Process modeling of non-contact reverse engineering process

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Abstract: - In presented paper a design model is developed which is used to find an optimal design space in order to improve precision and accuracy of reversed 3D models. Significant parameters and their mutual effects in scanning process are recognized with the help of Design of Experiments (DOE) principles, and in second step recognized significant parameters are also optimized using the RSM (Response Surface Methodology). Back propagated neural network is used for prediction of response factors whose input variables are not possible to set during experimentation due to the nature of the scan device. With neural network (NN) predicted response-design data, the Analysis of Variance (ANOVA) test was performed. On a basis of significant parameters the analytical model is established, which enables prediction and optimization of critical scan parameters, according to the prescribed standard deviation (abberation) of analysed 3D CAD models. After getting knowledge about the relationships between significant parameters it is possible to predict and optimize them using a model established in the RSM on a basis of D-optimal Design of Experiment test (DOE). At the end also the precision assessment of predicted response factors by DOE approach and by neural network approach is done and results are beeing compared.

Key-Words: - DOE, Neural network, ANOVA, D-optimality, RSM

1 Introduction

Like in any technical process, as for instance cutting, deep drawing, injection molding, etc., it is also possible to define a model of laser scanning process in reverse engineering discipline. Laser scanning process is quite a complex process, where many different factors interacts simultaneously and their mutual effects are not always easy to predict. Generally, all parameters which appear in a scanning process, can be divided in three groups: optical inside process parameters, cnc machine parameters, and external parameters, which are hard or impossible to control or predict.

In a modern literature there is not much work, which would describe a laser scanning process on an input/output process box basis. There are many contributions which investigate usually one or two parameters and their influence on a quality (precision) of laser scann results [1,2,3], but there are practically no scientific investigations which would describe a process as a whole, taking into account wide range of crucial parameters and their mutual interactions, and moreover there are very few attempts of optimizing those factors [4], or even less to predict them.

There are a few good accesses which investigated the influence of free form surface lean angle and distance of laser head from scanned object on quality of reconstructed surface [5,6], but we seriously believe that in order to establish a reliable model of scanning process, at least the mayority of most important possible input scan parameters should be considered. But in this area it is noticeable lack of scientific contributions and investigations. Mostly there are only recomendations of some laser scann device producers, which are fitted only to their particular developed device, or are only inteneded for use in calibration process [7,8].

2 Statistical modelling approach to investigated process

When a large number of process influencing factors have to be investigated, it is a reasonable way, to consider and study all kinds of statistical based experimental designs, that should already be considered when preparing experiments, which will make our experimental data base for setting the model of investigated process.

In statistical theory there is a technical definition of the amount of information in an experimental design, and maximizing D criterion corresponds to maximizing the information content in this sense. Commonly used designs for first/second order response surface models include Factorial and Fractional Factorial designs, Central Composite Designs (CCD), Box-Behnken designs etc. These work well with regularly shaped design spaces and small number of variables. For non-regular spaces, such as those encountered in many engineering problems with constraints, computer algorithms have been developed for choosing the best set of designs based on minimizing certain statistical

criteria. Amongst the most popular such criterion is D-Optimality. [9]
The optimization capability of scan process in presented paper is based on Response Surface Methodology (RSM) performed with data set constructed on a basis of D-optimal criterion. D-Optimality criterion is used for the effective distribution of sampling points which enables generalization of the design response. A design is said to be D-optimal, if inverse product

$$\left|(X'X)^{-1}\right| \quad (1)$$

is minimized, where X is the matrix of design point vectors, and X'X is a simulation matrix [10] D-Optimal design minimizes the maximum variance of any predicted value. The algorithm used to find D-optimal design is as follows [11]:
1. Select a non-singular initial design of p points (central composite design in presented paper)
2. Pick the candidates point with the largest Euclidean norm as the first design point. This first point will be one of the perimeter design points, i.e., one of the points furthest from the center of the design space.
3. Pick each subsequent design point to give the maximum information about the estimable linear combinations of model coefficients and to increase the rank of the design matrix.

2.1 Response Surface Methodology as a method used for model evaluation

Response Surface Methodology (RSM) is a collection of statistical and mathematical techniques used for developing, improving and optimizing the mathematical described design process. RSM encompasses a point selection method (also referred to as Design of Experiments), Approximation methods and Design optimization methods to determine optimal settings of the design dimensions. RSM has important applications in the design, development, and formulation of new products, as well as in the improvement of existing product designs. A Successive Response Surface Methodology allows convergence of the design response. A space filling sampling scheme is used to update the sampling set by maximizing the minimum distances amongst new and existing sampling points.
Main part of RSM is analysis of variance (ANOVA) to estimate accuracy of the fitted model and to provide statistical guidelines to adjust the model for an improved fit. However, as the number of variables increases, this criterion becomes rapidly intractable as the associated combinatorial optimization problem becomes extremely complex. The most widely used models in RSM are the linear and quadratic models (first/second degree polynomials) because of the wealth of experience associated with them and also because the DOE methods developed are mostly limited to linear/quadratic models [12].

3 Identification of process modelling parameters

Schematic overview of presented scan model process with involved model parameters is shown on figure 1. Investigation was performed on seven input and two output parameters. Two of input parameters are uncontrollable and depend on instantaneous light circumstances.
It is supposed that modelling of scan process deals with the identification of the process transfer function denoted by $f(\cdot)$ that represents the relation between the outputs Y and the inputs X, considering random process disturbances Z(X) causing system fluctuations:

$$\boldsymbol{Y}=f(\boldsymbol{\beta},\boldsymbol{X})+Z(\boldsymbol{X}) \quad (2)$$

Generally, process transfer function $f(\cdot)$ with unknown structure and parameters $\boldsymbol{\beta}$ can be modelled via $g(\cdot)$ [13]:

$$\hat{\boldsymbol{Y}}(\boldsymbol{X})=g(\hat{\boldsymbol{\beta}},\boldsymbol{X}) \quad (3)$$

where $\hat{\boldsymbol{Y}}$ represents the modelled output, and $\hat{\boldsymbol{\beta}}$ the estimated model parameters [13].
Identification of complex process transfer functions can be approached on a system level.

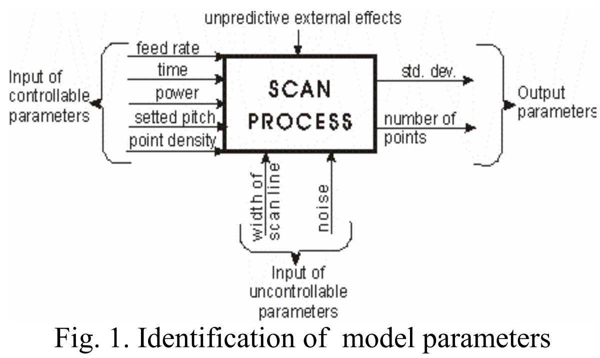


Fig. 1. Identification of model parameters

On a basis of scanned point clouds the response factors (R1,R2) presented in historical data modeling vector in Table 1. were determined.

F1: A	F2: B	F3: C	F4: D	F5: E	F6: F	F7: G	R1	R2
line width	noise	feed rate	int. time	power	setted pitch	point density	standard deviation	number of points
INPUT PARAMETERS							OUTPUT PARAMETERS	

Table 1. Data model vector construction

There are 74 such model vectors included in an experimental data set (also called Historical data set), each consisting of input (setted) and output (measured) parameters. Each model vector consist of 7 input factors (2 numerical and 5 categorical) and 2 output numerical parameters. These parameters have indirect influence on later surface acquisition and its accuracy in final 3D reversed model, therefore should be well chosen. [14,15]
Input and response factors studied in presented paper are the following:
-line width is a common name and it means the width of a scanning line measured in pixels
-noise is a nondimensional value for measuring external disturbances, and tells about efficiency of laser beam
-feed rate is a drive speed of kreon scanning head fixed on a CNC machine spindle, as shown in figure 2. and it travelles in one of machine axes directions. Three values which were used are: 2.5mm/s, 5.0mm/s and 10mm/s.
-integration time in seconds has five values: 0.001s, 0.002s, 0.004s, 0.008s and 0.017s. It means time of laser beam integration in CCD camera [15]
-power of laser beam has three values: 2mW, 2.5mW, and 4mW
-setted pitch is a distance between measured points in X and Y direction. Values used are: 0.1mm, 0.2mm, and 0.3mm.
-point density means which sequential point was measured in axes direction, and it has values: 1by1, 1by2, amd 1by4
-standard deviation of reversed CAD model from point cloud as a statistical measure for quality of reversed model
-number of points represents number of scanned points in reversed CAD model

3.1 Adapted milling machine for laser scanning operation

This 3D non-contact measurement system consists of an X,Y,Z-table from the Flexmatic company (SLO), a 1D laser displacement sensor type Zephyr KZ-50 from the Kreon company (France), a PC-486 computer and multifunction interface cards PCL-711, PCL-726 and PCL-833 from the Advantech company. The layout of this 3D measuring system is shown in Fig. 2. The X,Y,Z-measuring table is driven by a.c. servo motors. The encoder for each a.c. servo motor has a resolution of 2000 pulses per revolution. Drivers for the a.c. servo motors are of the voltage control type. A multifunction interface card, PCL-833, which includes three channel encoders and counters, was used to read in the displacement data for each axis. The table was controlled using PC controller. The accuracy of the measuring table is 0.01 mm for each axis. The interface card PCL-711 has a 12 bit A/D channel to read in the laser displacement data. Divisibility of laser sensor is 0.005mm, and repeatability is 0.006mm. Hence, the measuring accuracy is 0.01 mm for the laser sensor. The control system was controlled by PC that was used to handle all the I/O data for the system and to calculate the control parameters.

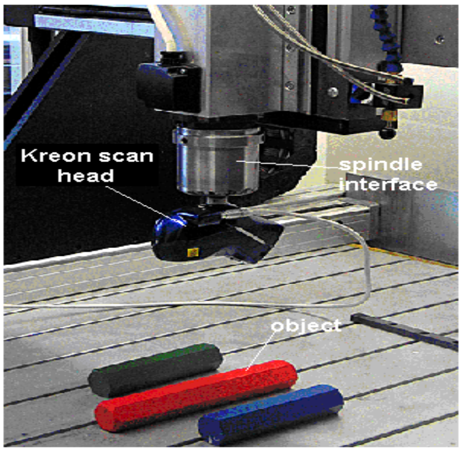


Fig. 2. 3D non-contact measurement structure, adapted to 3 axis milling machine

Machine information is used to find the position of the laser plane in 3D space. This allows us to create a transformation matrix between the UV sensor system of coordinates and the object in XYZ world coordinates. This information has to be perfectly synchronized with video scanned data. CNC machine is moving along paths programmed by Kreon software, named Polygonia. Connection through RS232 serial link. on the »fly« mode requires the retrieval of data from the machine encoders. [16,17] Positions can be captured while the machine is moving, using Kreon's real time electronics process unit. Machine and laser head is shown in figure 2. As a scan object six-angles steel bars were used, painted in green, red and blue color. Red, green and blue are colors that represents RGB scale and are part of any mixed color on arbitrary objects in praxis. These bars are convenient to establish a design model of a process, because their height is uniform in length and surface break has the same angle in all scanning length. So it was possible to set the best uniform optimal distance between object and camera for all exemples. The length of scan snaps was 75 mm for all 74 examples.

4 Problem formulation

It is impossible to exactly set some of input parameters as prescribed with the D-optimal test, due to the technical properties of Kreon scanning head and posibilities of Polygonia software interface which is used to controll and drive Kreon scanning head. For five parameters only values of a few levels (3 or 5) are possible to set, so they are not possible to set as continuous numeric values. There are also two parameters (line width and noise) which are not possible to adjust by any mean, although they change themselves according to the experiment conditions. So problem arises how to exactly match the prescribed values (which are to be followed in D-optimal test), with the actual feasible values. This problem will be overcome with the use of neural network for output parameters prediction on a basis of input parameters which were not possible to set during experimentation. After prediction of output parameters, it is possible to perform ANOVA analysis in D-optimal DOE procedure.

Bad alternative would be use of RSM on a basis of Historical data sets (these are data not obtained in DOE) instead of D-optimal test, but in praxis Historical data sets are omitted. There are some significant lacks of Historical data sets yield within DOE procedure. Instability is typical of models based on Historical data sets. Many times factors are mutual aliased, which means that there are not enough unique design points to independetly estimate all the coefficients for such models. So model could become unstable. That is why in Historical DOE many times the order of the model must be downgraded to linear to avoid aliasing coefficients. [18]

5 Data acquisition for –D- test using back propagated neural network

As stated in Chapter 2. the Historical data set consists of 74 model vectors. Seven input parameters of this data set are feed into back propagated neural network, which is trained and later used for prediction of output parameters for D-optimal data set. After introducing D-optimal test inside DOE software, the data set was reduced to 52 modelling vectors.

5.1 Construction and training of neural network

The most common neural network model is the multilayer perceptron (MLP). Let us suppose that the scanning process can be modelled by a two hidden-layered network as:

$$\hat{Y}(\boldsymbol{X}) = g(\hat{\boldsymbol{\beta}}_i, \boldsymbol{X}, \boldsymbol{a}_j, b_j) = \sum_{j=1}^{K} \hat{\beta}_{ij} \tanh\left(\boldsymbol{a}_j^T \boldsymbol{X} + b_j\right) \tag{4}$$

where $g(\cdot)$ is represented by K neurons with hyperbolic tangent sigmoidal basis function with synaptic weights, $\boldsymbol{a}_j$, threshold parameter, b_j, and linear neuron with synaptic weights, $\hat{\boldsymbol{\beta}}_i = (\hat{\beta}_{i1}, \dots, \hat{\beta}_{iK})$ [3]. The learning algorithm is called momentum backpropagation.

Neural network consists of 4 layers: input, two hidden and one output layer. Input layer has 7 neurons, for each input one. First hidden layer has 7 neurons or processing elements, second five, and output layer has two neurons, each for one output.

This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output, using historical data organized in a data vector from figure 2., and gathered with Kreon scan head mounted on a 3 axes CNC milling machine as shown in figure 3. After training, the model can be used to produce the output when the desired output is unknown. Figure 3. shows learning curves for both the training and cross validation data sets as well as the mean squared error (MSE) achieved during training. [11]

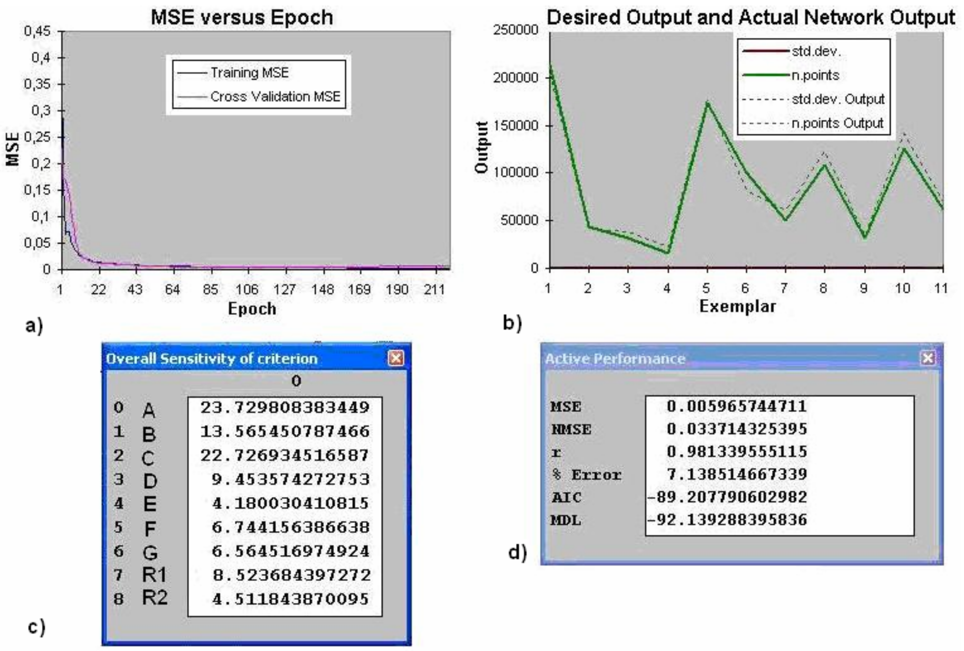


Fig. 3. a)Learning curves of training and cross validation data sets; b) neural network tested on 11 unknown 3D models; c) sensitivity analysis for weight changes during training; d) neural network performance estimation

Network weights are automatically saved at the point where the cross validation error is at the lowest value. For the example above, the weights were saved after epoch number 116. The true power and advantage of neural networks lies in their ability to learn relationships directly from the data being modeled.
Sensitivity analysis found out how much particular input parameter contributed to the weight changes during neural network processing. The contribution of particular parameter on weight changes in % is as presented in figure 3c. It is obvious that first four parameters have greatest influence during neural network training process. These parameters will be also shown in next chapter to be the most significant in ANOVA test. .
For testing purposes 11 exemplars (15%) of 74 model vectors were left aside and prediction with the trained NN was done for those 11 models, whose outputs were not known to the neural network. Figure 3b.. shows the comparison of desired and actual network outputs.
The trained network will be used for prediction of output data as prescribed by D-optimal design test (52 modelling vectors), because this is the only way to obtain output values for D test, due to the constrain posibilities of parameter settings in experimental procedure.

6 Checking for model adequacy and its verification

The right model was evaluated and selected, according to the evaluation analysis whose result is shown in Table 2. It is important that chosen model is most significant and that it is not aliased. Small Prob > F value (less than 0.05) indicates that there is a strong model effect, while values greater than 0.10 suggest no significant effects.

Table 2. Model selection table in ANOVA analysis

Sequential Model Sum of Squares [Type I]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Mean vs Total	0.12	1	0.12			
Linear vs Mean	8.738E-003	8	1.092E-003	174.08	< 0.0001	Suggested
2FI vs Linear	2.318E-004	27	8.584E-006	3.61	0.0048	Suggested
Quadratic vs 2FI	2.446E-005	6	4.076E-006	3.01	0.0602	
Cubic vs Quadra	1.356E-005	5	2.712E-006	6.366E+007	< 0.0001	Aliased
Residual	0.000	5	0.000			
Total	0.13	52	2.532E-003			

Selected is the most significant model (linear vs mean), which is also suggested in a Table 2. The high F-value of 174.08 in table 2. associated with the linear model means ratio of the Model SS / Residual SS and shows the relative contribution of the model variance to the residual variance. A large number indicates more of the variance being explained by the model; a small number means the variance may be more due to noise.

7 Anova test of predicted D-optimal data set

Table 3. Analysis of variance for standard deviation

Analysis of variance table [Classical sum of squares - Type II] Std.dev

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	8.738E-003	8	1.092E-003	174.08	< 0.0001	significant
A-line_width	6.866E-003	1	6.866E-003	1094.40	< 0.0001	
B-Noise	1.719E-004	1	1.719E-004	27.39	< 0.0001	
C-feed_rate	5.260E-005	1	5.260E-005	8.38	0.0059	
D-time	1.310E-003	1	1.310E-003	208.74	< 0.0001	
E-power	1.428E-004	1	1.428E-004	22.76	< 0.0001	
F-setted_pitch	1.001E-005	1	1.001E-005	1.60	0.2133	
G-point_densi	1.254E-005	2	6.268E-006	1.00	0.3766	
Residual	2.698E-004	43	6.274E-006			
Lack of Fit	2.698E-004	38	7.100E-006			

The Model F-value of 174.08 in Table 3. implies the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.05 indicate model terms are significant In this case A, B, C, D, E are significant model terms Values greater than 0.10 indicate the model terms are not significant If there would be many insignificant model terms, then some measures should be taken in order to improve the existing model. But this is not the case in presented model. Selected significant parameters are also in well agreement with sensitivity analysis of neural network weights shown in figure 3, which is one more proof that the design model was well chosen.

Table 4. Analysis of variance for number of points

Analysis of variance table [Classical sum of squares - Type II] n.points

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	5.197E-011	8	6.497E-010	27.17	< 0.0001	significant
A-line_width	9.481E-009	1	9.481E-009	3.97	0.0528	
B-Noise	5.650E-009	1	5.650E-009	2.36	0.1316	
C-feed_rate	2.484E-011	1	2.484E-011	103.89	< 0.0001	
D-time	3.807E-010	1	3.807E-010	15.92	0.0003	
E-power	2.320E-008	1	2.320E-008	0.097	0.7569	
F-setted_pitch	6.639E-008	1	6.639E-008	0.28	0.6010	
G-point_densi	1.525E-011	2	7.624E-010	31.88	< 0.0001	
Residual	1.028E-011	43	2.391E-009			
Lack of Fit	1.028E-011	38	2.706E-009			

Table 4. shows significant terms for response factor »number of points«. In this case most significant parameters indicated are C »feed rate«, D »integration time« and G »point density«. This was also expected since it is obvious that travelling speed of scan head and density of points picking should influence the scan point number in a great deal. This is also one more confirnation that the model was well chosen. Particular important are parameters C and D, because they have a great influence in std.dev. as well as in point number prediction. It will be shown in chapter 7.3 that there exist only one real interaction between parameters, and this is between D »integration time« and G »point density«, so parameter D should be changed very carefully, because it can happen that when it improves response of std.dev., it can at the same time make worser point number prediction, indirectly changing parameter G. Special attention should be paid to the parameters C and D, because they reveal in both ANOVA reports as significant. This means when changing parameters C or D at one response prediction, it may unintentionally also affect the other response factor prediction.

Table 5. Statistical estimates of selected design model

Std. Dev.	2.505E-003	R-Squared	0.9700
Mean	0.049	Adj R-Squared	0.9645
C.V. %	5.16	Pred R-Squared	0.9560
PRESS	3.963E-004	Adeq Precision	42.029

Table 5. indicates a few other estimates of selected model. The "Pred R-Squared" of 0.9560 is in reasonable agreement with the "Adj R-Squared" of 0.9645. "Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. Ratio of 42.029 indicates an adequate signal. It means that this model can be used to navigate the design space.
Now final equations in terms of coded factors for prediction of both responses can be written:

std.dev = +0.048 + .012* A + 1.980E-003 * B - 1.090E-003 * C + 5.384E-003* D + 1.751E-003* E - 4.790E-004 * F + 2.056E-004* G[1] - 6.925E-004* G[2]
and
npoints = +1.246E+005 - 14380.73 *A + 11353.66 *B - 74875.31*C - 29025.62*D + 2232.03*E - 3900.72*F + 72057.26*G[1] - 12448.89*G[2]

Data members were checked and proved according to the normal plot of residuals to represent normal probability distribution. It was also proved by Box-Cox plot that there is no need to make any power transformation of designed model. The variance inflation factor (VIF) was also checked in order to find out how much the variance of the model is inflated by the lack of orthogonality in the design, according to the both limits of 95% confidence intervals.

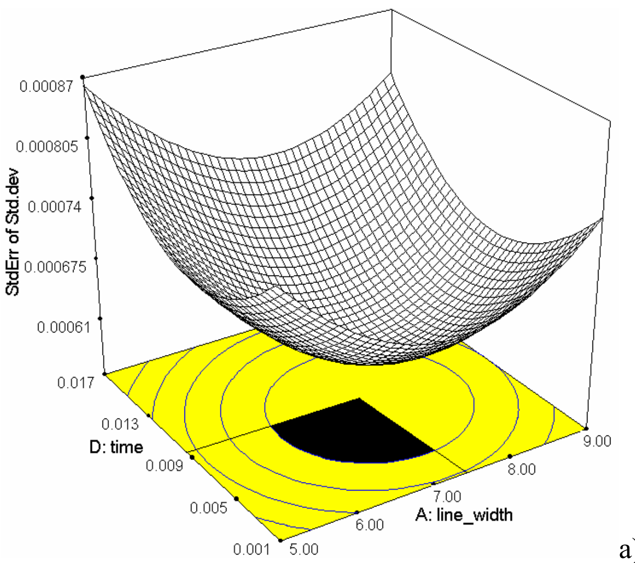
If the factor is orthogonal to all the other factors in the model, the VIF should be as close to value of 1.00 as possible. But it should not exceed the value of 10.00. In our case this condition is fulfilled, since the VIF for A, B, C, D and F is between 1.00 and 1.05 which is excellent.

8 Model optimization

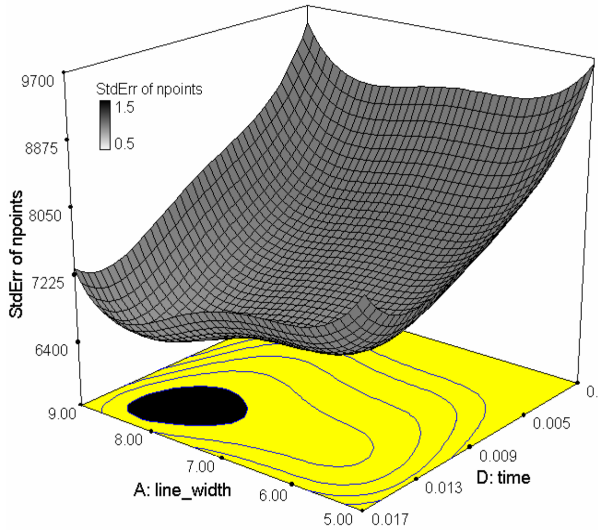
8.1 Standard Error Plot

Models obtained with D-Optimal DOE as shown in previous chapters, will now be optimized by some most significant parameters. The plot of standard error of the mean shows how the error in the predicted response varies over the design space. StdErr% is a different representation of the standard deviation and it shows the accuracy at which the optimized predictions will happen. It is simply the result of the following (stddev / mean * 100). Typically, if the StdErr% exceeds 30 or 40%, then this could be a sign for a high amount of deviation within that particular group of values, and usually one or more of the values is anaomalous to a large degree. In our case the maximum exceed is about 18%, which is acceptable. [17]

The shape of the standard error plot is set by design points and the actual values are set by how well the model fits the response of accurate source model. For our design space this plot is shown in Fig. 4. StdErr is analysed for first (Std.dev.), and second (n.points) response factor according to the two most significant parameters, »line width« and »integration time«. Contours of constant standard error are displayed on the two-dimensional surface.



a)



b)

Fig. 4.: The response surface plot of standard error for both response factors

Lines on 2D surfaces denote constant height of StdErr values, and dark surfaces show design space, where the standard error is minimized, and this is the space where the best accuracy of reversed point model is expected. So before performing particular scan process it is very useful to checkif the setted input parameter design points fall inside dark shaded range. If the answer is affirmative, then high accuracy of reversed point model could be expected, otherwise not.

8.2 Analysis of response surface for both predictive parameters, (point number and std. deviation)

Two most significant input parameters (laser beam width (x1) and integration time (x2)), when taken at optimal run conditions are presented in function Y of two levels:

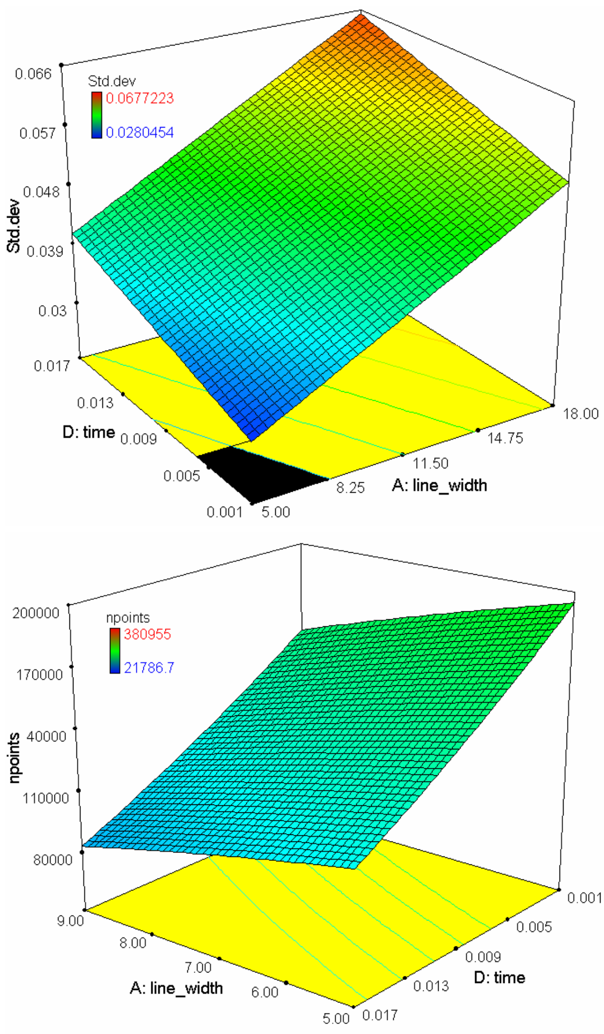
$$Y = f(x1, x2) + \varepsilon \qquad (5)$$

where ε represents the noise or error observed in the response Y, which is Std.dev. and number of points. If the expected response is denoted by $E(y) = f(x1, x2) = \eta$, then surface represented by

$$\eta = f(x1,x2) \qquad (6)$$

is called a response surface. As suggested by ANOVA, the most appropriate model for this design would be approximation of first-order model function [10]

$$y = \beta o + \beta 1x1 + \beta 2x2 + \ldots\ldots + \beta kxk + \varepsilon \quad (7)$$



a)

b)

Fig. 5. Response surface plot of both response factors for 3D reversed models

Black shaded region in figure 5a. is design area where optimal solutions (but not necessary also the minimum design error of process solutions) should be found Because number of predicted points is not a physical parameter, it is not possible to detect optimum area as is in case of minimum, maximum, or saddle example etc. So number of points can be optimized according to the standard error plot in Figure 4, which indicates a region where deviation of std.err is minimized.

9 Performance assessment of developed models

Predictions of developed model were tested at an optimal parameter setings, which were taken from portion of optimal design space. In this way also the accuracy of reversed 3D model is checked against original 3D models. Then it is possible to perform confirmation runs to verify proposed predictions at optimal running conditions. It is also possible to go in oposite direction and make assesment of suitable input parameters on a basis of known response factors std.dev. and number of points. [12,13]

The 95% PI (prediction interval) will be used which is the range in which can be expected any individual value to fall into 95% of the time. The prediction interval will be larger (a wider spread) than the confidence interval since we can expect more scatter in individual values than in averages.

Table 6: Test set for modelling and performance assessment

	Standard deviation				Point numbers			
model	measured	NN	D-test	Historic	measured	NN	D-test	Historic
1	0,032682	0,036587	0,032001	0,023658	213813	203308	192115	172314
2	0,043160	0,043444	0,043770	0,034561	43456	41269	39256	33321
3	0,066322	0,058237	0,058706	0,054011	31638	35500	30236	23108
4	0,060623	0,066326	0,063984	0,058341	15888	22841	13821	24531
5	0,035597	0,038300	0,042525	0,045617	173429	176854	162341	153421
6	0,034902	0,037100	0,040000	0,044351	101043	81539	115236	110008
7	0,023547	0,028400	0,027000	0,025109	49996	61089	51237	62729
8	0,035793	0,033520	0,033519	0,031146	108663	123348	107298	115976
9	0,064059	0,059504	0,057325	0,057001	31772	34244	30109	53000
10	0,065301	0,061870	0,059025	0,072113	126069	141410	131027	111509
11	0,068398	0,065411	0,062511	0,060304	62350	69718	59108	74831

In table 6. are collected measured and predictable data from eleven reversed 3D models, according to different modelling approaches, as already mentioned at neural network testing.

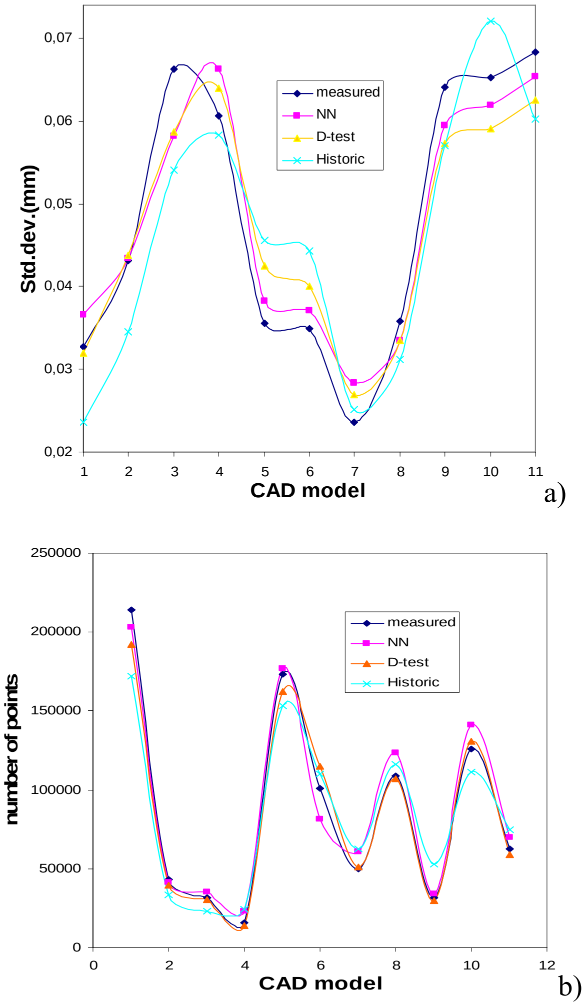


Fig. 6. Modelling performances of all approaches for a) Std.dev. and b) npoints responses

The difference between the measured and simulated response factors is illustrated in Fig. 6. The performance assessment has been measured with three different criteria, related to the test set in table 7. The first is the relative prediction error (RPE), shown in Fig. 7., which is defined as, $RPE = \hat{Y}_k / Y_k$, where $\hat{Y}_k$ is the simulated/predicted output, and Y_k is the corresponding measured output. A prediction is considered to be good if the RPEs are close to one. Second performance measure is the mean squared error of prediction (MSEP), defined as $MSEP = 1/m \sum_{k=1}^{m} (Y_k - \hat{Y}_k)^2$. [12] The prime advantage of the MSEP lies in its ability to incorporate a measure of both the variance and square of the mean of the prediction errors. And the third is the mean absolute percentage deviation (MAPD), which is defined as $MAPD = 1/m \sum_{k=1}^{m} \left| (\hat{Y}_k - Y_k)/Y_k \right|$ and is also considered to compare the relative performance of the particular models [13,19]. The last two criteria results are shown in table 7.

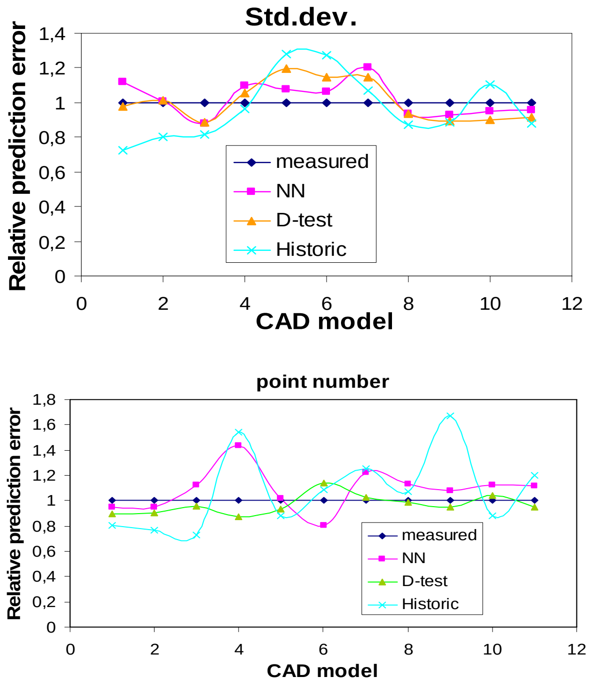


Fig. 7. Relative prediction error for std.dev. and point number responses

	Std.dev.		n.points	
Model	MSEP	MAPD [%]	MSEP	MAPD [%]
NN	1,77.E-5	8,34	109,5.E6	14,06
D-test	2,55.E-5	9,48	78,2.E6	6,89
Hist. Test	6,25.E-5	16,18	317,0.E6	25

Table 7. Quantitative performance assessment.

Looking at figure 7. and table 7., it is obvious that better results are achieved in a case of standard deviationt prediction than in case of point number prediction. Neural network predictive model gave better results in standard deviation prediction (8.34%). It is also noticeable that generally speaking neural network based D-test gave best results in both responses. The other useful aspect of presented design model is also that after establishing mathematical design model also "reversed" prediction of optimal input parameters on a basis of assessed output parameters is possible.

10 Conclusion

The primary purpose of this study was to investigate the efficiency of different modelling approaches to simulate and understand importance of different laser scan parameters, as well as their mutual interactions. The other purpose was to use developed models to evaluate best optimized crucial parameters, which have to be employed in a scanning process. On a basis of upper results and findings it is now possible to input desired range of std. dev. into derived model, and the model will answer with best – optimized input parameters, which have to be brought into the driving software for controlling the laser-scann device. Successful optimization also benefits in a rise of reliability and accurateness. In our lab this scan model is already being successfully used for scanning with 3 axis milling machine. Some possible existing model uncertainties may be attributed to the lack of some geometrical and topological properties (curvature, slope gradient etc.) of the scanning object. But this are assumptions, which should be cheked in future works. In this directions the future investigations will be going on.

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