World Academy of Science, Engineering and Technology
International Journal of Mechanical and Mechatronics Engineering
Vol:10, No:10, 2016

Using Single Decision Tree to Assess the Impact of Cutting Conditions on Vibration

S. Ghorbani, N. I. Polushin

Open Science Index, Mechanical and Mechatronics Engineering Vol:10, No:10, 2016 waset.org/Publication/10005430

Abstract**—**Vibration during machining process is crucial since it affects cutting tool, machine, and workpiece leading to a tool wear, tool breakage, and an unacceptable surface roughness. This paper applies a nonparametric statistical method, single decision tree (SDT), to identify factors affecting on vibration in machining process. Workpiece material (AISI 1045 Steel, AA2024 Aluminum alloy, A48-class30 Gray Cast Iron), cutting tool (conventional, cutting tool with holes in toolholder, cutting tool filled up with epoxy-granite), tool overhang (41-65 mm), spindle speed (630-1000 rpm), feed rate (0.05-0.075 mm/rev) and depth of cut (0.05-0.15 mm) were used as input variables, while vibration was the output parameter. It is concluded that workpiece material is the most important parameters for natural frequency followed by cutting tool and overhang.

Keywords**—**Cutting condition, vibration, natural frequency, decision tree, CART algorithm.

I. Introduction

FOR manufacturing of metal parts, turning is commonly used metal cutting process and specially for finishing machined parts. In a turning operation, the workpiece rotates, while the fixed tool cuts in the workpiece [1]. One of the most important problems during turning operation is unstable cutting due to chatter vibration, which results tool breakage, tool wear, dimensional errors, high cutting forces, reduced productivity and poor machined surface finish. Therefore, it is an important task to avoid chatter vibrations [2]. During the past decades, much research has been undertaken in the field of stability during a turning process. Turning operation contains many parameters such as spindle speed, feed rate, depth of cut, workpiece, cutting tool, coolant, tool nose radius, tool edge angles and tool overhang. Therefore, it is difficult to obtain an optimum cutting condition for achieving the required surface quality [3]-[5]. One of the methods to reduce the chatter in a machining process and improve the productivity is selection of stable cutting conditions [6]. Process damping by tool-workpiece contact is another successful strategy to avoid the chatter vibration as severe chatter occurs due to a relative dynamic motion between cutting tool and work piece [7]-[9]. Reference [2] proposed a realistic analytical stability model of regenerative chatter in orthogonal turning operation. They concluded that work cross-section and tool overhang are the main factors affecting the stability. Reference [7] improved stiffness and damping capability of the tool and suppressed the chatter using impact dampers with different materials such as cast iron, copper, phosphor, brass, structured steel, aluminum, gun metal, and bronze in boring tools. Reference [9] proposed a multiple degree of freedom model for chatter prediction while investigating the compliance between the workpiece and cutting tool in turning process. A new tool design with an increased vibration damping ability was suggested by [10], which includes special elements made of damping materials. They experimentally investigated the impact of damping properties of the proposed model on vibration amplitude, tool life, and surface roughness. References [11] and [12], in their investigation, improved the surface finish in machining operation by predicting and suppressing the vibration level of cutting tool using a passive damping pad of viscoelastic material of neoprene and a passive vibration damping, respectively. Consequently, literature review revealed that vibration during machining process can be reduced by increasing dynamic stiffness of machining system, changing its main natural frequency or feedback-controlled actuators using toolholder made of material with high damping capability, special coating on a cutting insert or vibration damper.

In order to achieve high cutting performance in a turning operation, the cutting parameters should be chosen properly. According to [13], data mining means “solving problems by analyzing data that already exist in databases”. Most of the studies [14]-[18] have mathematically established the cause and effect relationship between cutting parameters and vibration based on statistical regression techniques. They then formulated an objective function to solve the optimal cutting parameters using optimization techniques. All developed equations, for any combinations of parameter levels in a range specified, have the form:

$$Y= b_0+b_1x_1+b_2x_2+b_3x_3 +...+b_px_p$$

where Y represents the estimated vibration value, b_0, b_1, b_2, b_3, …, b_p estimate the regression parameters, and x_1, x_2, x_3, …, x_p are the logarithmic transformation of independent parameters (such as cutting speed (m/min), feed rate (mm/rev), depth of cut (mm), tool nose radius (mm), tool overhang, and material hardness (HRB)).

Although the studies using regression techniques as a method estimate vibration, the optimal cutting parameters and the effect relationship between cutting parameters, they have difficulties in showing the important factors affecting on

S. Ghorbani and N. I. Polushin are with the Department of Functional Nanosystems and High-temperature Materials, National University of Science and Technology “MISiS”, Russia, Moscow, No. 4, Leninsky Prospect, Moscow, Russia (phone: +79269801269, email: siamak.ghorbani@yahoo.com).

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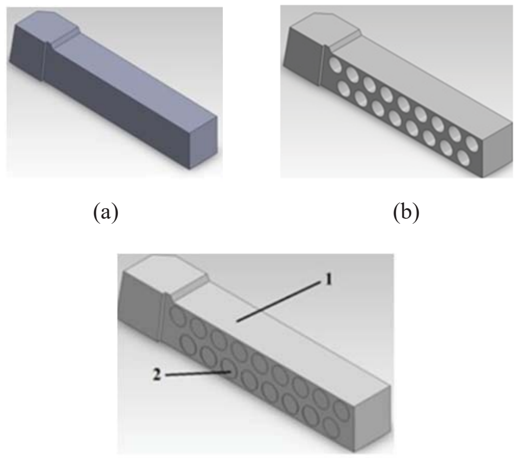
vibration. Besides, linear regression techniques need assumptions to be made, including assumptions about the normality, linearity, and homoscedasticity of the data among others; therefore, it is likely that the assumptions that are made in a regression technique may be violated [19]. The prediction of significant cutting parameters for vibration is not easy to accomplish by using deterministic equations. The growth in the database industry and the resulting market needs for methods that are capable of extracting valuable knowledge from large data stores. For such data, the flexible and robust analytical method is required to deal with high-order interactions, nonlinear relationships and missing values. In addition, the method should be simple to understand and give easily interpretable results. Decision trees method repeatedly splits the data into more homogeneous groups in order to explain the variation of a single response variable using combinations of explanatory variables that may be numeric (regression tree) and/or categorical (classification tree) [20]. The characterization of each group is defined by the value of the response and explanatory variables and the number of observations in the group. The graphical representation of the tree makes it easy to explore and understand [21]. Decision trees method can explore the interactive to descript and predict the patterns and processes. As compared to the other methods, decision tree has several advantages such as flexibility to handle a broad range of response types, including categorical, numeric, survival data and ratings; ease and robustness of construction; invariance to monotonic transformations of the explanatory variables; ease of interpretation and the ability to handle missing values in both response and explanatory variables. Therefore, decision trees represent an alternative method to many traditional statistical techniques such as analysis of variance, multiple regression, linear discriminant analysis, logistic regression, survival models, and log-linear models [20].

Reference [22] used decision tree in their investigation and they stated that the proposed approach has a higher recognition rate than other methods on the same dataset. Reference [23] applied decision tree to diagnose the component fault of rotational mechanical system and assess the workpiece surface roughness. Reference [24] provided a simple way to monitor machine status by synthesizing the knowledge and experiences on the diagnostic case histories of the rotating machinery. For this purpose, a traditional decision tree has been constructed using vibration-based inputs. Reference [25] applied decision tree method to select machine tools and cutting tools, calculate machining parameters and generate CNC part programs for process planning in machining process.

The present study uses SDT model to assess the effect of different parameters such as workpiece material, cutting tool design, and cutting parameters on the vibration during machining operation.

II. Materials And Method

To perform machining experiments, the lathe machine model 16K20VF1 (Russia) with a maximum power of 5.5 kW and maximum spindle speed of 1600 rpm was used. Three types of cutting tools were used: conventional cutting tool, cutting tool with horizontal holes (Ø 7 mm) in toolholder arranged in a chess-board pattern, and cutting tool with horizontal holes (Ø 7 mm) filled up with epoxy-granite, with general specification of PCLNR 2525M12 made of AISI 5140 (Fig. 1). The cutting tool with holes in Fig. 1 (c) is filled up with epoxy granite, the physical and mechanical characteristics of which is illustrated in Table I. Carbide rhombic cutting insert with a general specification of CT35M coated with TiC, manufactured by Sandvik Coromant, was used as a tool insert. AISI 1045 steel, A48-class30 gray cast iron and AA2024 Aluminum alloy were used as workpieces with 65 mm diameter and 200 mm length. This research applies the Taguchi approach to design experiments. Taguchi method is one of the important tools used in the industry to shortage product design, develop time and produce lower product cost. Taguchi method is highly flexible and can allocate different levels of factors, even when the numbers of the levels of factors are not the same [26]. Conventional cutting parameters were spindle speed (s), feed rate (f), depth of cut (d), and tool overhang (l). Three levels were specified for each of the factors as shown in Table II.



(a) (b)

(c)

Fig. 1 (a) Conventional cutting tool (b) cutting tool with holes in toolholder; (c) modified cutting tool filled up with epoxy granite: 1 — toolholder and 2 — epoxy granite

In this study, the natural frequency, which is one of the most important criteria in machining process, is selected. Frequencies occurred during machining was measured by using piezoelectric accelerometer KD-35 attached on the lower side of the cutting edge of the tools and ZETLAB software (Russia). Accelerometer KD-35, multifunctional spectrum analyzer A17-U8 and personal computer were used for recording and visualizing vibration during machining process. Design of experiment based on Taguchi approach and natural frequency values achieved in experimental results during machining of three different workpieces are shown in Tables III-V.

TABLE I
PHYSICAL AND MECHANICAL CHARACTERISTICS OF EPOXY GRANITE

Parameter	Epoxy-granite
Density (kg/m^3)	2400–2600
Strength stress (MPa) Compression Tensile	150-160 15-20
Elasticity module (MPa*10^{-4})	3.5–4.0
Poisson's ratio	0.25–0.40
Thermal conductivity (W/(m*K))	1.7–1.75
Linear expansion coefficient (1/°C)	(12–16)*10^{-6}
Damping ratio	0.6

TABLE II
CUTTING PARAMETERS AND THEIR LEVELS

Variables	Level 1	Level 2	Level 3
s - Spindle speed (rpm)	630	800	1000
f - Feed rate (mm/rev)	0.05	0.06	0.075
d- Depth of cut (mm)	0.05	0.1	0.15
l- Overhang (mm)	41	50	65

TABLE III
NATURAL FREQUENCY VALUE DURING MACHINING OF AA2024 ALUMINUM ALLOY

Experiment No.	s	f	d	l	f_1 (Hz)	f_2(Hz)	f_3 (Hz)
1	1	1	1	1	3491.2	3332.5	3039.6
2	1	2	2	2	2771.0	2917.5	2417.0
3	1	3	3	3	2038.6	2124	2050.8
4	2	1	2	3	2148.4	2148.4	1928.7
5	2	2	3	1	3198.2	3973.4	2917.5
6	2	3	1	2	2868.7	2764.9	2685.5
7	3	1	3	2	2978.5	2740.5	2392.6
8	3	2	1	3	2038.6	2185.1	1843.1
9	3	3	2	1	3173.8	3314.2	3155.5

TABLE IV
NATURAL FREQUENCY VALUE DURING MACHINING OF AISI 1045 STEEL

Experiment No.	s	f	d	l	f_4 (Hz)	f_5(Hz)	f_3 (Hz)
1	1	1	1	1	2795,4	3271,5	2978,5
2	1	2	2	2	3161,6	2844,2	2453,6
3	1	3	3	3	2069,1	2185,1	2087,4
4	2	1	2	3	2111,8	2124	2014,2
5	2	2	3	1	3173,8	3727,8	3027,3
6	2	3	1	2	2856,4	2905,3	2380,4
7	3	1	3	2	2636,7	2966,3	2368,2
8	3	2	1	3	2075,2	2136,2	3521,7
9	3	3	2	1	3039,6	3192,1	3167,6

Refer to Tables III-V, the f_1, f_4 and f_7 represent natural frequency values for conventional cutting tool; f_2, f_5 and f_8 — natural frequency values for cutting tool with holes and f_3, f_6 and f_9 —natural frequency values for cutting tool with epoxy granite.

TABLE V
NATURAL FREQUENCY VALUE DURING MACHINING OF A48-CLASS30 GRAY CAST IRON

Experiment No.	s	f	d	l	f_7 (Hz)	f_8(Hz)	f_9 (Hz)
1	1	1	1	1	3405.8	3271.5	3094.5
2	1	2	2	2	2697.8	2807.6	2673.3
3	1	3	3	3	2050.8	2185.1	2044.7
4	2	1	2	3	2087.4	2148.4	2026.4
5	2	2	3	1	3112.8	4028.3	3448.5
6	2	3	1	2	2819.8	2905.3	2417
7	3	1	3	2	1452.6	2862.5	2612.3
8	3	2	1	3	2331.5	2105.7	1989.7
9	3	3	2	1	3283.7	3137.2	3112.8

Data mining, such as statistical analysis, machine learning and other processes, is the science of extracting useful information from various data sets to discover patterns, models and relationships in data used to make predictions. All of the data mining processes are concerned with certain aspects of data analysis, so they have much in common; but each data mining process also has its own distinct flavor, emphasizing particular problems and types of solution [27].

To classify and predict problems, the decision trees can be applied as a powerful and simple data mining [28]. Decision tree is a diagnostic tool that builds the knowledge-based system by the inductive inference from case histories. A decision tree consists of leaf nodes that contain class name and decision nodes that specify some test to be carried out on a single attribute value of an instance, with one branch and sub-tree for each possible outcome of the test. Starting at the root node of the tree, the instance is classified [29]. If this node is a test, the outcome for the instance is determined, and the process continues using the appropriate subtree. When a leaf is eventually encountered, its label gives the predicted class of the instance [27]. The decision is described graphically in order to obtain a target value through the classification and analysis. Once the relationship between the object of analysis and input fields is extracted, then the decision rules can be derived describing the relationships between inputs and targets. Decision rules can predict the values of new or unseen observations that contain values for the inputs, but might not contain values for the targets [30].

In 1986, the application of decision trees to classification in machine learning was popularized by [31] where a tree-growing algorithm to induce decision trees ID3 was introduced. Then, in 1993, the ID3 was upgraded with an algorithm called C4.5 [29]. These algorithms build a decision tree using the statistical calculation of information gain from a single attribute. The algorithm basically chooses the attribute that provides the maximum degree of discrimination between classes locally. Theoretical concepts related to decision trees can be found in many text books [27], [31].

Classification and Regression Trees (CART) analysis is a tree-building technique which has been found quite effective to create decision rules. CART is a nonparametric technique, which is able to select the most important variables and their interactions to determine the outcome variable to be explained.

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CART is also able to uncover complex interactions between predictors, which are difficult or impossible using traditional multivariate techniques. The CART methodology was developed in 80s by [32] in their paper called "Classification and Regression trees".

In CART, the observations are successively separated into two subsets based on associated variables significantly related to the response variable. CART as a recursive partitioning method builds classification and regression trees to predict categorical predictor variables (classification) and continuous dependent variables (regression). Each (classification and regression) deals with the prediction of a response variable *y* given the values of a vector of predictor variables *x*. The major tasks in classification or regression tree algorithm are: how to partition the data at each step?, when to stop partitioning?, and how to predict the value of *y* for each *x* in a partition? [33]. The objective is to partition the response into homogeneous groups, but also to keep the tree reasonably small. Splitting is continued until an overlarge tree is grown, which is then pruned back to the desired size [34]. For interpretation of the model, a large majority of algorithms apply univariate splits of the form $X_i \in B$ (if X_i is a categorical dependent variables) or $X_i \leq d$ (if X_i is a continuous dependent variable). The split set B or the variable X_i and the split point d are found by an exhaustive search optimizing a node impurity criterion such as sum of squared residuals (for regression) or entropy (for classification). The predicted *y* value at a leaf node is the class minimizing the estimated misclassification cost (for classification), or the fitted value from a model estimated at the node (for regression) [33]. In regression tree, the least squared deviation (LSD) impurity measure is applied to split rules and goodness of fit criteria. The LSD measure *R(t)* is the weighted within node variance for node *t*, and it is equal to the resubstitution estimate of risk for the node. It is defined as:

$$R(t) = \frac{1}{N_w(t)} \sum_{i \in t} w_i f_i (y_i - \bar{y}(t))^2 \tag{1}$$

$$\bar{y}(t) = \frac{1}{N_w(t)} w_i f_i y_i \tag{2}$$

$$N_w(t) = \sum_{i \in t} w_i f_i \tag{3}$$

The $N_W(t)$ represents the weighted number of records in node t, the weighting field value for record i (if any) and the frequency field value (if any) are shown as w_i and f_i, respectively. y_i is the value of the target field, and $\bar{y}(t)$ is the mean of the dependent variable (target field) at node *t*. The LSD criterion function for split s at node *t* is defined as:

$$Q(S,T) = R(t) - R(t_L) - R(t_R) \tag{4}$$

where, $R(t_R)$ and $R(t_L)$ are the sum of squares of the right and left child nodes, correspondently. Maximization of *Q(s,t)* is done by choosing the split s. Decision of the algorithm for stopping the splitting nodes in the tree are controlled by stopping rules. Tree growth continues until each tree leaf node causes at least one stopping rule. A node may not be split if:

a. All records in the node have the same value for all predictor fields used by the model.
b. The number of records in the node is less than the minimum parent node size (user defined).
c. If the number of records in any of the child nodes resulting from the node's best split is less than the minimum child node size (user defined).
d. The best split for the node decreases impurity which is less than the minimum change in impurity (user defined). In regression trees the $\bar{y}(t)$ is the predicted category of each terminal node.

III. Application of Decision Tree and the Results

In order to develop a model, using single decision, a tree should be created. At first, after examination of each node the best possible split is found. Then, each predictor variable and each possible split on each predictor are examined. In the next stage, it should be determined each row goes into which child node. This may involve using surrogate splitters. The process continues when the criterion is stopped (e.g. the minimum node size is reached). The next step is pruning the tree. Firstly, a set of cross-validation trees is created. Then, for each possible tree size, the cross validated misclassification cost is computed. Finally, the primary tree is pruned to the optimal size.

TABLE VI
Results of the Error Statistics Calculated Natural Frequency

Correlation between actual and predicted	0.8632
Maximum error	0.9471
RMSE (Root Mean Squared Error)	0.3884
MSE (Mean Squared Error)	0.1508
MAE (Mean Absolute Error)	25.890
MAPE (Mean Absolute Percentage Error)	27.915
Normalized mean square error (NMSE)	0.3230

TABLE VII
Relative Importance of Variable on Natural Frequency

Workpiece material	100
Cutting tool	23.3
Overhang	13.9
Spindle speed	8.4
Depth of cut	7.3
Feed rate	6.2

At the end of a training process, the model with the lowest error was selected as the final model. For qualitative evaluation of the models, the statistical measures such as the correlation between actual and predicted, maximum error, root mean squared error, mean squared error, mean absolute error, mean absolute percentage error, and the normalized mean square error were used. The SDT diagrams and the error statistics of calculated significant cutting parameter on natural frequency by CART are illustrated in Fig. 2 and Table VI, respectively. The information displayed in each node in Fig. 2, depends on whether it is part of a classification tree (categorical target variable). Each decision tree is a

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hierarchical structure that contains rules of prediction. Relative abundance of a functional group was first split into two branches by a variable which best explained the variance. In order to define the predicted value of a row start with the root node (node 1 in Fig. 2). Then, decide whether to go into the left or right child node based on the value of the splitting variable. Continue this process using the splitting variable for successive child nodes until one reaches a terminal, leaf node. The value of the target variable shown in the leaf node is the predicted value of the target variable.

The relative importance of environmental and management variables in influencing the functional group abundance in a decision tree was indicated by the order they were selected in splitting the tree. The variable selected first was more influential than those selected after it. As can be seen from Fig. 2, the greatest number of branching was performed using workpiece material Thus, workpiece material is the most important parameters for natural frequency. Table VII illustrates the relative importance of variables on natural frequency.

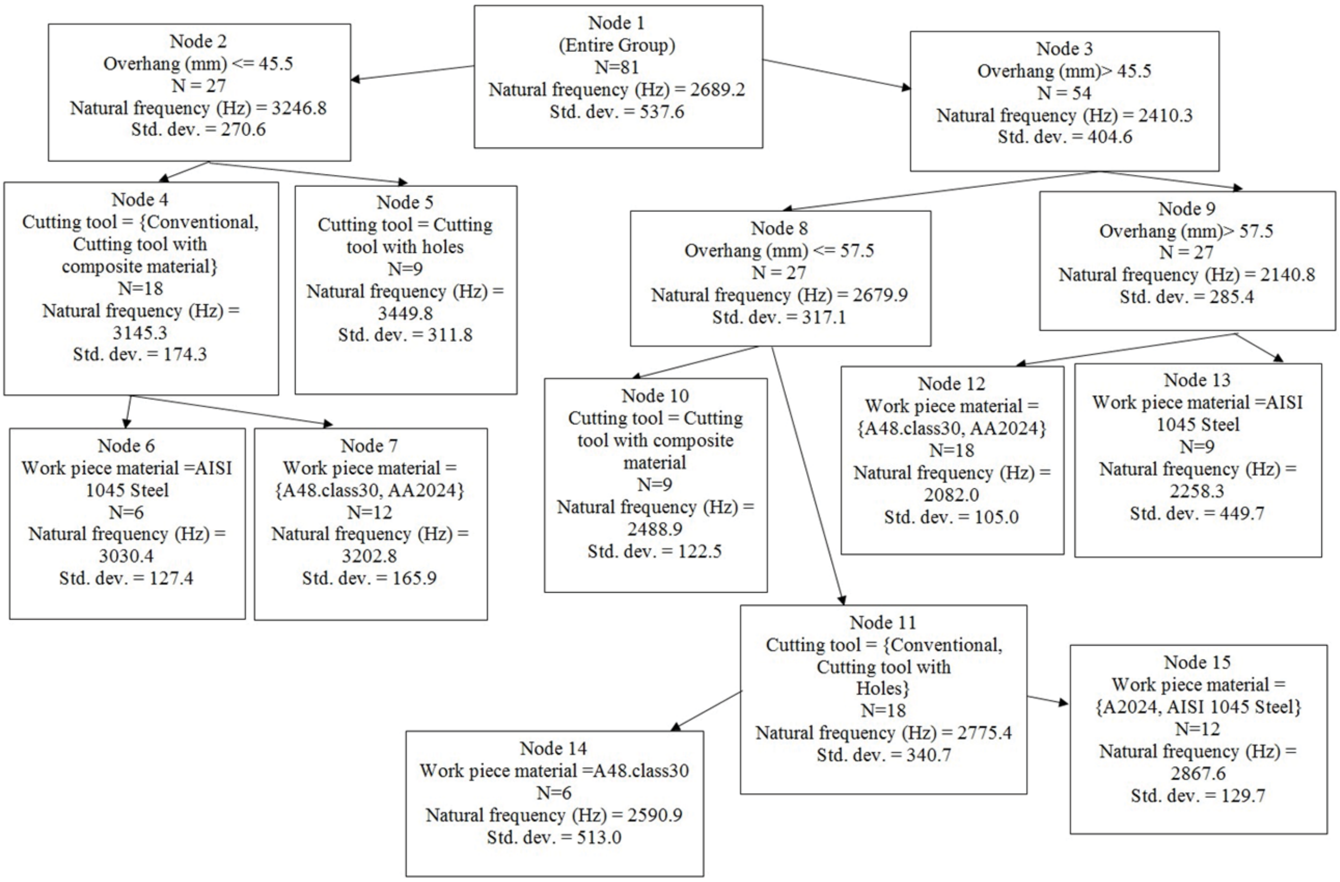

Fig. 2 SDT generated by CART algorithm

IV. Conclusion

Decision tree learning is a promising approach for classification and regression problems. In this paper, we have applied this approach to assessment the impact of cutting conditions (workpiece material, cutting tool, spindle speed, feed rate, depth of cut and tool overhang) on vibration. The overall predictive accuracy of R^2=0.86 is high considering the strict criterion used in the model validation. The hierarchical structure of the decision trees clearly revealed the relative importance of environmental and management variables in influencing relative abundance of the functional groups. Workpiece material was indicated as the most important factors influencing the abundance of vibration. In addition, we can use the tree to make inferences that help us understand the "big picture" of the model. One of the great advantages of decision trees is that they are easy to interpret even by non-technical people.

Acknowledgment

The work was carried out with financial support from the Ministry of Education and Science of the Russian Federation in the framework of Increase Competitiveness Program of NUST «MISiS» (№ К4-2015-053).

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