer several unique features that make it a particularly good choice for many control problems. The fuzzy logic can offer estimated answers to problems that other systems find hard to explain and can process incomplete data. It has been shown that radar data calculation and radar adjustment is based on fuzzy concepts. The theory of fuzzy sets can be applied to radar detection problems. Fundamental studies in fuzzy logic when combined with other statistical methods such as Kriging and co-Kriging base-on Bayesian show acceptable results. The recent cases are applied to radar detector problems (Saade, 1994).

The fuzzy logic technique in classification of dual polarization radar data showed that it is well suited for hydrometeor classification. Moreover, it is able to recognize hydrometeor forms with overlapping and noisy capacities(Chandrasekar et al., 2011).Using fuzzy rule base systems (RBS) in predicting meteorological conditions events, researchers managed to implement a fuzzy rule (design eight-step procedure) for solving the problem of predicting weather happenings based on different weather limitations in Lahore. Here rule base used by the inference engine was developed by three sources: a) expert opinion, b) automated rule generation and c) literature survey. So, the presentation of the total fuzzy RBS was found with an accuracy of 96.9% in the first experiment [2].

For a project in the Czech Republic in order to determine the boundary layer of storm locations based on 0-1 hour time, they used the combination of observations and numerical models with a statistical objective model (SAM) based on fuzzy logic techniques (Sokol and Pesice, 2012). The enhancement of information seeking for the radar modeling module by fuzzy logic includes three processes: content indicator creation, user indicator creation and needs extraction (Shih et al., 2012). The fuzzy logic approach is one of the most successful techniques in artificial intelligence methods to identify ground clutter echoes in the radar data field. For example, Brissaud et al., (2011) found a satisfactory presentation of fuzzy system to categorize atmospheric echoes from non-meteorological echoes. Actually, an advantage of the Fuzzy method is the slight amount of input variables and simplicity in design. It is a good method for identifying the data domain.

V. CONCLUSION

Among all of the mathematical-statistic parameters, the regression is one of the best and most practical statistical methods in the radar data field. It is very simple and ready to use.The statistical techniques are more applicable and freely available, but data mining is present and expensive in radar data forecasting. The review on statistical techniques shows that the equations and mathematical relationships are growing wildly. Also these techniques enable noise removal and outlying data filtering, and are applied for descriptive statistics and cluster analysis. Of course, these techniques have some deficiencies such as: a) Data implementation in a small range, b) basic assumptions are needed, c) only numerical data are used, d) just demonstrated by two-dimensional and three-dimensional charts and cannot show data visualization too.

Data mining is a up-to-date method based on artificial intelligence that can widely forecast in extreme data range.Data mining is often based on overlapping samples; it is not based on probability. The answers in data mining are dependent on data accuracy and are more employed in non-regulated learning. The main advantage of data mining is data visualization.

The major benefits of the Fuzzy method over physical models are the slight amount of input variables and simplicity in the calculation. It is a good method for identifying the domain that can usually identify intermediate data. In comparison with data mining, statistical techniques and fuzzy logic in ground base radar showed that Fuzzy Logic can model nonlinear functions of arbitrary complexity to a desired degree of accuracy. It is based on reasoning and the result is approximated. Further, the results of studies in radar data estimation error illustrate that the performance of the fuzzy logic is very similar than regression models. The fuzzy rule has been shown that the performance of the partial least square regression method is more accurate than the decision tree and fuzzy models in forecasting meteorological events.

The Kriging is a unique method to interpolate data in radar data forecasting that can show results close to the real data. The Co-Kriging is an economical method to measure, and much more applicable to radar data adjustment. Certainly, there are no comprehensive statistical or mathematical methods that can exactly forecast ground-based radar data, because all of the methods are relatively accurate. In the radar calibration field, it is proposed to find a complete management including: applicable methods based on mathematics, computing program based on statistics, available and cost-effective. Indeed, it is recommended, that researchers find a new approach through a hybrid set of statistical parameters with artificial intelligence to achieve the most accurate result.

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