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Utilizing support vector regression for magnetic statistical modeling and using a fuzzy inference system for comprehending the status of subsurface structures

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Abstract
This paper is mainly about creating a novel method for detecting potential subsurface structures in the study area for future investigation. This paper is divided into two sections. In the first section, for notifying the statistical status of data points, two types of support vector regression are proposed. In the second section, by using a fuzzy inference system, potential parts of the study area are detected. For this research, 812 magnetic surveying points were collected in the southern part of Iran with a range of magnetic between. -105.718 to 2.20 two types of SVR are proposed, and in both methods, firstly, an MLP neural network predicts magnetic rates by using easting, northing, and elevation, and in MLP_SVR by trial and error main parameters of SVR are chosen but in MLP_PSO_SVR optimized parameters of SVR are chosen by the PSO algorithm. Main parameters of support vector regression are epsilon, penalty term, and kernel function (in this study we choose RBF kernel function), In MLP_SVR, epsilon is 24, penalty term is 27 and sigma of RBF kernel is 12, and optimized parameters in second type are estimated 28.27 for epsilon, and 21.99 for penalty term, and 15.70 for sigma of RBF kernel,, and by this parameters, SVR is performed. In the second section, utilizing unique FIS platform is created, and parameters of this intelligent system are predicted magnetic rate, which is predicted by an MLP neural network, and depth. To obtain depth, Standard Euler deconvolution is offered, which uses least-squares as an inversion method. MLP_SVR puts 753 data points inside model and MLP_PSO_SVR puts 775 data points inside model which means MLP_PSO_SVR has 2.70 % better performance in comparison of MLP_SVR, in second section, the condition of the subsurface structure is defined, and the outcome of the model illustrates that in this area, if the magnetic rate is more than -80 and Simultaneously, the depth is less than 2000, that parts are proper area for future investigation. Main finding of this study are; (1) MLP_PSO_SVR causes that more data points in comparison of MLP_SVR be inside of Support vector regression model and this proposed type has better performance in comparison of MLP_SVR (2) particle swarm particle is great tool for optimizing main parameters of support vector regression (epsilon, penalty term, and sigma of kernel function) and The function of norm(sin(x)) causes that choosing of optimized parameters of support vector regression becomes attainable (3) fuzzy inference system creates novel procedure for notifying status of subsurface structure which can be used in future research in study area.

Keywords: Magnetic surveying, multilayer perceptron, support vector regression, particle swarm optimization, fuzzy inference system

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1 Introduction

Exploration geophysics illustrates the subsurface of the Earth by inverting calculated physical area at the surface (Yu and Ma, 2021). Identifying and describing the regions of the crust of Earth, which have an unusual (anomalous) magnetization, is the purpose of magnetic surveying (Lowrie, 2007). The modern exploration is the certain goal of the examination of geophysics, so, multiple geophysical maps will be provided for generating of examine of exploration area, for notifying the best area, drilling boreholes are essential, also, the most dependable examination for finding potential area is drilling, but the procedure of this method is expensive, so applying another suitable manner is fundamental until risk of drilling is decrease, and mentioned alternative method promotes accuracy of sites of drilling. Statistical methods can play a significant role for enhancing the rate of success, and in overcome the exploration success (Feizi, et al. 2021). The connection among data of geophysics and the subsurface of earth's properties is calculated out of modeling process which solves nonlinear problem (Pace et al. 2021). To answer the nonlinear regression issue, Support vector regression is created out of support vector machine, and outstanding generalization performance, lack of neighbor minima, sparse representation of the solution are the main features of this method, and this algorithm has the capacity to solve complex model (Lu et al. 2015).

Fuzzy logic is the method which has capability to utilize for taking into the account of uncertainties existed in phenomenon into probabilistic or modeling in mathematic. Fuzzy theory set firstly introduced by prof. Zadeh in 1965 who extended the classical sets' concepts. In this method, information is calculated out of measurement, data, and past knowledge, also approximation in often time that made it as uncertainties. Model out of fuzzy expert system can be solve the problem as same as experts. fuzzy logic has ability to use in so many studies like geophysics, and fuzzy inference system is a manner that utilizes fuzzy set theory for mapping inputs into outputs (Taghizadeh Farahmand and Eslami 2020). Decision-makers are easily allowed to unify their experience into the process of decision-making by Fuzzy inference systems (Dragović et al. 2015). an expert's knowledge and experience are the requirements of a fuzzy inference system(FIS), For designing a control process system whose function is to determine a set of fuzzy control rules, e.g., IF_THEN rules by input-output relations (Cavallaro, 2015) and this approach is used to clarify the condition of the subsurface structure until the researchers make a better decision about the subsurface structure.

This paper includes two sections, in first section of this paper, statistical modeling for increasing validity of data are performed, also for enhancing quality of data driven to support vector regression, two methods are used. in first method, multilayer perceptron predicts magnetic rate and support vector regression defines regression modeling, and in second type, after utilizing multilayer perceptron, particle swarm optimization optimizes parameters of support vector regression then regression by optimized parameters and predicted target are performed. After statistical evaluation, in second section of this paper, we apply fuzzy inference system for notifying condition of subsurface structure and introducing proper area for future investigation. In second section of this study, fuzzy inference system is utilized for creating automatic platform for noticing condition of subsurface structure, in this step, firstly primary parameters of the system are defined secondly, proposed variables are described thirdly, the best rules for the model are applied and finally, by mentioned steps, fuzzy inference system is trained.

Support vector regression has the capacity for fast data-processing speed and higher precision than regression types (Moazenzadeh et al.2018); however, the overtraining problem, which reduces generalization ability, is the main disadvantageous of support vector regression but also support vector regression by selecting an appropriate ε , defines the maximum total training error (Karahan et al. 2014) and the dimensionality of the input space has no connection with support vector regression (Liu et al. 2018). Nowadays, multiple models with the basis of mathematic were extended like regression modeling (Mihi et al.2022). (Khalili, and Zamani, 2016) had research that used regression modeling for log data and (Sadeghi, et al. 2021) was research that utilized regression method for seismic data, but it both studies lack of special machine learning type that control the regression problem is obvious. In support vector regression, controlling parameters of this algorithm like epsilon, kernel function, and penalty term are defined in the kernel function, the type of kernel function is significant and epsilon cause that regression to become more accurate, and penalty term causes that smoothness of model increases and the regression fit more with data. In this method non-linear line with mentioned parameters define the model and data points inside line are acceptable for the model. Mamdani is better than Sugeno for interpretation however, Sugeno is more flexible for designing fuzzy inferences systems. Sugeno causes that accuracy of system increase, but this inference system is caused that no effective manner is created to define the coefficients parameters that play the principal role in the efficacy of the model (Rout et al. 2018). Recently, fuzzy set theory (fuzzy inference system is one of the method of fuzzy set theory) has been used so much in many fields of geophysics like magnetic studies, resistivity inversion, and seismic (Raj et al. 2015). (Hadiloo et al. 2018) had research about fuzzy method that utilize in seismic data, and (Ding et al.2022) presented fuzzy method for geophysical data but in both studies any fuzzy methods do not apply for decision making. Main goal of this research is detecting proper area of study area for future investigation by using novel method. For reaching this goal, firstly two statistical models are proposed until validity of data points are considered then by using fuzzy inference system, main goal of this study is calculated, also main goal of this study is finding proper area for future investigation.

2 Material and Methods

it is better to introduce the study area then describing Support Vector Regression and Fuzzy Inference System.

2.1 Study area

The study area is placed in the southern part of Iran where is shown in Figure.1, and the main body is near larestan. in this area, and between two survey points, we put 100 meter distances on easting side and near 500 meters distance on northing side and the area of this field is 880 km^2 and 51 profiles were proposed for surveying and type of surveying profile is north-south and the grid of study area is shown in the figure.2, and in this area, gypsum and halite along with dolomites are so much and inside dolomites of this area, and by random few detrital quartz grains, and some gypsum are distributed (Nokhbatolfoghahaei et al. 2019). And table1 shows the k value of different mineral of study area.

Table 1. k value of different rocks of study area (*10^{-6} SI) (Hunt et al. 1995).

Rock type	K value (*10^{-6} SI)	Rock type	K values (*10^{-6} SI)
Gypsum	-13 to 29	Dolomite	-10 to 940
Halite	-10 to 16	Quartz	-13 to 17

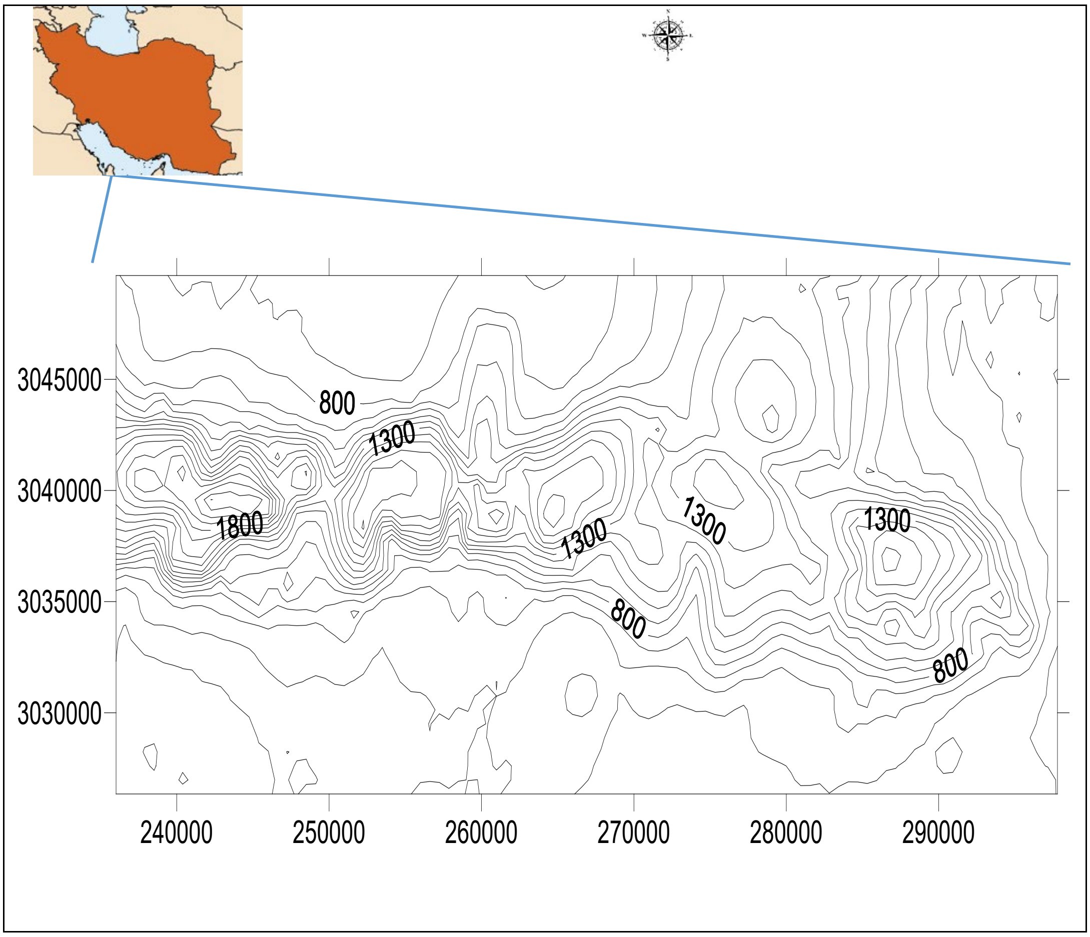

Figure 1. Study area in the southern part of Iran with contour line (full graph) (m).

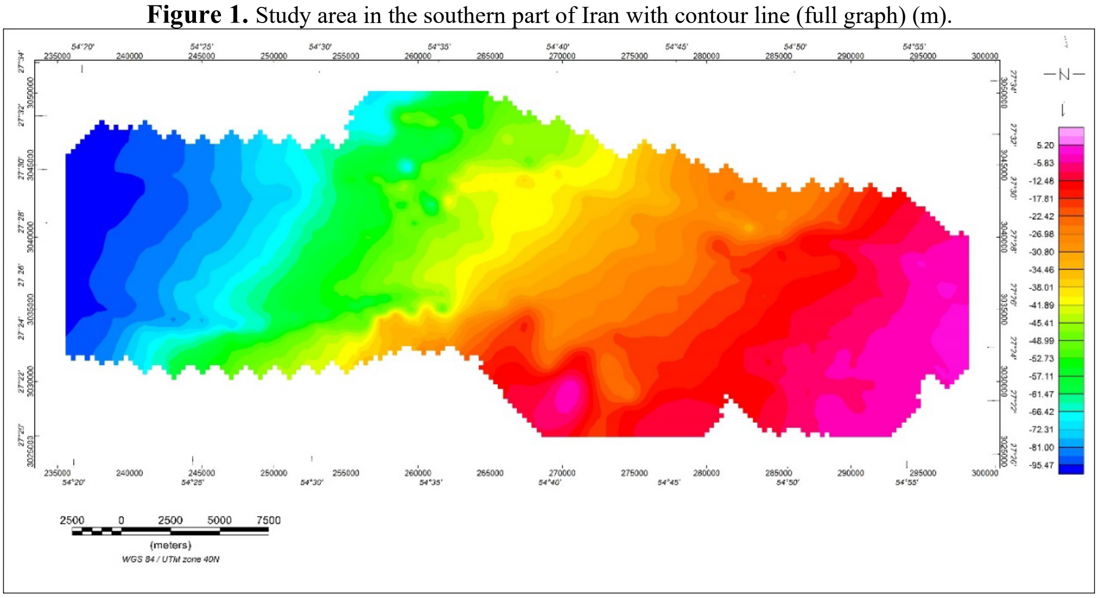

Figure 2. Grid of study area based on easting and northing (m) and magnetic rate (nT).

The figure.2 shows magnetic rate of study area and rate of this parameter is between -105.718 to 2.207, and eastern part of study area, also southern part of study area has higher amount of magnetic rate in comparison of other part of study area.

2.2 Methods of Support Vector Regression(SVR)

Vapnik presented the support vector machine, and if this is used for a regression problem, it is called support vector regression. It builds to minimize the structure risk for answering the complex problems. the training data of support is $\{(x_1,y_1),\ldots,(x_L,y_L)\}cx * \mathbb{R}$, here X is the space of input forms(e.g.$X = \mathbb{R}^d$). In ε–SVR, the aim of the method is detecting $f(x)$ which consists maximum deviation ε out of the gained aim y_i And be as smooth as possible. Firstly, it is better to determine the linear function f, which takes the form;

$$f(x) = \langle W.x \rangle + b \quad (1)$$

$$with\, W \in \ X \ \in \mathbb{R}$$

Where, in X , the dot product is $\langle .,. \rangle$ and the minimize of the norm is $\|W\|^2 = \langle W,W \rangle$ to ensure that the model's surf become a small W. So it can be defined like below:

$$Minimize \ \ \frac{1}{2}\|W\|^2 \quad (2)$$

$$subject\ to \begin{cases} y_i - \langle W,x_i \rangle - b \ \le \varepsilon \\ \langle W,x_i \rangle + b - y_i \le \varepsilon \end{cases} \quad (3)$$

The function of f approximates accuracy of all pairs(x_i,y_i) , and sometimes models have errors, so the slack Variable ζ_i,ζ_i^* are employed for overcoming constraints of the optimization problem.

$$Minimize \ \frac{1}{2}\|W\|^2 + C\sum_{i=1}^{l}(\zeta_i + \zeta_i^*), \quad (4)$$

$$subject\ to \begin{cases} y_i - \langle W,x_i \rangle - b \le \varepsilon + \zeta_i \\ \langle W,x_i \rangle + b - y_i \le \varepsilon + \zeta_i^* \\ \zeta_i,\ \zeta_i^* \ge 0 \end{cases} \quad (5)$$

The penalty term C (which is positive)defines the balance among the flatness of $f$and the amount up to which deviations larger than ε, therefore, the ε insensitive loss function$|\zeta|_\varepsilon$ can be described as follows:

$$|\zeta|_\varepsilon := \begin{cases} 0 \quad if\ |\zeta| \le \varepsilon \\ |\zeta| - \varepsilon \ \ otherwise. \end{cases} \quad (6)$$

The final nonlinear function is:

$$f(x) = \sum_{i=1}^{N}(\alpha_i^* - \alpha_i)K(x,x_i) + B \quad (7)$$

In which, α_i,α_i^* are defined kernel function$K(x,x_i)$ and bias term is B (Sun et al. 2021) and the figure.3 shows structure of support vector regression.

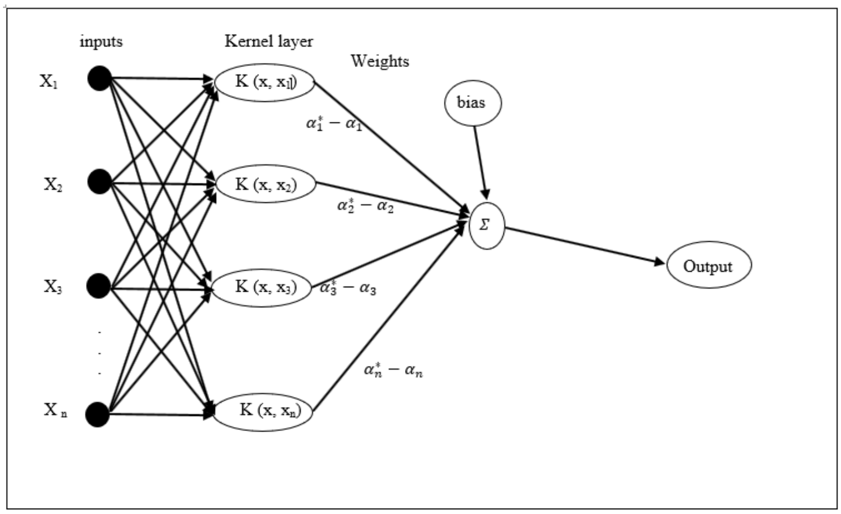

Figure 3. structure of SVR with the basis of inputs and kernel layers and weights.

2.2.1 Kernel function

Different kernel functions have been offered, whose formulation is cited in table 2.

Table 2. types of kernel.

Kernel type	Formula
Linear	$\langle x_i, x_j \rangle$
Polynomial	$(\langle x_i, x_j \rangle + c)^p$
Sigmoid	$\tan h(c + y \langle x_i, x_j \rangle)$
Radial basis function (RBF)/Gaussian	$\exp(-y\|x_i - x_j\|^2$

In our research, we choose Radial basis function (RBF), and because of this reason, only, we explain this type of kernel function; This is a particular category of neural networks. it is one of the popular classical methods for developing nonlinear models. The radial basis functions are the activation functions of this network, which can be utilized in Support Vector Regression as kernels (Gaussian kernel). Centered at node centers are the basic functions in the radial basis function network, which are either adjusted manually for good validation's outcomes or finding some clustering technique. Centers in the model's building exercise which can be a difficult task, have to be adjusted manually to the number of such nodes and the parameters. This function describes as a solution to be an optimization problem, which is framed to minimize the model estimating errors, computing the given weights to the nodes. The resemblance between the Radial basis function network model and RBF-kernel of SVR model can be notified if someone designs the Support Vector Regression model as a two-layered network. The Support Vector Regression model is fundamentally a weighted linear mixture of the kernel function values which is evaluated at the support vectors. In the classical RBF network model, the support vectors are analogous to the node centers. To solve the optimization problem in the Support Vector Regression method, the automatic decision is made by both the weights and the number of nodes (support vectors). Thus, in the structure of the Radial basis function(RBF) network, a RBF-kernel-based SVR model is much more trainable (Chitralekha and Shah 2010).

2.2.2 Multilayer perceptron

One of the usual applied artificial neural network is multilayer perceptron, this type of neural network is created by the structure of feedforward (Hunasigi et al.2023) Multilayer network(feedforward) stand out great results in the task of parameter estimating, also it is designing and utilizing relatively easy . At least three layer create multilayer perceptron; 1-input layer 2-hidden layer 3-output layer (Waszkiewicz, et al. 2019). this neural network includes one or more than one hidden layer (Madhiarasan and Louzazni, 2022). For training multilayer perceptron Backpropagation algorithm is used. Multilayer perceptron requires for adjusting multiple hyper parameters like number of hidden layers, iterations, and neurons, which have ability to solve the complicated model calculating, also this kind of ANN suggests advantages of learning the nonlinear model (Sarker, 2021).

2.2.3 Particle swarm optimization

With the basis of population and stochastic method, particle swarm optimization requires a swarm of particle for handing optimization procedure. Applying the seeking range for the problem and random generation of values to reach the decision about variables. The mentioned values in next step, utilizes for random distribution of particles. in solution for searching space, then the algorithm initiates iterative process. In the procedure of optimizing, new detection to others are connected by each particle and this procedure occurs during the searching space, and defines further movement of particles. In any trial of iteration, each particle utilizes two main kinds of information: 1- the experience of algorithm 2- available neighbor's experience for guiding algorithm search. In addition, the target function of optimal problem is utilized for calculation the rate of quality of the detection of any particle (Olusanya et al. 2015). For moving of particle and velocity D dimensional vectors represent each particle.

$$x_i = (x_{i1}, x_{i2}, \dots, x_{iD}) \epsilon S \quad (8)$$

This PSO algorithm by random way generates the beginning population's velocity and any particle has below beginning velocity:

$$v_i = (v_{i1}, v_{i2}, \dots, v_{iD}) \quad (9)$$

The best global and local places are applied, where the supreme local place face with each particle and it determines as:

$$p_i = (p_{i1}, p_{i2}, \dots, p_{iD}) \epsilon S \quad (10)$$

At any iteration, the particle tunes it personal place due to the supreme local place and the global place between particles in neighborhood as:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}, i = 1, \dots, p \quad (11)$$

$$v_i^{(t+1)} = v_i^{(t)} + c_1 r_{i1} * (pbest_i^{(t)} - x_i^{(t)}) + c_2 r_{i2} * (gbest - x_i^{(t)})\ i = 1, \dots, p \quad (12)$$

C_1 and C_2 are two acceleration constants with name of cognitive and social parameters and r_1 and r_2 are random vectors and this random vector is between 0 to 1 (Ali and Tawhid 2017).and figure 4 is shown the PSO algorithm.

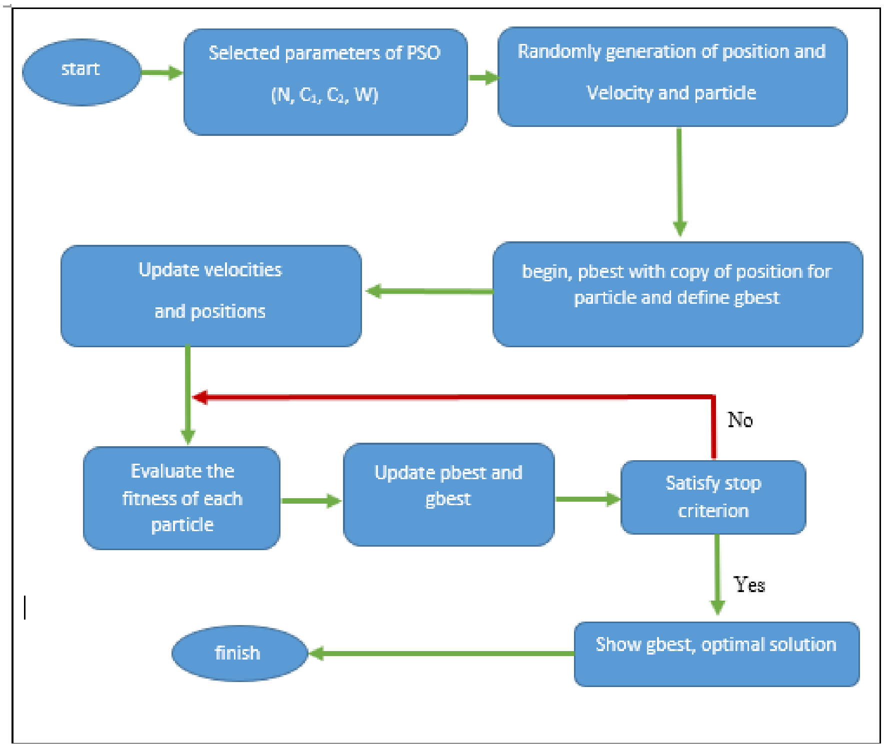

Figure 4. Algorithm of PSO.

2.2.4 Proposed MLP_SVR

In this method, firstly multilayer perceptron estimates target by using inputs then via using support vector regression and estimated target and real target, regression modeling is performed. Main steps of this algorithm;

In this method, firstly multilayer perceptron trains data points to estimate target by using inputs data. In second step, by using main parameters of support vector regression and estimated target via using MLP neural network, support vector regression is created. In first step, MLP is designed by Levenberg-Marquardt backpropagation and hidden layer and diving rate of data points to train data and validation and test data. In second step by using epsilon and penalty term and sigma of kernel function, support vector regression is designed Main scheme of MLP_SVR is designed in figure 5.

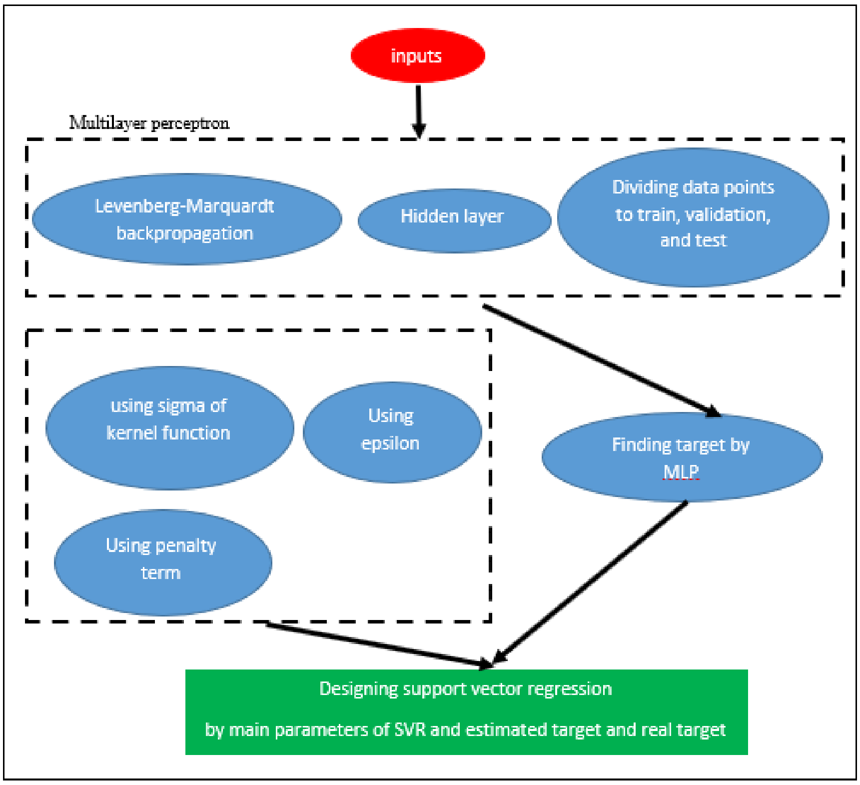

Figure 5. Scheme of MLP_SVR.

2.2.5 Proposed MLP_PSO_SVR

In this novel method multilayer perceptron uses for estimating rates of target by using inputs, then by utilizing particle swarm optimization main parameters of support vector regression is optimized by PSO algorithm, and particle swarm optimization is applied in optimizing phase.

MLP_PSO_SVR has three main steps; In this method, firstly multilayer perceptron trains input data points to estimate target.

In second step, particle swarm optimization by the function of $norm(\sin(x))$ optimized main parameters of support vector regression like epsilon and penalty term and sigma of kernel function.

In third steps, by using optimized parameters and estimated target and real value of target, support vector regression is built.

In first step, MLP is designed by Levenberg-Marquardt backpropagation and hidden layer and diving rate of data points to train data and validation and test data.

In second step by defining lower bound(Lb) and upper bound(Ub) and proper function and function of $norm(\sin(x))$ parameters of SVR are computed.

In third step by using epsilon and penalty term and sigma of kernel function that optimized by MLP_PSO, support vector regression is designed, the scheme of MLP_PSO_SVR is shown in figure 6.

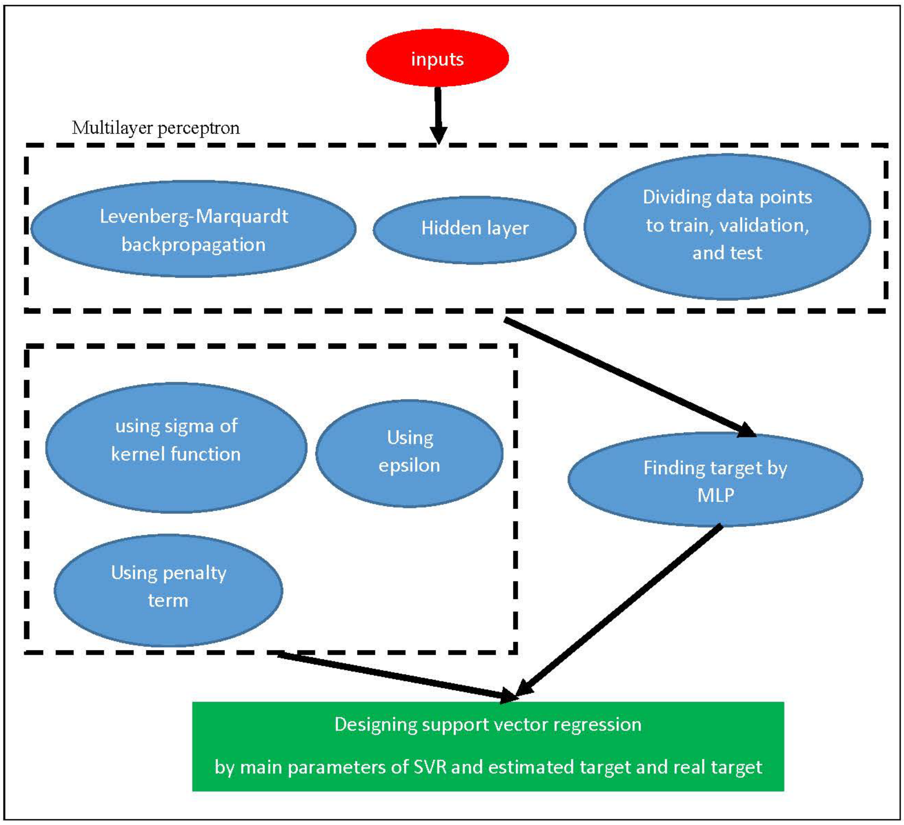

Figure 6. scheme of MLP_PSO_SVR.

2.3 Methods of Fuzzy Inference system

2.3.1 Fuzzy Set

Fuzzy set theory prepares a basis for creating the model of vagueness and ambiguity in intricate systems. Membership function in fuzzy sets can be related as a semantics to linguistic labels, and the interval of this function may be assumed as different values between 0 to 1 (Muñoz et al. 2017).

2.3.2 Fuzzy Inference system

Based on knowledge stated (if-then rules), a fuzzy inference system is operated, and this method has the ability to predict many undefined system's behaviors and by utilizing process of data-driven this algorithm takes decisions (Ahamed et al. 2017).

The Fuzzy Inference System is the construct of 5 functional steps:

(1) A fuzzy if-then rules' number that is called a rule base;

(2) Determining the fuzzy set's membership functions which are utilized in the fuzzy rules , and this membership functions are called relational databases;

(3) Transforming crisp inputs to degrees of the match by using linguistic values that are called a fuzzification interface;

(4) Accomplishing inference process on the rules; in fuzzy inference system applications that are called fuzzy reasoning (the max-min and max outcome mixture operators) are utilized popularly due to their simplicity calculation and efficiency;

(5) Altering a mixed output of fuzzy rules to a crisp value that is called a defuzzification interface (Chang et al. 2013) The structure of the fuzzy Inference system is shown in Figure 7.

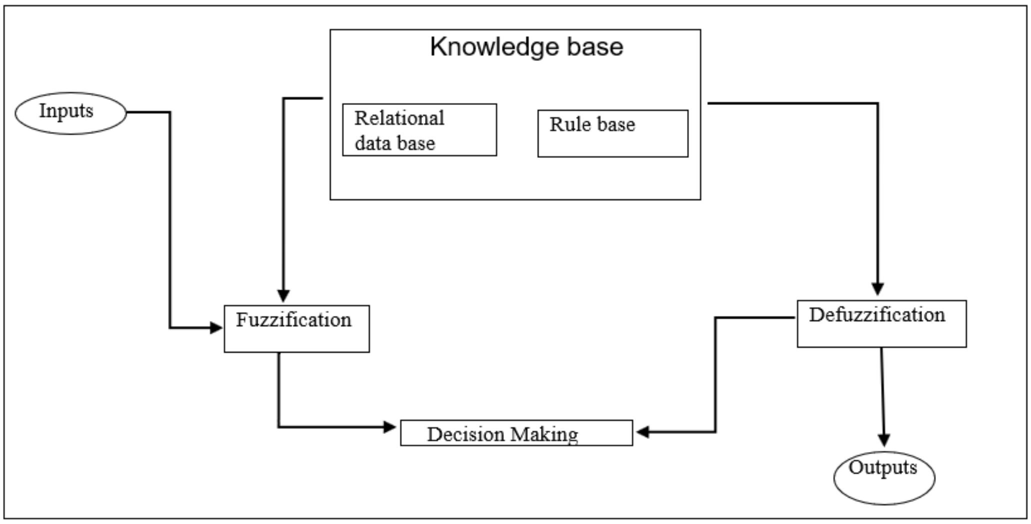

Figure 7. Diagram of Fuzzy inference system.

For this research, in fuzzy inference system two inputs are considered and that two inputs are predicted magnetic rate by using multilayer perceptron (MLP) and second input is depth which is calculated by Standard Euler deconvolution and by this two inputs status of subsurface structure is defined.

3 Results and Discussion

In this study, firstly two regression modeling are performed for evaluating statistical modeling by using two types of support vector regression. first type is MLP_SVR and second type is MLP_PSO_SVR, then by utilizing Fuzzy inference system best area of exploration for future study are introduced. In this research, due to same multilayer perceptron is utilized in both sections firstly we describe MLP neural network then we consider both methods (MLP-SVR and MLP-PSO_SVR); In first step of MLP neural network, the inputs are easting, northing, and elevation of study area and algorithm estimates value of magnetic rate, also training type is Levenberg-Marquardt backpropagation, two steps of hidden layers are proposed and number of hidden layer in first step is 30, and in second step number of hidden layer is 35, and 65% of data points consider for training and 20% of data points consider for validation, and 15% of data points consider for test, and figure 8 shows results of this type of neural network via mentioned parameters.

Prediction by using MLP neural network is done and figure .8 shows high adaptability with actual magnetic rate.

3.1 support vector regression

Support vector regression is regression modeling that more parameters like epsilon and penalty term and kernel function create model in comparison common regression modeling types which create regression models.

3.1.1 MLP_SVR

In this algorithm, firstly MLP by mentioned parameters is defined, then support vector regression is calculated by using actual rate of magnetic and predicted magnetic rate, In support vector regression algorithm, the errors less than ε are not important for Support Vector Regression, but the errors which are larger than ε do not accept by opinion behind the Support Vector Regression method, ε is the tube that is equivalent to the approximation accuracy to be applied to data points. The appropriate ε for this model is 24. Support Vector Regression (SVR) solves the regression problem

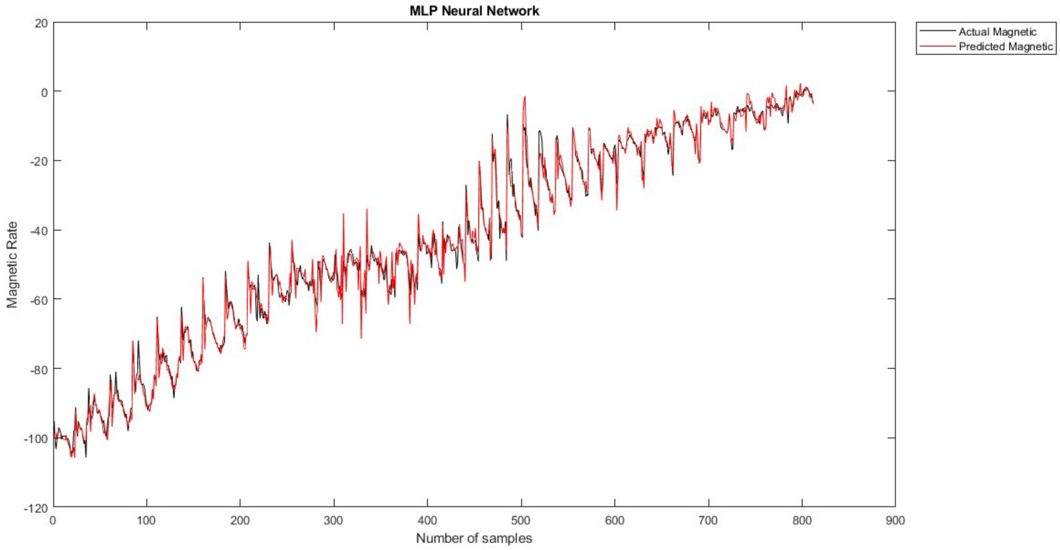

Figure 8. MLP prediction by using easting, northing, elevation as inputs and magnetic rate(nT) as output.

by using different kernels; it permits to Support Vector Regression to adjust itself to the different data dimensions. Kernel function, which is used in this paper, is radial basis function(RBF), and another main parameter is C. C is the penalty term whose higher amount endeavors to classify all data but also lower amount of this parameter makes smoother classification. The appropriate C for this model is 27 and sigma of kernel function is considered 12. By using defined parameters, this model is created, and the result of this analysis is shown in Figure.9. This model is given good information related to regression prediction among real magnetic value and predicted magnetic value.

Figure.9 shows MLP_SVR and this algorithm puts 753 data pints out of 812 data points inside model which is 92.73% of all data points.

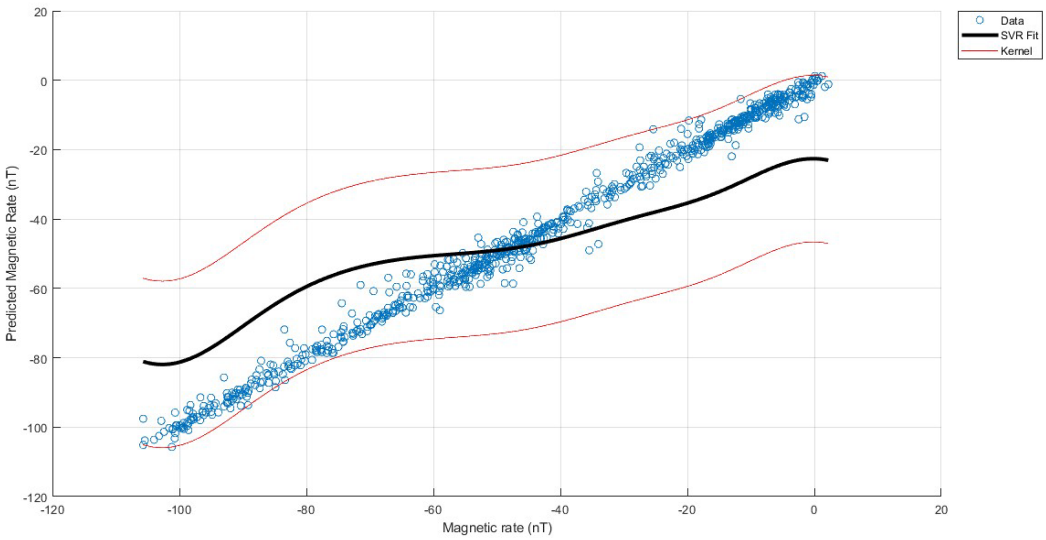

Figure 9. MLP_SVR by using real magnetic rate(nT) and predicted magnetic rate(nT).

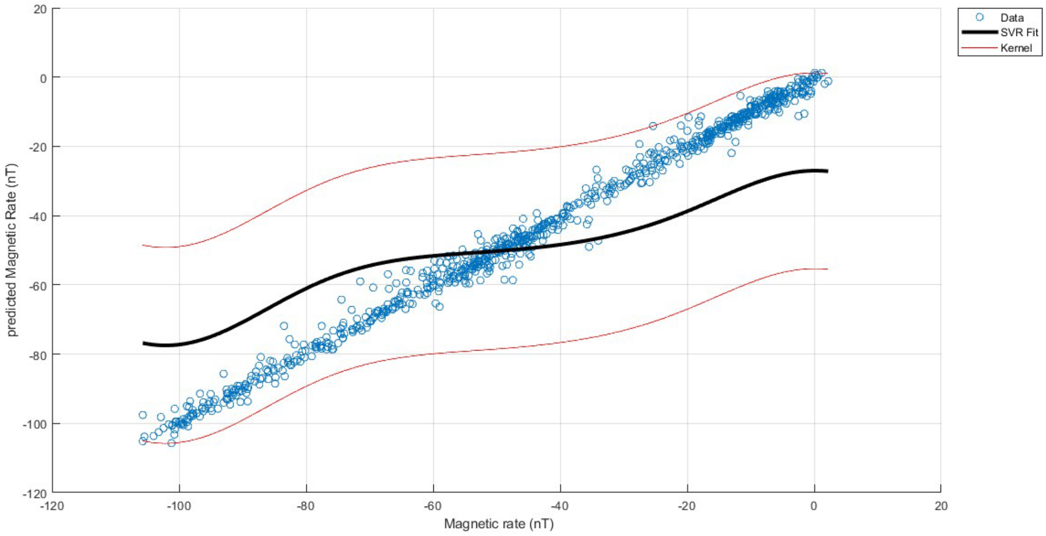

Figure 10. MLP_PSO_SVR between estimated magnetic rate(nT) and real magnetic rate(nT).

3.1.2 MLP_PSO_SVR

In second type of support vector regression, we propose novel type of parameters selection. In this kind firstly, multilayer perceptron is trained by mentioned parameters, then particle swarm optimization, optimizes main parameters of support vector regression which are chosen by this optimizing type, and number of particle swarm optimization is four and Lb =15, and Ub= 35 are proposed for epsilon, and Lb=20, and Ub=30 are proposed for penalty term and Lb=14, and Ub=18 are proposed for sigma of RBF kernel. In last step, support vector regression is created by optimized parameters. Three parameters of SVR optimized by PSO, and that three parameters are epsilon, penalty term, and sigma of RBF kernel, and optimized rates for mentioned parameters of SVR are 28.27 for epsilon, and 21.99 for penalty term, and 15.70 for sigma of RBF kernel, and figure.10 shows MLP_PSO_SVR model.

Figure.10 shows novel type of support vector regression which utilizes PSO for selecting main parameters of support vector regression and this type of support vector regression (MLP_PSO_SVR) puts 775 data pints out of 812 data points inside model which is 95.44% of all data points. MLP_PSO_SVR has better performance in comparison of MLP_SVR, MLP_PSO_SVR increases quality of support vector regression 2.7% based on data points that are inside model and MLP-PSO_SVR puts 22 more data points inside the model in comparison of MLP_SVR, and reason of this enhancing is in MLP_SVR by trying and error researchers choose main parameters of support vector regression, but in MLP_PSO_SVR, automatic model choose main parameters of support vector regression.

Also comparing this approach with the previous study, such as regression is available. Regression has some limitations such as lack of flexibility and lack of controllability because only regression is defined the model, but in support vector regression, three main parameters:1-epsilon 2-penalty term 3-kernel function are supervised the model, (and in MLP_PSO_SVR accuracy of mentioned parameters are more), and each of main parameters of support vector regression add some features to models. Epsilon adds more accuracy to the model and penalty term adds more flexibility, and kernel function adds much more trainability; however, training of regression is easier than support vector regression but also support vector regression is more accurate.

3.2 Fuzzy Inference System(FIS)

in second section of this study, after evaluating statistical modeling, fuzzy Inference system is utilized for measuring the status of the subsurface structure by using depth that are categorized to different classes and predicted magnetic rate by using multilayer perceptron. For estimating depth conditions, Standard Euler Deconvolution is utilized, and by applying least-squares inversion for each solution location point, the inversion problem is solved and Figure.13 shows the standard Euler deconvolution depth point whose appropriate Structure index is 1 (the study area is near salt diapir due to figure.11 and because of subsurface structure resemblance of the near area of salt diapir to sill due to figure.12, we only use one structure index and that is one) and window size is considered 6, and max depth tolerance is considered 10 percent.

Figure.11 shows main salt diapirs of Iran, and study area in southern part of Iran which is near one of the diapir of Iran.

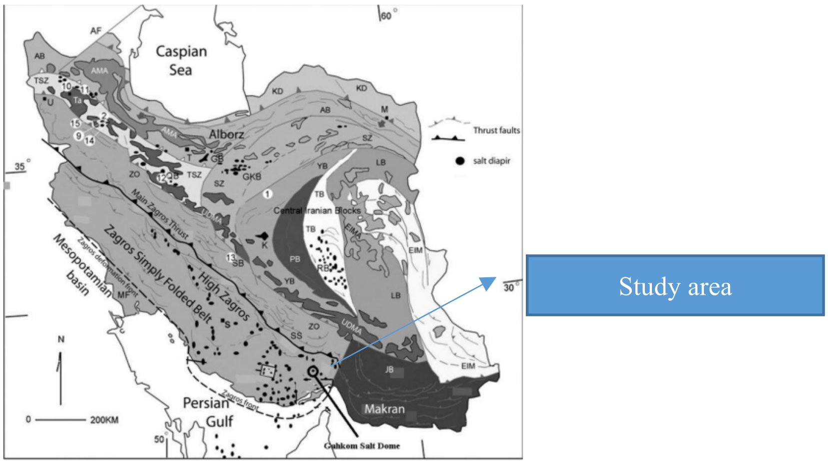

Figure 11. Salt diapir of Iran and study area that near salt diapir [20]. (Mortazavi et al.2017).

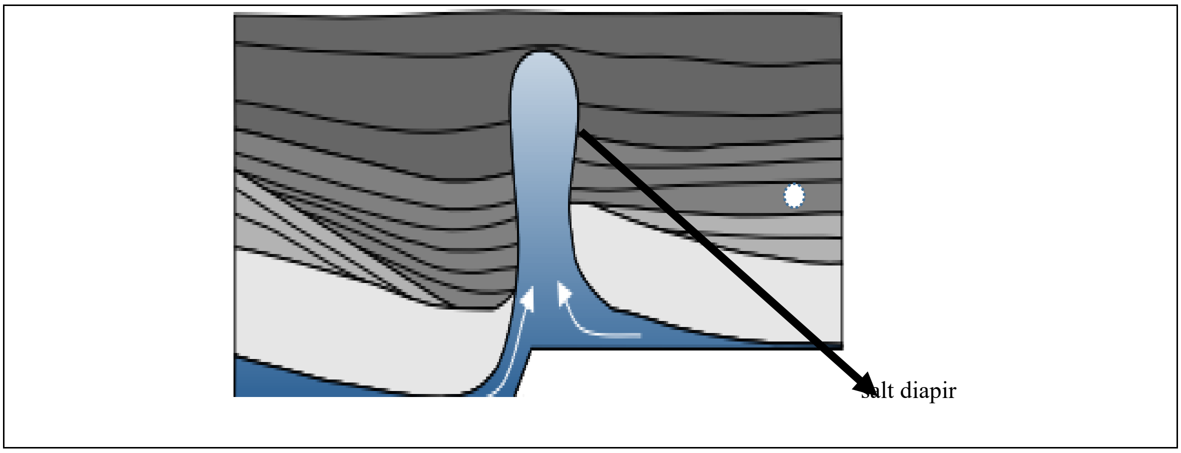

Figure 12. Example of salt diapir for illustrating form of near structure of this type of diapir [31]. (Warsitzka et al. 2015).

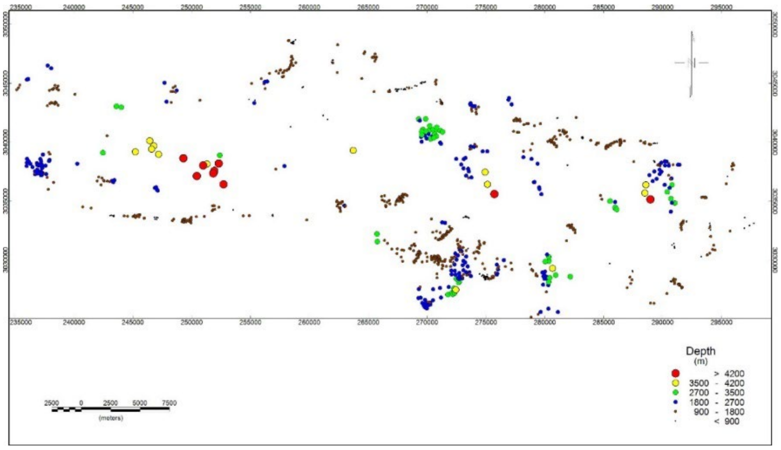

Figure 13. Standard Euler deconvolution for depth (m) prediction.

Figure.13 shows depth prediction with the basis of Euler deconvolution and central part of study area are involved with deeper resources and southern and northern area of study are involved with shallower resources.

3.2.1 Rules

The rules that can be appropriate for this research are;

1)If predicted Magnetic is High and Depth is Shallow then Status is Good.

2) If predicted Magnetic is Low and Depth is deep then Status is Bad.

3)If predicted Magnetic is Medium and Depth is medium then Status is Average.

4)If predicted Magnetic is High and Depth is medium then Status is Average.

5)If predicted Magnetic is Medium and Depth is Shallow then Status is Good.

6) If predicted Magnetic is Low and Depth is Medium then Status is Bad.

Rules cause the main condition of the subsurface structure to be defined clearly.

3.2.2 Membership value

The membership value for rule 1and rule 2 and rule 3 is supposed 1 and membership value for rule 4and rule 5 is supposed 0.5, and this parameter for rule 6 is supposed 0.25, where the assumed amount has the ability of dividing effects of rules.

3.2.3 Rule view

The relation among inputs and output variables are conformed to the determined rules, which is shown in Figure14.

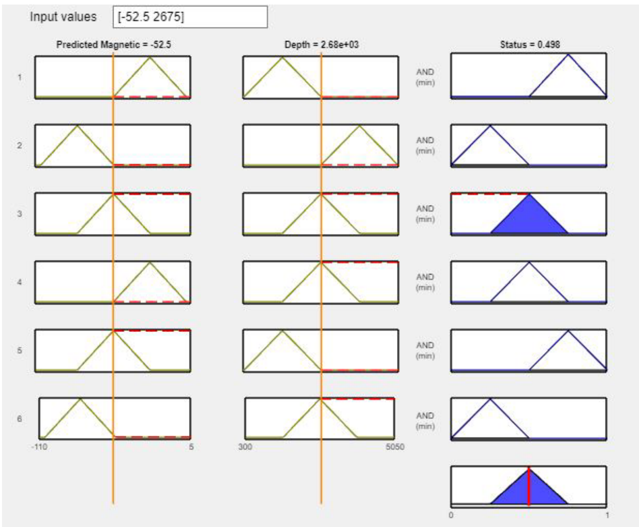

Figure 14. Rule base of the system based on magnetic rate(nT) and predicted depth(m) and rate of the status of the subsurface area.

3.2.4 Surface view

In this model, by applying predicted magnetic rate and depth, the status of subsurface structure is estimated. for obtaining depth, method of Euler deconvolution is utilized which is by using least-squares inversion solves depth prediction subjects, in next step, rules of the model are defined and after that rules are weighted and rules 1,2 and 3 are weighted 1 and rules 4 and 5 are weighted 0.5 and rules 6 is weighted 0.25 and the model is simulated by Mamdani-type of FIS, and the surface view of this system is shown in Figure. 15 which is caused that one innovative model is designed.

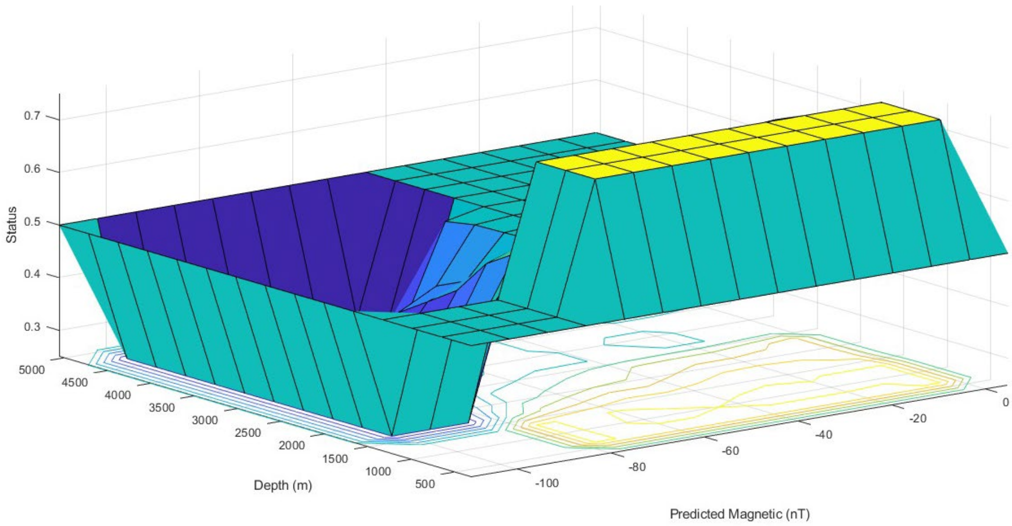

Figure 15. Surface view of fuzzy inference system with the basis of magnetic (nT) and depth(m) and status of subsurface structures which shows the quality of the mentioned area.

In this area, figure 15 shows if the predicted magnetic rate is more than -80 and Simultaneously, the depth is less than 2000, the status of that area is good.

The comparing of Mamdani-fuzzy inference system with Sugeno-fuzzy inference system are available, Mamdani-fuzzy inference system has control on defined rules which can cause better results with defining effective rules but Sugeno-fuzzy inference system by using some algorithms define the rules and decision-maker does not have any control over rules .and uncontrollability of rules cause that calculated model in Sugeno type has much less flexibility.

The overall accuracy of the Sugeno-fuzzy inference system is more, but Mamdani –fuzzy inference system because of defining coefficients parameters has more efficacy in making decisions.

Then via utilizing outcomes of fuzzy inference system, parts of study area where have simultaneously, predicted magnetic rate more than -80 and depth less than 2000 are introduced as proper area for future investigation and figure.16 shows proper parts of study area for future investigation which is resulted by outcomes of fuzzy inference system.

The figure16 shows proper area of study area, where that parts are obtained predicted magnetic rate is more than -80 and simultaneously depth less than 2000, the green points are best parts of study area for future investigation.

Comparison of this unique system with fuzzy inference system by using actual magnetic rate and depth which is calculated by using Standard Euler deconvolution is available and figure 17 shows surface view of fuzzy inference system by mentioned inputs.

Proposed area for future investigation by using fuzzy inference system via using mentioned inputs is shown in figure 18.

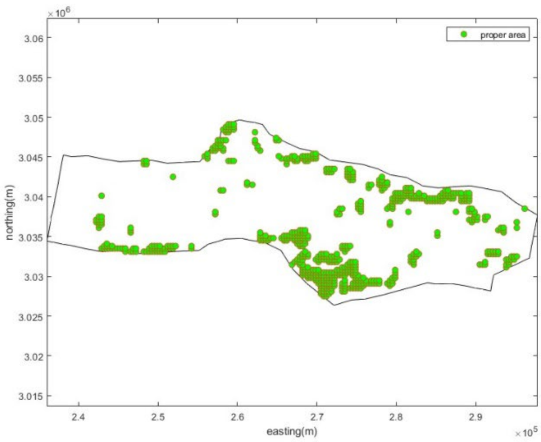

Figure 16. Proposed proper area of study area.

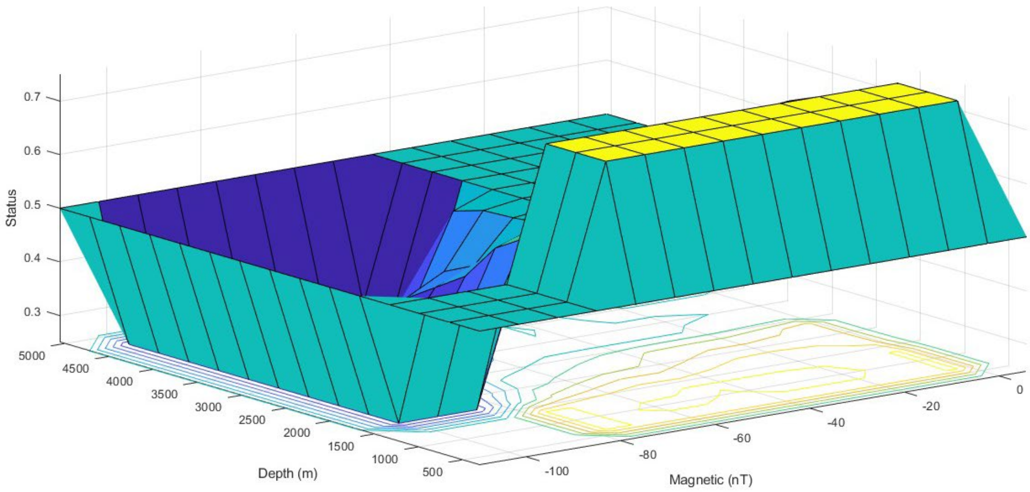

Figure 17. fuzzy inference system by using magnetic rate(nT) and depth(m).

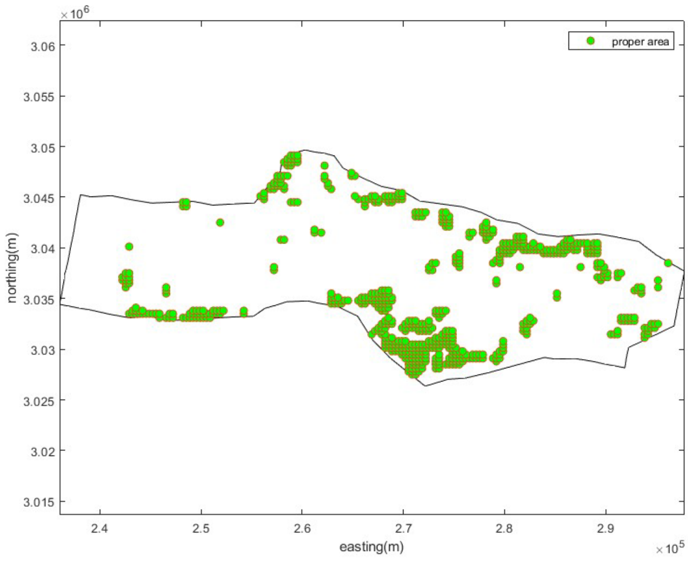

Figure 18. Proposed by using magnetic rate(nT) and depth(m).

The figure18 shows proper area of study area, where that parts are obtained magnetic rate more than -80 and simultaneously depth less than 2000, the green points are best parts of study area for future investigation.

Comparison of fuzzy inference system by using predicted magnetic rate by using MLP and fuzzy inference system by using actual magnetic rate illustrates that fuzzy inference system by using predicted magnetic rate has high similarity with fuzzy inference system by using actual magnetic rate.

4 Conclusions

In most regression modeling, only regression solves the problem without any special type of modeling, and lower rate of accuracy is calculated, but in support vector regression, epsilon and penalty term and kernel function assist to this modeling type. By using this type of modeling, accuracy of regression modeling increases, for this statistical evaluation, we propose two novel types of support vector regression that in first type, via using multilayer perceptron target is estimated then by using support vector regression modeling via estimated target and real value of target is performed, also in regression modeling and MLP_SVR because main parameters of regression modeling and support vector regression are chosen by trial and error, and maybe reaching to higher rate of accuracy is not available, because of this reason in second type of support vector regression, parameters of support vector regression are selected by optimized method by novel type of machine learning, in proposed method firstly multilayer perceptron is utilized until target data points are estimated secondly by using particle swarm optimization, optimized parameters of support vector regression are chosen thirdly by optimized parameters of support vector regression and estimated target and real value of target, support vector regression is created.

Also in most studies related to magnetic surveying, any type of decision making which researchers create model that shows the status of subsurface structures is obvious, but by using fuzzy inference system special system is designed and this system creates model that calculates status of subsurface structures also after designing this system, introducing of proper parts of study area for future investigation is available.

Main finding of this study are;

1-Multilayer perceptron causes that estimating of target is available and this neural network is applicable way for predicting target for solving regression problem.

2- The function of $norm(\sin(x))$ causes that choosing of optimized parameters of support vector regression becomes attainable

3-MLP_PSO_SVR causes that more data points in comparison of MLP_SVR be inside model and this proposed type has better performance in comparison of MLP_SVR.

4-Particle swarm particle is great tool for optimizing main parameters of support vector regression (epsilon, penalty term, and sigma of kernel function)

5-Results of the Fuzzy Inference System illustrates that calculated unique system via predicted magnetic rate and depth has high adaptability with fuzzy inference system that is computed by actual magnetic rate and depth.

6- Fuzzy inference system creates novel manner for notifying status of subsurface structure which can be used in future investigation in study area.

7- By using fuzzy inference system, we have ability to introduce parts of study area that are proper for future investigation.

Conflict of interest The authors declare that they have no conflict of interest.

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