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A new hyper hybrid method of prediction with an intelligent system

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Abstract. Intelligent computing has attracted many scientists and researchers working on intelligent techniques for solving complex real-world problems. We use a method which combines an intelligent neural network system, genetic algorithm and multiple regression to predict the topographical properties of hardened specimens. We use fractal dimension to describe their complexity. Fractal dimensions are calculated by image processing of SEM micrographs in combination with a box-counting algorithm using the ImageJ software. Hybrid evolutionary computation is a generic, flexible, robust, and versatile method for solving complex global optimisation problems and can also be used in practical applications in industry. This paper explores the use of an intelligent system with such a hybrid method to improve the existing hybrids. It describes a new hybrid method based on the loop integration method. At the end, another new hybrid method is presented, a hyper hybrid.

Keywords: intelligent system, hybrid system, machine learning,

Nova hibridna metoda za napovedovanje z inteligentnimi sistemi

Inteligentno računalništvo je pritegnilo številne znanstvenike in raziskovalce, ki delajo na inteligentnih tehnikah za reševanje kompleksnih problemov. Za napovedovanje topografije lasersko kaljenih vzorcev uporabimo metodo, ki združuje inteligentni sistem nevronskih mrež, genetskih algoritmov in multiple regresije. Za opis njihove kompleksnosti uporabljamo fraktalno dimenzijo. Fraktalne dimenzije so bile izračunane z obdelavo SEM slik v kombinaciji z algoritmom štetja škatel s programsko opremo ImageJ. Hibridno evolucijsko računanje je generična, prožna, robustna in vsestranska metoda za reševanje zapletenih globalnih problemov optimizacije in se lahko uporablja tudi v praktičnih aplikacijah v industriji. Ta članek raziskuje uporabo inteligentnega sistema s hibridno metodo za izboljšanje obstoječih hibridov. Opisuje novo hibridno metodo, ki temelji na metodi integracije zanke. Na koncu predstavimo še eno novo metodo hibridnega sistema, hiper hibrid.

1 INTRODUCTION

One of the problems facing researchers is how to improve machine learning methods to avoid their current defects. An obvious solution is to improve individual methods, but there is a constraint problem which we cannot ignore. An alternative is to connect the methods together in a certain way, the so-called hybrid method (hybrid system). Using a hybrid system, we want to improve methods of machine learning. Hybrid methods represent a combination of different machine learning methods. Many authors [1-4] use a variety of hybrid machine learning methods. Most of them combine intelligent systems, neural networks, fuzzy logic, near-neighbour method and genetic algorithms. Author [5] focuses on the system architecture and a usability study of proof-of-concept for these hybrid learning environments. In this work we present a new method for a hybrid system, the loop hybrid.

Robot laser hardening is a technology of the heat treatment process. Today, the technologists who operate various CNC machines only have the knowledge based on practical experience. Each technologist must consider numerous CNC machine parameters to get the best desired results. As this is a very time-consuming process, we use the method of intelligent systems which allows us to obtain results more quickly. Heat treatment is known as a quicker way to access information according to the desired specifications. It was necessary to develop intelligent systems based on individual samples to disclose the topological properties of a material after heat treatment.

In developing our new hybrid system, we were aware that some intelligent system methods do not give good results. Input parameters are the fractal dimensions and process parameters of robot laser hardening, speed and temperature.

In fractal geometry [6], the fractal dimension, D [7], is a statistical quantity that gives an indication of how completely a fractal appears to fill the space as one zooms down to finer and finer scales. The fractal dimension means self-similarity in mathematics and its value is used to estimate the irregularity of fractured surfaces in materials science. Fractal structures can be found in robot laser-hardened patterns [8], too, when they are observed by electron microscopy.

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2 MATERIAL PREPARATION AND METHODOLOGY

We hardened tool steel with a robot laser cell (Fig. 1). After hardening we polished and etched all specimens. A detailed characterization of their microstructure before and after surface modifications was conducted using a JEOL JSM-7600F field emission scanning electron microscope (SEM). We used the program ImageJ (available from the National Institute of Health, USA) to analyse these pictures.

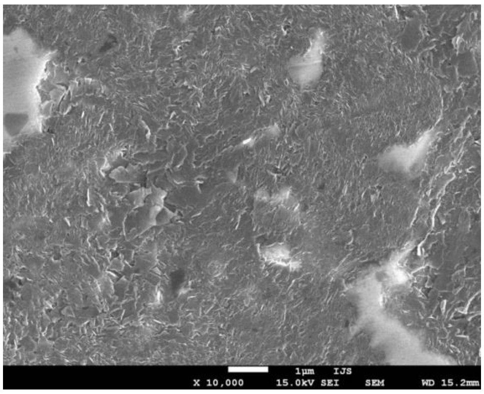

Fig. 1. Fractal structure of a robot laser-hardened specimen

The SEM pictures were converted into binary images, from which we calculated the fractal dimension with a box-counting method.

To analyse of the results, we used an intelligent system method, namely a neural network, genetic programming method and multiple regression. Neural networks are a model-less approximation which perform approximation-modelling operations regardless of any relational knowledge of the nature of the modelled problem. The relational knowledge is typically represented by a set of equations describing the observed variables and constants that are used to describe the system's dependencies. A common use of the neural networks is in multi-dimensional function modelling, i.e., re-creation of a system's behaviour on the basis of a set of known discrete points representing the various states of the system. We use feed-forward neural networks with supervised training algorithms. The basic building element of the neural network used is an artificial neural network cell (ANN) (Fig. 2 left).

In a feed-forward ANN system, the input data is processed from the input to the output. The neurons are classified in four layers called the input layer, hidden layer and output layer. In a supervised training, the ANN applications require a training data set to learn the relationship between the inputs and outputs. The training set should consist of a sufficient number of samples that define a process. Otherwise, an insufficient learning can limit the performance of the ANN approach.

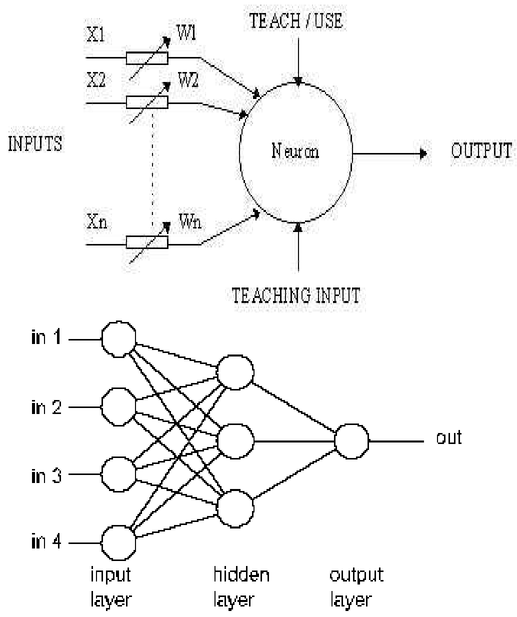

Fig. 2. Symbolic representation of an artificial neural network cell (left), and a general multi-layer neural network system (right).

Genetic programming [9] is a collection of methods for an automatic generation of computer programs that solve carefully specified problems, via the core, but highly abstracted principles of a natural selection. The organisms that undergo adaptation are in fact mathematical expressions (models) for the % part of carbides of hardened specimens prediction in the present work. The % part of carbides prediction is based on the available function genes (i.e., basic arithmetical functions) and terminal genes (i.e., independent input parameters and random floating-point constants). In our case, the models consist of the function genes, such as addition (+), subtraction (-), multiplication (*) and division (/), and the following terminal genes: air temperature [°C] (X1), speed of hardening [m/s] (X2), fractal dimension (X2), and basic % part of carbides (X4).

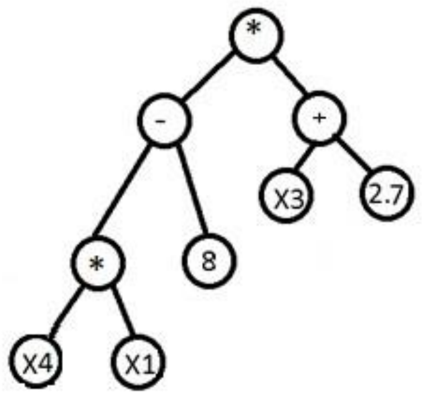

Fig. 3. Randomly generated mathematical model for the % part of carbides of hardened specimens prediction represented in a program tree form.

One of the randomly generated mathematical models (X4×X1-8)×(X3+2.7) is schematically represented in Fig. 3 as a program tree with included function genes (*, - ,/) and terminal genes (X1, X2, X3 and real number constants 7 and 2.8).

The main challenge in evolutionary algorithms is parameter setting. For instance, an inadequate parameter setting can critically worsen the performance of Genetic Algorithms (GA) such as search efficiency. The following evolutionary parameters were selected for the process of simulated evolutions: 500 for the size of the population of organisms, 100 for the maximum number of generations, 0.4 for the reproduction probability, 0.6 for the crossover probability, 6 for the maximum permissible depth in the creation of the population, 10 for the maximum permissible depth after the operation of crossover of two organisms, and 2 for the smallest permissible depth of organisms in generating new organisms. Genetic operations of reproduction and crossover were used. For the selection of organisms, the tournament method with a tournament size 7 was used.

The Analysis of Covariance (generally known as ANCOVA) is a technique that sits between analysis of variance and regression analysis. Covariance is a measure of how much two variables change together and how strong the relationship is between them. ANCOVA can be extended to include one or more continuous variables that predict, the outcome or dependent variable. In Fig. 4 Analysis of Covariance is presented.

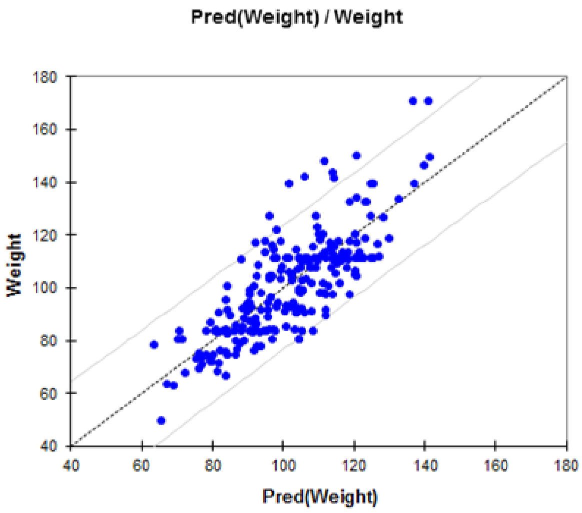

Fig. 4. Analysis of covariance

Hybrid evolutionary computation is a generic, flexible, robust, and versatile method for solving complex global optimisation problems and can also be used in practical applications in industry. A well known method of hybrid system is a sequences hybrid (Fig. 5).

We present a new hybrid system method. Loop hybrid (Fig. 6) methods are connected in series in the direction of the entrance to method n. All methods work independently from one another. The results of input method 1 are transferred to input method 2, the results of input method 2 are transferred to input method 3, and so on, the results of input n-1 method are transferred to the n input method and the results of n input method n are transferred to input method 1. The resilts of input method 1 are transferred to the input loop hybrid. This hybrid has the name loop hybrid.

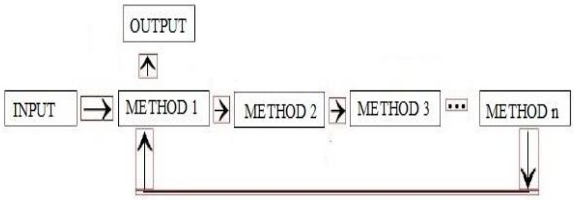

Fig. 6. Loop hybrid

Another new method of the hybrid system is the hyper hybrid. In the hyper hybrid hybrid methods are connected together. We can make different combinations of the hibrid methods.

In a parallel hyper hybrid method (Fig. 7) of the intelligent system, all the hybrid methods are independent. The maximum result of both input hybrid method 1 and hybrid method 2 is transferred to the input of the parallel hybrid.

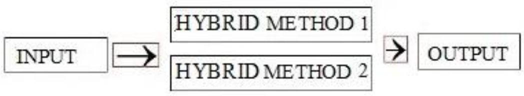

Fig. 7. Parallel hyper hybrid

In our case, in the sequences hyper hybrid, the results of the input sequences hybrid are transferred to the input loop hybrid. The results of the input loop hybrid are transferred to the input sequences hyper hybrid. Method 1 presents genetic programing, method 2 presents the neural network and method 3 presents the analysis of covariance. Hybrid method 1 presents the loop hybrid, hybrid method 2 presents the parallel hybrid.

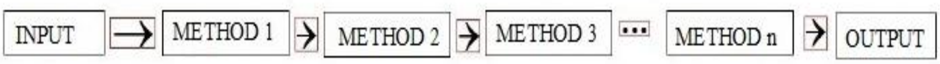

Fig. 5. Sequences hybrid

3 RESULTS AND DISCUSSION

Table 1 presents, the parameters of hardened specimens impacting on % part of carbides. Specimens from P1 to P20, are marked. Parameter X1 presents the parameter of temperature [°C], X2 presents the speed of hardening [mm/s], X3 presents the fractal dimension and X4 presents the base % part of carbides (% part of carbides before hardening). The last parameter is the measured % part of carbides of laser-hardened robot specimens. With the fractal dimension we describe the complexity of hardened specimens. In Table 1 we can see that specimen P11 has the largest fractal dimension, 1.9784. Thus specimen P11 is the most complex. Specimen P18 has the most % part of carbides after hardening, that is 52%. In Table 2, the experimental and prediction data are presented. S presents the name of the specimens, ED presents the experimental data.

Table 1. Parameters of hardened specimens

Specimen	X1	X2	X3	X4	Y
P1	1000	2	1.9135	34	46
P2	1000	3	1.9595	34	45
P3	1000	4	1.9474	34	43
P4	1000	5	1.9384	34	41
P5	1400	2	1.9225	34	36
P6	1400	3	1.9784	34	49
P7	1400	4	1.954	34	45
P8	1400	5	1.9776	34	48
P9	1000	2	1.972	60	46
P10	1000	3	1.858	58.7	32
P11	1000	4	1.9784	56	45
P12	1000	5	1.941	56.5	42
P13	1400	2	1.9784	58	28
P14	1400	3	1.581	57.8	19
P15	1400	4	1.965	58.1	41
P16	1400	5	1.8113	58.2	38
P17	800	0	1.9669	34	47
P18	1400	0	1.9753	34	52
P19	2000	0	1.9706	34	50
P20	950	0	1.6931	34	66

Predictions with the neural network are presented in columns P NN 36% (in our case we use 14 data for the learn test set and 8 data for the test set), P NN 50% (we use 10 data for learn the test set and 10 data for the test set) and P NN 95% (we use 19 data for the learn test set and 1 data for the test set, we use the method one-live-out). Prediction with regression is presented in columns P R, prediction with genetic programming is presented in columns P GP, prediction the with sequences hybrid is presented in columns P SH. Prediction with the new loop hybrid method is presented in columns P LH and prediction with the new parallel hyper hybrid is presented in columns P HH. The measured and predicted % part of carbides of laser-hardened robot specimens is shown in the graph in Fig. 8. The regression model is presented by Eq. (1) and genetic programming model is presented by Eq. (2). The genetic programming model presents a 7.88% deviation from the measured data, which is less than with the regression model with a 19.78% deviation. The best neural network presents a 6.70% deviation from the measured data. The sequences hybrid presents a 12.78% deviation from the measured data, which is less than with the loop hybrid model with a 12.88% deviation. The new hyper hybrid method presents a 12.47% deviation from the measured data, which is less than with both hybrid system methods.

Table 2. Experimental and prediction data

S	ED	P NN 36%	P NN 50%	P NN 95%	P R	P GP	P SH	P LH	P HH
P1	46	50.3	46.8	43.9	56.7	43.6	41.5	47.5	47.5
P2	45	48.5	42.5	43.7	56.7	44.7	47.2	48.0	48.0
P3	43	45.1	43.3	43.7	53.7	43.5	44.8	45.4	45.4
P4	41	43.2	44.1	43.7	50.8	46.0	49.6	48.5	49.6
P5	36	39.6	41.0	43.7	50.6	36.8	43.0	42.8	43.0
P6	49	45.9	44.0	43.7	51.2	45.0	49.3	49.7	49.7
P7	45	48.7	44.3	43.7	47.5	43.6	39.4	39.6	39.6
P8	48	50.9	46.0	43.7	46.4	46.7	42.7	41.2	42.7
P9	46	57.9	41.1	43.6	51.6	39.0	38.5	38.2	38.5
P10	32	56.2	38.5	31.6	44.3	42.7	32.4	33.6	33.6
P11	45	61.7	43.6	43.7	47.8	41.0	45.5	45.8	45.8
P12	42	52.6	43.5	43.7	43.2	41.8	37.8	34.9	37.8
P13	28	46.1	42.2	25.9	44.9	39.2	34.8	35.6	35.6
P14	19	38.7	31.1	22.1	24.0	19.1	23.7	23.3	23.7
P15	41	58.2	44.1	43.7	41.0	40.9	39.1	40.7	40.7
P16	38	53.1	40.3	38.1	31.1	40.1	27.2	26.9	27.2
P17	47	52.3	38.8	53.8	67.5	50.1	57.5	57.9	57.9
P18	52	43.3	40.4	50.4	58.2	50.2	47.9	49.9	50.9
P19	50	33.7	41.5	46.9	48.2	50.1	41.1	41.5	41.5
P20	66	45.8	39.0	60.6	64.9	50.0	47.1	53.1	53.1

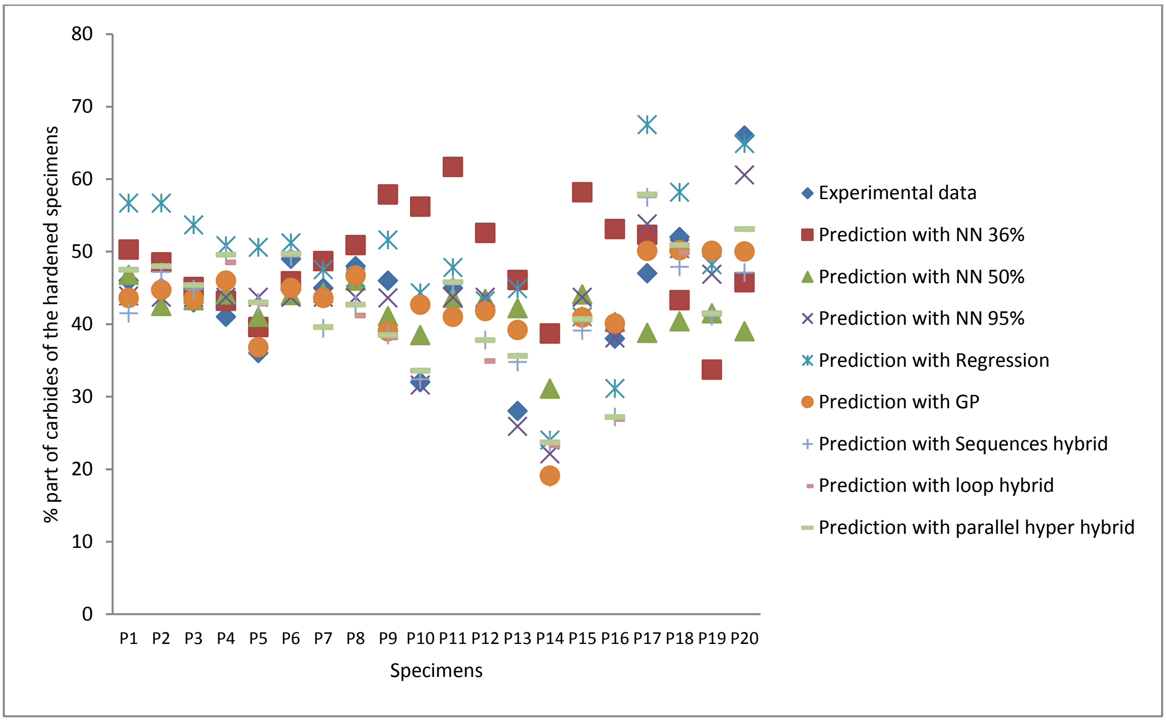

Fig. 8. Measured and predicted % part of carbides of the hardened specimens

Model Regression

Y=−37.31829024−0.016274407*X1−2. 380428751*X2 +52.21955402*X3+0.177886732*X4 Eq. (1)

Model of genetic programming

$$Y = (1.12714 + X3) * (9.28294 + \frac{1.1274*X3*X4}{1.12714+X4}) + 0.112062 * (X3 * (3.41223 + 1.12714*X3*(1.12714+1.12714*X3)) + X4 - \frac{X4+\frac{(4.98722-X2)*X4}{X3}}{X2} + \frac{X4-X2+\frac{(2.28509*(2.58279+X4)}{X4}}{X3*(8.60085-X2-\frac{X4}{X2}} + \frac{(3.58279+X3)*(-4.98722*X3+1.43762*X4)}{X4-X2+\frac{5.86788-X2+X4}{-2.28509+X2-1.12714*X3}} + \frac{(3.58279+X3)*(-3.86008+0.43762*X3*(-2.8509+X4)+X4)}{X1-X2-\frac{2.28509*(3.58279+X4-X2+\frac{2.28509-X2+X4)}{X3*(4.57018-\frac{X4)}{X2})})}{X4}} +$$

Eq. (2)

The porous structure of a material is an important mechanical property that affects the hardness of materials. We cannot apply the Euclidian geometry to describe the % part of carbides of hardened specimens because the % part of carbides is very complex. Here we use fractal geometry to describe the % part of carbides of the robot laser-hardened specimens. In this paper we describe how the parameters (speed and temperature) of the robot laser cell affect the % part of carbides metal materials using a new method, e.g. fractal geometry. The % part of carbides has a large impact on the mechanical properties of a material. With the fractal dimensions we describe the % part of carbides of the robot laser-hardened specimens with overlap. We find the optimal parameters of the robot laser cell that give the minimal % part of carbides. The fractal approach is more appropriate in the characterization of complex and irregular surface microstructures observed in the surface of the robot laser-hardened specimens and can be effectively utilized for predicting the properties of material from fractal dimensions of the microstructure. The fractal analysis of a series of digitized surface microstructures from the robot laser-surface-modified specimens indicates that useful correlations can be derived between the fractal dimensions and the surface microstructural features such as the % part of carbides. The % part of carbides is a good predictor of the performance of a mechanical component. since irregularities in the surface may form nucleation sites for cracks or corrosion. A statistically significant relationship is found between the % part of the carbides measured using the method of determining the % part of carbides from the SEM images of the microstructure. the parameters of the robot laser cell and image analysis with the fractal geometry. In addition, the image analysis of the SEM images of the robot laser-hardened specimens is an interesting approach. We use three methods of the intelligent system to predict the % part of carbides of the robot laser-hardened specimens. Specimen P14 has a minimal %

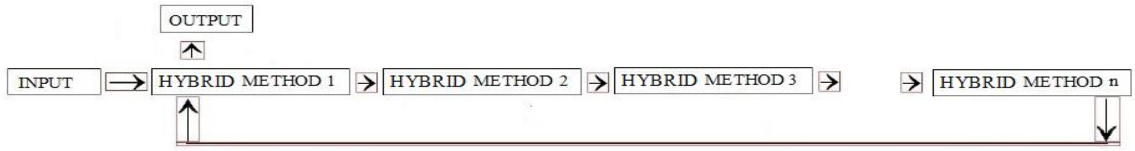

Fig. 10. Loop hyper hybrid

part of carbides after hardening. that is 19 %. We use three methods of the intelligent system to predict the % part of the carbides of robot laser-hardened specimens. We show that the model of genetic programming gives a better predicted result. The neural network model is better than regression, but less than genetic programming. We present a new method of the hybrid system loop hybrid and hyper hybrid. The sequences hybrid presents a 12.78% deviation from the measured data, which is less than the loop hybrid model. which presents a 12.88% deviation. The new hyper hybrid presents a 12.47% deviation from the measured data which is less than both hybrid system methods.

4 CONCLUSSION

The paper presents a new method of the intelligent system to predict the % part of carbides of the robot laser-hardened specimens. We use the fractal geometry to describe the mechanical property, the % part of carbides of the robot laser-hardened specimens. The use of an intelligent system with such a hybrid method to improve the existing hybrids is explored. A new hybrid method based on the cycle integration method is described. The main originality findings can be summarized as follows:

1. To predict the % part of carbides of hardened specimens, we use a neural network, genetic algorithm and multiple regression.
2. The genetic programming modelling results show a good agreement with the measured % part of carbides of the hardened specimens.
3. We develop a new loop hybrid method of prediction with an intelligent system.
4. We develop a new parallel hyper hybrid method of prediction with an intelligent system.

In future, we will suggest new hyper hybrid methods of prediction with an intelligent system, until will make a loop hyper hybrid, such as the one presented in Fig. 10.

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