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ABSTRACT

Predictive Analytics is a crucial part of a Big Data application. Lately, developers have turned their attention to deep learning models due to their huge success in various implementations. Meanwhile, there is lack of deep learning implementations in manufacturing applications due to insufficient data. This phenomenon has been slowly shifting due to the application of IoT and Industry 4.0 concept within the manufacturing industry. Streaming and batch data producing sources are becoming more and more common in the machining industry. In this paper, we propose a deep learning predictive analytics model based on the data generated by a particular machining process. The results indicate that using such a model can make very accurate predictions and can be used as part of a real-time decision-making process in the manufacturing industry. In this study, the prediction models of three crucial metrics of machining such as quality, performance and energy consumption have been developed by utilizing artificial neural networks and deep learning methods. Specific measures of quality, performance and energy consumption refer to material removal rate (MRR), surface roughness (Ra) and specific energy consumption (SEC) respectively. The control parameters of machining are selected as stepover (a_e), depth of cut (a_p), feed per tooth (f_z) and cutting speed (V_c). In addition, variance analysis (ANOVA) has been used to examine the effects of the input parameters on the output parameters.

Keywords—free-form machining; manufacturing; deep neural networks; big data; machine learning

I. INTRODUCTION

Impellers are mostly used in the automotive and aerospace industries and there are generally at least six free-form surfaces on an impeller, as shown in Fig 1. Each of the free-form surfaces are machined separately on a 5-axis machine tool. The materials of the impellers often used are stainless steel and Ti-6Al-4V alloy, which are considered difficult to cut materials; hence its manufacturing is costly and inherently difficult. These difficulties also increase energy need during its manufacturing process. However, there are not many studies focused on impellers, for predicting and improving its process and energy efficiency in literature. Use of artificial intelligence methods such as artificial neural networks for prediction is also very limited on such complex geometries and associated processes.

During his Master Thesis, Gokberk has developed an estimation model of energy consumption of impeller machined on turn-mill machine tools based on AISI 304 stainless steel. In this model, energy consumption estimation model has been developed for both rough cut and finish cut of milling operation of the impeller for free-form surface generation, by using response surface method and artificial neural networks. Equation (1) has been utilized to predict energy consumption for each feature such as a free-form surface. Mazak I-200ST turn-mill machine tool has been used during the experiments. Furthermore, the estimation models for surface roughness and material removal rate of the impeller using ANN has been developed by Gokberk [1].

$$E_{feature} = E_{idle} + E_{auxiliary} + E_{cutting} \tag{1}$$

In this equation, "idle" represents constant energy consumption of machine tool such as computer, fan, "auxiliary" represents energy consumption of sub-units such as spindle, feed axes, cooling pumps, conveyor, chiller etc. and "cutting" represents energy consumption during only cutting operation.

In the area of Deep Learning, advanced research have been conducted in recent years. Krizhevsky et al. developed a huge convolutional neural network in ImageNet competition and draw attention to deep learning area [2]. LeCun et al. [3] stated that state-of-the-art improvements have been done in self-driving cars[4], trend prediction, image recognition[2], drug discovery and many other domains. However, in manufacturing one of the barriers seem to be collection of large amounts of data required for deep learning. By means recent technological advances such as Internet of Things(IoT) and Industry 4.0, large amounts of data can be collected at multi-plant scale and more accurate and advanced prediction algorithms can be developed with deep learning.

In this study, the prediction accuracy with the estimation model developed by Gokberk will be compared against the prediction by a deep neural network model [1]. The primary motivation for such an approach is to demonstrate the applicability of a prediction model that can work with big data generated by sensors and sources in a large scale manufacturing environment, i.e. IoT and Industry 4.0 enabled operating conditions where data inflow from tens/hundreds of sensors is possible. In order to realistically simulate such an environment, the estimation model developed by Gokberk will be used for the generation of 42K synthetic data points as if they are coming from an actual machining process sensor. In Gokberk's study, it is shown that the data generated by the neural network model is able to produce statistically similar process outputs when compared with the actual process outputs. In other words, the difference between the results from the actual machining process and the neural network estimations are statistically insignificant [1]. Hence, in this study, we are able to use 42k synthetic process data, as if they were retrieved from an actual machining process.

Figure 1. A sample impeller and its free-form surface

A. Theoritical Background on Energy Efficient Machining

From the past to the present, extensive research has focused on design and manufacturing of free-form surfaces because of its complexity and difficulty. Free-form surfaces can be machine with a 5-axis Computer numerical Controlled (CNC) vertical machining center or a turn-mill machine tool. Both of these machine tools are very complex systems that can machine complex geometries on very hard materials with a high precision however the cost of these technological advances is having very large energy footprint. A lot of research on energy consumption has been carried out in recent years since reducing the energy consumption in manufacturing is crucial for conservation of resources on earth and curbing green House Gas (GHG) emissions. The reduction in energy consumption cannot compromise quality properties (eg. Surface roughness) or process efficiency (e.g. material removal rate). Generally, improvement studies of machining are performed on process control parameters like stepover (a_e), depth of cut (a_p), feed per tooth (f_z) and cutting velocity (v_c), and measured performance outputs are Specific Cutting energy(SEC), surfaces roughness (Ra), or material removal rate (MRR). Kordonowy, who made one of earliest work in this regard, has determined the energy need of the sub-units of many machine tools and segregated the energy consumption of the machine tool into two, idle energy as fixed and variable energy as cutting during machining. In his work, the power required by sub-units and the cutting power is calculated by analyzing and segregating the total power drawn by a Cincinnati Milacron machine tool [5]. Dahmus and Gutowski have further developed these studies and proposed the first general energy consumption model for machine tools as shown in Equation (2).

$$E = (P_o + kQ) \cdot t \quad (2)$$

Where P_o is idle power drawn by machine, k is specific cutting energy, Q is Material removal rate and t is cutting time [6]. While this model is a pioneer and enlightened many other work, it does not capture all complex sub-components in an advanced machine tools.

Following the first model developed by Dahmus and Gutowski, many researchers have attempted to adapt and develop the theoretical prediction models for a variety of machine tools. Rajemi et al. also have added the tool life to the energy consumption model developed by Gutowski. The new energy model developed by Rajemi appears in Equation (3)

$$E = P_0 \cdot t_1 + (P_0 + kQ) \cdot t_2 + P_0 \cdot t_3 \cdot \left(\frac{t_2}{T}\right) + y_E \cdot \left(\frac{t_2}{T}\right) \quad (3)$$

Where P_0 is idle power consumed by machine module without cutting t_1 is machining setup time, t_2 is actual cutting time t_3 is tool change time, T is tool life, Y_E is energy footprint per tool edge, k is specific cutting energy and Q is material removal rate [7].

The energy model developed by Diaz, which is one of the most referenced in this area, is shown in Equation (4). As seen in this equation, the total energy consumed is divided into two as the cutting power and the power drawn during an air cut [8].

$$E = (P_{cut} + P_{air}) \cdot \Delta t \quad (4)$$

Where P_{cut} is Power drawn for cutting, P_{air} is power drawn for air cut and Δt is processing time. He et al have developed the energy consumption model of parts machined by using NC commands generated for a part cut. The model is based on determination energy consuming sub-units and determination of their energy consumption amounts by observing commissioning time of these sub-units. The energy consumed by the sub-units is calculated by multiplying the power value of each sub-unit by its activation time

$$E_{total} = E_{spindle} + E_{feed} + E_{tool} + E_{coolant} + E_{fix} \quad (5)$$

Where $E_{spindle}$ is energy consumption of the spindle at the ready position and cutting, E_{feed} is energy consumption of feed axes, E_{tool} is energy consumed for tool change, $E_{coolant}$ is energy consumed by coolant and E_{fix} is energy consumption of the machine in the ready position such as lightening, fans, computers, etc [9].

Kara and Li have developed generalized empirical energy consumption models for machine tool. As shown in Equation (6), specific energy consumption values that are specific to each machine are obtained and these values are multiplied by the volume removed during the machining operation to calculate the energy consumed by the machine tool as seen in Eqauation (7). C_0 and C_1, which are specific constant to each machine tool, should be determined by conducting experiments on a specific machine tool. Model verification tests have been carried out for four different milling and turning machine tools. When the energy values estimated using the model and the values measured during the experiments were compared, the consistency level of the model developed was 90% [10].

$$SEC = \left(C_0 + \frac{C_1}{MRR}\right) \quad (6)$$

$$E = SEC \cdot V \quad (7)$$

Uluer et al. have developed a new estimation method for energy consumption using ISO/STEP AP224 protocol. The novelty of this method is that the cut energy estimate can be calculated with the help of the volume of features defined in the ISO/STEP AP224 standard [11]. Furthermore, Uluer and Unver (2016) have extended this model for automatic serial production lines and have applied the model to the selected production lines of the refrigerator-compressor factory of Turkish household appliance industry (Arcelik A.S.). As a result of the study, reductions of up to 10% in energy consumption have been achieved in these lines without sacrificing process efficiency [12].

In another study, Altintas et al. have created estimation and optimization model of energy consumption for milling operation based on ISO/STEP AP224 standards as well [13]. In this model, the total energy requirement of a prismatic part is predicted by the Equation (7).

$$E_{part} = \sum_{i=0}^{n} E_{feature,i} \quad (8)$$

In the Equation (8), "part" represents all the parts to be machined and "feature" represents each Step AP224 feature in the part. The detailed energy Equation (1) that contains each element has been used for the model developed by Altintas et al. This model has been tested for milling operations on the DMG-65 Monoblock vertical machining center using Aluminum 6061 [13].

In Moradnazhad and Unver's study, the energy estimation model based on STEP AP224 which has been developed by Altintas et al. was adapted to turn-mill machine tools. During the processing of the workpieces compliant with ISO/STEP AP 224, specific estimation model of the Mazak Integrex I200-ST machine tool has been established. In the study, the energy consumed by the auxiliary units in Equation (1) is calculated by summing the energy values consumed by all sub-units of the turn-mill machine tool as given in Equation (9) [14].

$$E_{auxiliary} = E_{main\ spindle} + E_{sub-spindle} + E_{milling\ spindle} + E_{milling\ head-feed} + E_{turret-feed} + E_{tool\ change} + E_{coolant} + E_{chiller} + E_{conveyor} + E_{lubrication} \quad (9)$$

II. Design of Experiment

In this study, the total power load of the Mazak i-200ST turn-mill machine tool during the machining of freeform surfaces have been measured using the Socomec DIRISA-40 smart energy meter, and the cutting power value ($P_{cutting}$) is obtained by subtracting the idle and auxiliary power values from the measured total power value using equation (10). Also, the material removal rate (MRR) value of free-form surface is calculated by using equation (11) and (12). In order to calculate the specific energy consumption (SEC) of any process step, the value $P_{cutting}$ is divided by the calculated material removal rate using equation (13).

$$P_{total} = P_{idle} + P_{auxiliary} + P_{cutting} \quad (10)$$

$$f_r = f_z \cdot z \cdot N \quad (11)$$

$$MRR = a_e \cdot a_p \cdot f_r \quad (12)$$

$$SEC = P_{cutting} / MRR \quad (13)$$

Where f_z is the feed per tooth (mm/tooth) of the cutter, z is the number of teeth, N is revolution per minute (rev/min) and f_r is feed rate (mm/min).

Furthermore, as a quality measure, surface roughness has been measured for each impeller free-form surface. Mitutoyo Surftest SJ-210 surface roughness meter has been used to measure the surface roughness (Ra).

Figure 2. The Mazak i-200 ST turn-mill machine tool

An experimental set has been created to collect data that have been used for prediction surface roughness, material removal rate and specific energy consumption by utilizing central composite design (CCD). The central composite design is a method that can be applied for RSM and is a useful experimental design for process optimization. In this study, the input parameters are set as stepover (a_e), depth of cut (a_p), feed per tooth (f_z) and cutting speed (V_c). As the output parameters, mean surface roughness (Ra) and specific energy consumption (SEC) and material removal rate (MRR) are used. All the output measures obtained after the experiments performed and the input parameters used for the experiments are given in table 1.

In the experimental tests, AISI 304 stainless steel with 65 mm diameter and 120 mm length was used. The cutting tool was SECO JH720050-TRIBON coded ball-end mill with 5 mm diameter. This is a coated carbide ball end mill tool manufactured by SECO tools.

Table 1. Central composite design and test results

Exp.	a_e (mm)	a_p (mm)	f_z (mm/tooth)	V_c (m/min)	SEC (J/mm^3)	MRR (mm3/s)	Ra (µm)
1	0,25	0,4	0,035	65	242,06	0,72	1,024
2	0,1	0,25	0,035	65	642,52	0,18	0,515
3	0,25	0,25	0,035	60	256,89	0,42	0,785
4	0,25	0,1	0,035	65	526,58	0,18	0,704
5	0,25	0,25	0,035	70	322,73	0,49	0,957
6	0,4	0,25	0,035	65	211,70	0,72	1,194
7	0,25	0,25	0,02	65	407,25	0,26	0,564
8	0,25	0,25	0,05	65	257,20	0,65	1,164
9	0,25	0,25	0,035	65	298,70	0,45	0,862
10	0,25	0,25	0,035	65	295,82	0,45	0,865
11	0,325	0,325	0,0275	67,5	248,84	0,62	1,043
12	0,325	0,175	0,0275	62,5	332,07	0,31	1,010
13	0,175	0,175	0,0425	67,5	458,84	0,28	0,813
14	0,175	0,175	0,0425	62,5	449,22	0,26	0,796
15	0,325	0,325	0,0425	67,5	192,10	0,97	1,430
16	0,175	0,175	0,0275	62,5	509,33	0,17	0,633
17	0,325	0,325	0,0425	62,5	194,04	0,89	1,432
18	0,175	0,175	0,0275	67,5	537,88	0,18	0,658
19	0,25	0,25	0,035	65	298,61	0,45	0,864
20	0,25	0,25	0,035	65	300,85	0,45	0,864
21	0,325	0,325	0,0275	62,5	247,99	0,58	1,031
22	0,325	0,175	0,0275	67,5	343,16	0,34	1,026
23	0,175	0,325	0,0425	67,5	322,12	0,52	0,876
24	0,175	0,325	0,0275	67,5	408,70	0,34	0,693
25	0,325	0,175	0,0425	67,5	279,78	0,52	1,435
26	0,175	0,325	0,0425	62,5	322,95	0,48	0,873
27	0,25	0,25	0,035	65	298,97	0,45	0,864
28	0,25	0,25	0,035	65	301,17	0,45	0,866
29	0,175	0,325	0,0275	62,5	402,74	0,31	0,648
30	0,325	0,175	0,0425	62,5	277,22	0,48	1,412

III. Variance analysis

Variance analysis (ANOVA) has been performed for understanding influence of input parameters on output measures. Table 2,3,4 show the ANOVA tables for specific energy cutting, material removal rate and surface roughness respectively [15].

Since ANOVA is defined in the 95% confidence interval, the P-Value that is below 0.05 indicates that the input parameter is effective on the output parameter. Thus, when examining at the ANOVA results in table 2, it can be observed that all input parameters except the cutting speed are influential on specific energy consumption. Also, the priority of the parameters whose P values are equal to zero can be determined by with secondary examination of F value. It can be said that stepover is the most effective parameters as seen from F-value in table 2. Furthermore, all input parameters influence material removal rate almost equivalently (table 3), whereas cutting speed is ineffective on the surface roughness of the free-form surface when P-values are taken into account (table 3). According to F values of the input parameters, stepover and depth of cut are the highest influence on the material removal rate and stepover is the most effective parameter on the surface roughness.

Table 2. Variance analysis of specific energy consumption for cutting of free-form surface

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	15	344908	22994	46,72	0
Blocks	1	685	685	1,39	0,258
Linear	4	308231	77058	156,57	0
a_e	1	194077	194077	394,34	0
a_p	1	83670	83670	170,01	0
f_z	1	29019	29019	58,96	0
V_c	1	1465	1465	2,98	0,106
Error	14	6890	492		
Lack-of-Fit	10	6873	687	160,62	0
Pure Error	4	17	4		
Total	29	351798			

Table 3. Variance analysis of material removal rate for cutting of free-form surface

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	15	1,17387	0,078258	841,81	0
Blocks	1	0	0	0	1
Linear	4	1,11908	0,27977	3009,44	0
a_e	1	0,44291	0,442912	4764,33	0
a_p	1	0,44291	0,442912	4764,33	0
f_z	1	0,22598	0,225975	2430,78	0
V_c	1	0,00728	0,00728	78,31	0
Error	14	0,0013	0,000093		
Lack-of-Fit	10	0,0013	0,00013	*	*
Pure Error	4	0	0		
Total	29	1,17517			

Table 4. Variance analysis of surface roughness for cutting of free-form surface

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	15	1,83064	0,12204	23,59	0
Blocks	1	0,06622	0,06622	12,8	0,003
Linear	4	1,68216	0,42054	81,3	0
a_e	1	1,12176	1,12176	216,86	0
a_p	1	0,03261	0,03261	6,3	0,025
f_z	1	0,51803	0,51803	100,15	0
V_c	1	0,00976	0,00976	1,89	0,191
Error	14	0,07242	0,00517		
Lack-of-Fit	10	0,07241	0,00724	2773,07	0
Pure Error	4	0,00001	0		
Total	29	1,90306			

IV. Development of Prediction models with Artificial neural network

In artificial neural networks, there are hidden layers of neurons between the input layer and the output layer to define the relationship between input and output parameters, and a generalization is made between the input layer and the output layer by each of the neurons in the hidden layer. The transfer functions used to carry out this generalization are linear, log-sigmoid, tan-sigmoid, and signum functions [16, 17]. In this study, the log-sigmoid function as given in equation (14) is used. In addition, the levenberg-marquardt algorithm (TrainLM) is used as the training function.

$$Log\_sigmoid = \left(\frac{1}{1+e^{-x}}\right) \tag{14}$$

The input parameters are stepover, depth of cut, feed per tooth and cutting speed. The output measures are specific energy consumption, material removal rate and surface roughness.

Table 1 contains the experimental groups used for the training of artificial neural networks for cutting of free-form surface. In order to train artificial neural networks, 30 experiments have been performed. Out of these 30 data points, we used 18 of them as training, 8 of them as cross-validation and 4 of them as test. We used 8-fold cross-validation and used all available data for testing.

The t-test result and absolute percentage error value that are average of eight data for cutting of the free-form surface are given in table 5. When reviewing the values in table 5, both t-test results and percentage error values are acceptable. Thus, the ANN model developed for cutting can be used to estimate specific energy consumption, material removal rate and surface roughness.

Table 5. Average t-test and absolute percentage error results for eight test data

t-test for SEC	Absolute percentage error for SEC (%)	t-test for MRR	Absolute percentage error for MRR (%)	t-test for Ra	Absolute percentage error for Ra (%)
5,47	2,72	6,47	2,77	8,60	3,66

Figure 3, 4, 5 show how the input parameters change the output parameter. When looking at figure 3, it can be seen that the specific energy consumption decreases as a result of the increase in all input parameters except the cutting speed. On the other hand, if any input parameters increased, material removal rate increases as shown in figure 4. Also, in figure 5, it is seen that the stepover among all the input parameters increases the surface roughness at the maximum amount.

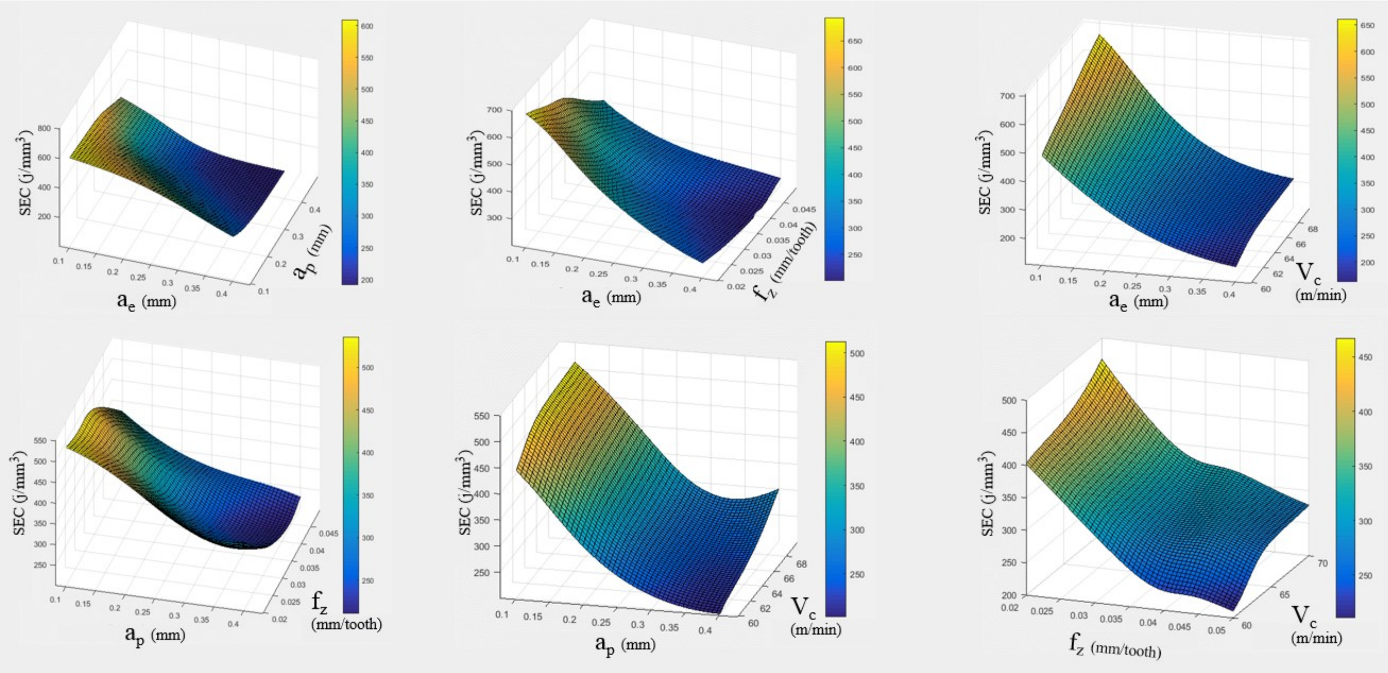

Figure 3. 3D Surface plots of estimated specific energy consumption by ANN model.for cutting of the free-form surface

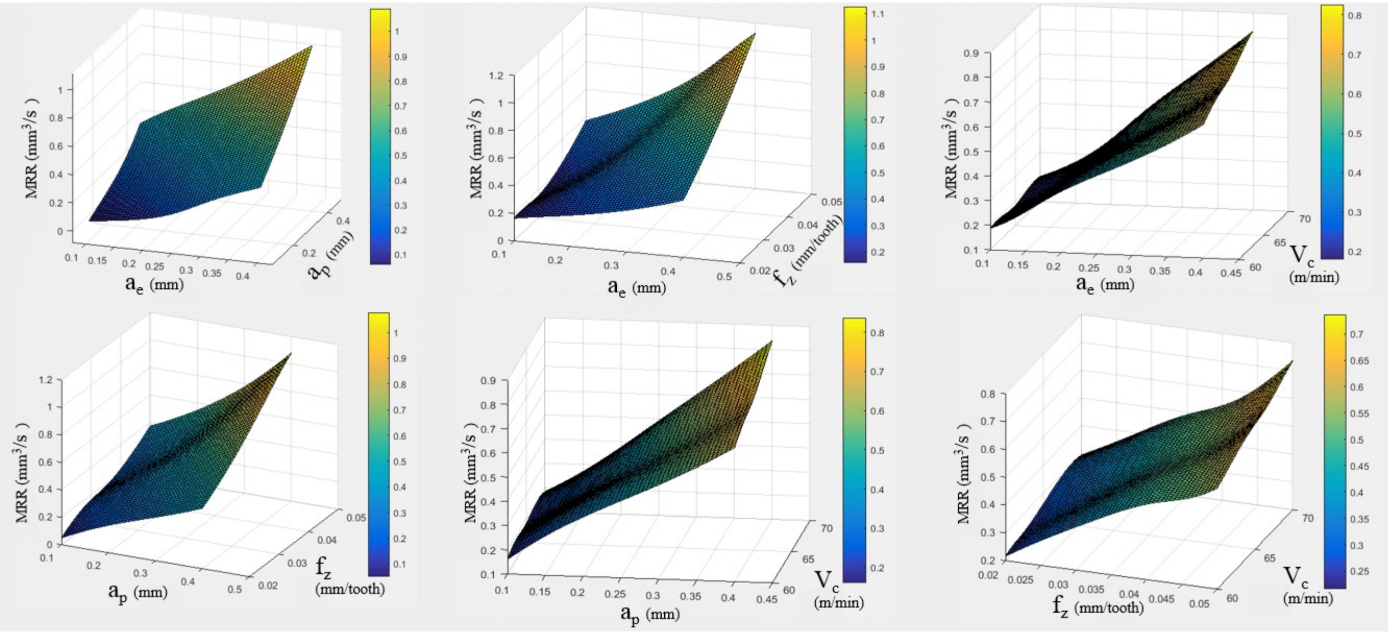

Figure 4. 3D Surface plots of estimated material removal rate by ANN model.for cutting of the free-form surface

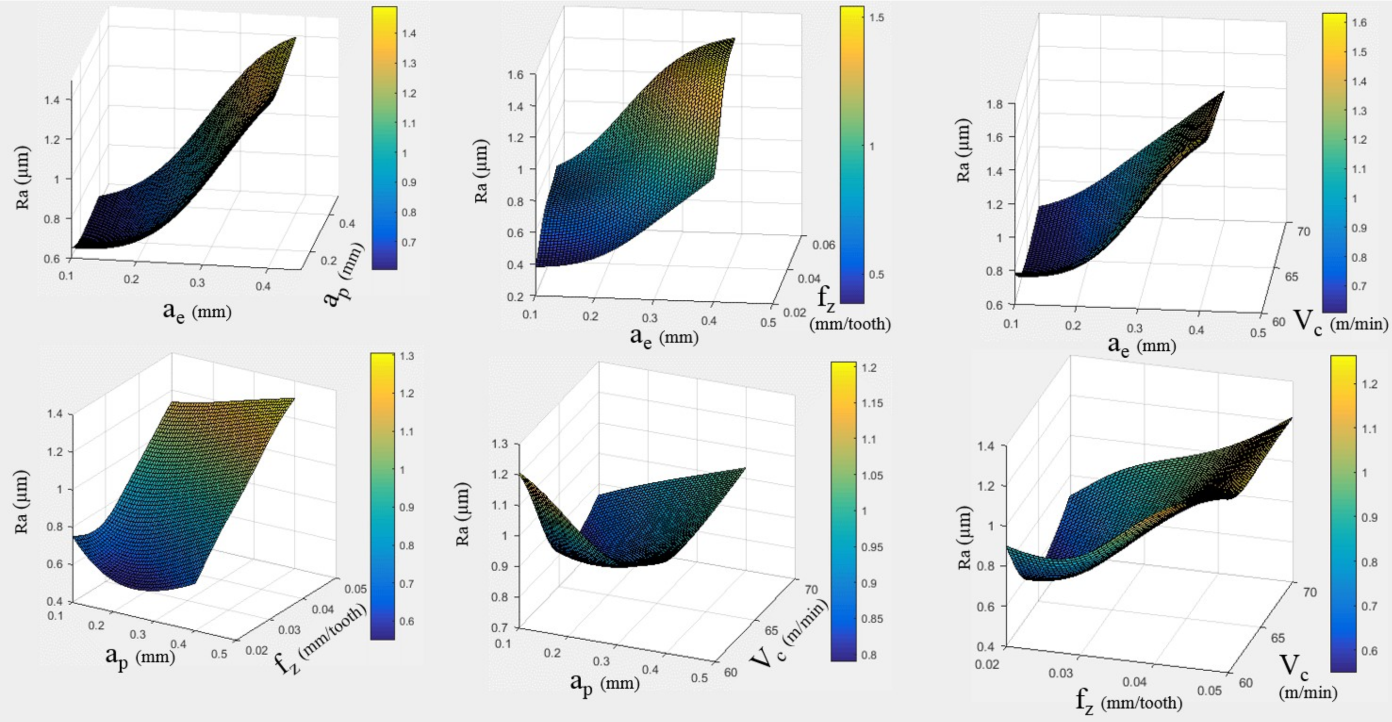

Figure 5. 3D Surface plots of estimated surface roughness by ANN model for cutting of the free-form surface

V. Deep learning, BIG DATA, IoT and INDUSTRY 4.0

In the last few years, deep learning models started appearing in different applications. Even though computer vision and image processing implementations have the majority of this interest, other fields such as finance, speech recognition, and bioinformatics are also incrementally getting their fare share.

Deep learning extends the capabilities of traditional machine learning models by providing a more layered structure (deeper) in order to assist the underlying system to associate the complex input-output associations through hierarchical learning. In other words, at each layer a new feature representation is formed, and this hierarchical formation goes from raw data (the highest complexity) to highly representative features (low complexity) at the end. As a result, at the final layer, a simple classifier will be able to perform the task. This approach results in a substantially better performance compared to the traditional machine learning models.

One drawback (or an opportunity, depending on how one looks at it) of these deep learning models is a large amount of data that is necessary for a successful implementation. Traditional (or shallow) classifiers do not need this excessive data, whereas, in order to maintain the feature transformations between the layers without jeopardizing the generalization capabilities of the overall model, deep learning models require more data.

This necessity fits well with the problems that are already dealing with big data, such as social data analysis, web image categorization, online streaming data implementations and IoT. Even though not many implementations of manufacturing utilize the power of deep learning, there is great potential for predictive and preventive analytics models for manufacturing, especially from the Industry 4.0 point of perspective. A clever and versatile data collection, processing Big Data, Industry 4.0 and IoT framework combined with an appropriate deep learning network can be used as part of such an intelligent decision-making process.

In this study, our primary aim is to provide the means of developing and testing such a deep learning model. The data that is fed into the learning model is obtained from 30 actual process outputs, and 42K generated synthetic data points through a basic MLP neural network that utilizes the real process input-output matching. Hence, even though the data is not collected through the machines directly, the overall concept and the underlying assumptions behind such an approach is still valid. Since this study is one of the first attempts in this interdisciplinary field, more studies and experiments need to be performed in order for such a system to be used in the industry.

VI. Results

The prediction results of the deep neural network model indicate achievements that are two-fold. Firstly, the model demonstrates that predictive analytics models that require working with large amounts of data (in this case 42K synthetic data) can be developed for machining or any other manufacturing processes. Secondly, the estimation performance of such models, i.e. deep learning network, can outperform traditional prediction or machine learning models in big data environments In our particular study, we trained a deep learning model with 5 hidden layers and 475 neurons (10,100,250,100,10 neurons for each hidden layer). The learning curves (figure 6) of training process shows that mean squared and absolute errors of training and validation data are decreased significantly even small number of epochs completed. This is a proof for the model learns fast and does not overfit the machining data.

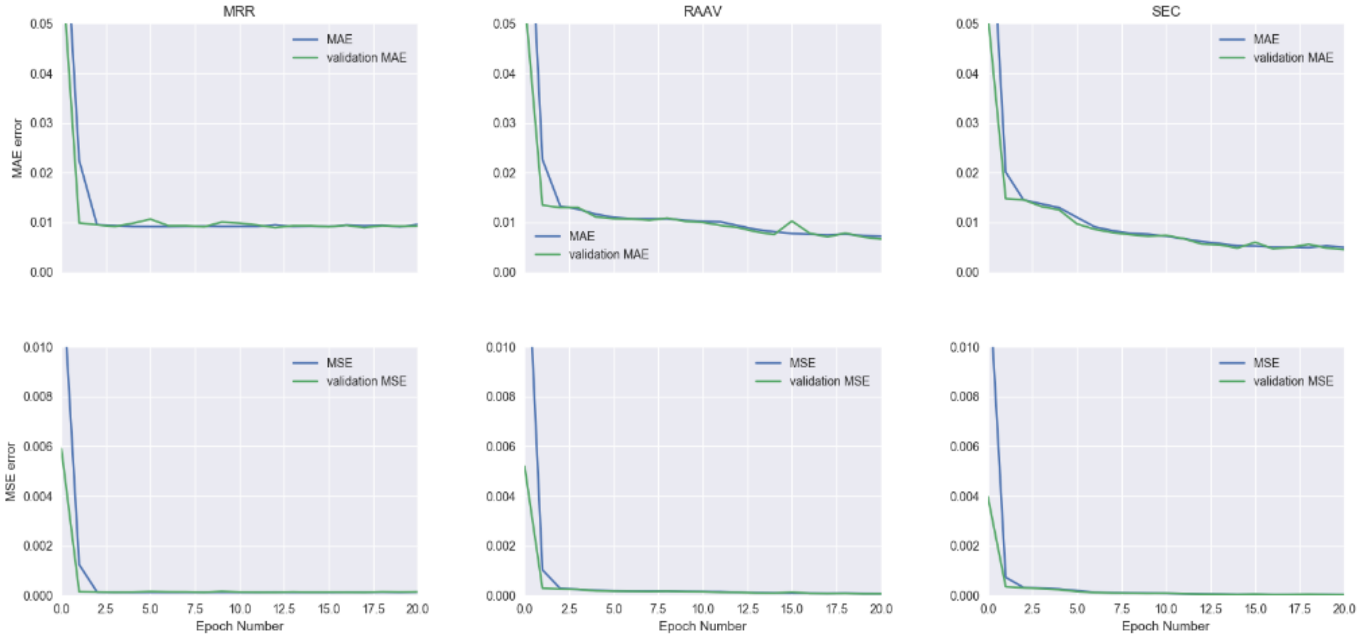

Figure 6. Learning curves of the deep learning model

The developed model estimated the process outputs with a 1.5%, 0.38%, 0.44% average absolute error for MRR, RA and SEC respectively, whereas the neural network model by Gokberk had a 2.77%, 3.66%, 2.72% average absolute error [1]. This means that errors of estimations are decreased by 46%, 90%, 84%. In addition, the absolute difference between prediction and the true value of machining data (figure 7) is distributed around 0 mean and small standard deviation, table 6 has detailed information. Meanwhile, since the t-test results of the deep learning model indicate the difference between this study and the neural network synthetic data (also statistically coming from the same distribution as the actual process outputs as shown in Gokberk's study is statistically insignificant [1]. We can claim not only we developed a model that can work on a Big Data environment (using 42K data, which can also be increased), but also improved the overall prediction performance.

Table 6. The properties of absolute difference between prediction and true values

	MRR	RA	SEC
mean	0.000127	-0.000164	0.000143
std	0.011252	0.002212	0.002785

VII. Conclusion

In this study, we propose a deep neural network based machining process parameter estimation model using data generated from actual process and synthetic data that is statistically the same as the actual process output. The developed model provides a use case of a predictive analytics model that is capable of working with big data. In the new era of Industry 4.0 and IoT (Internet of Things), working with large amounts of data will be the industry requirement in the coming years. This study provides an attempt to demonstrate the predictive analytics use case for a machining process in the aforementioned manufacturing environment. Even though this is a preliminary work, the achievements are promising. Future work includes introducing various manufacturing processes and different deep learning models (unsupervised, semisupervised, etc.) and enhance the performance and effectiveness of prediction in manufacturing.

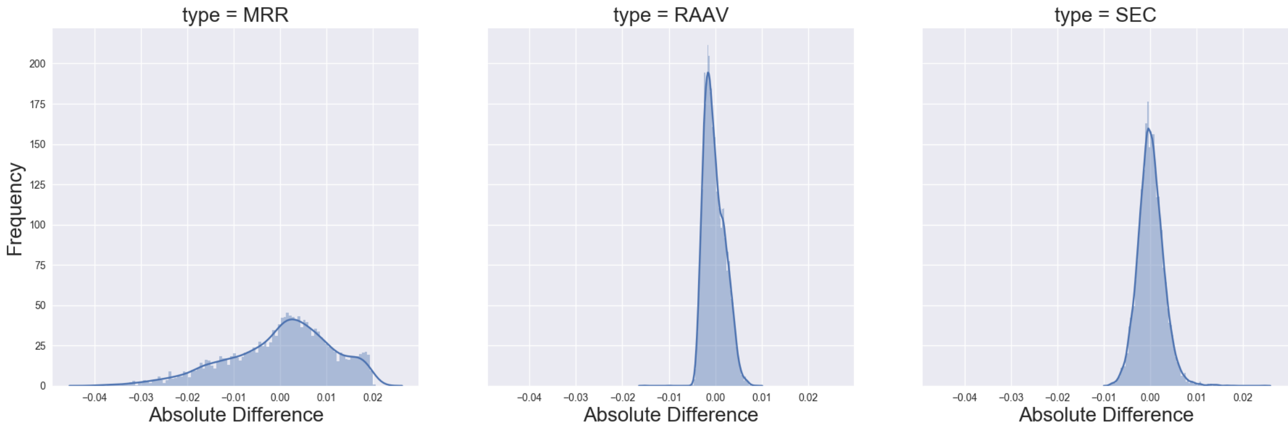

Figure 7. The absolute difference between true and prediction values of MRR(a), RAAV(b), SEC(c)

VIII. References

[1] Gökberk SERİN, "5-axis energy efficient machining of rotary impellers on turn-mill machine tools and development of process prediction models using artificial neural networks", Master Thesis, TOBB University of Economics and Technology, 2017.

[2] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Image Net Classification with Deep Convolutional Neural Networks", *The Twenty-sixth Annual Conference on Neural Information Processing Systems (NIPS)*, Lake Tahoe, California, 2012, pp. 1097–1105.

[3] L. Yann, B. Yoshua, and H. Geoffrey, "Deep Learning", *Nature*, vol 521, pp. 436-444, May 2015.

[4] M. Bojarski, D. D. Testa, D. Dworakowski, B. Firner, B. Flepp, P. Goyal, L. D. Jackel, M. Monfort, U. Muller, J. Zhang, X. Zhang, J. Zhao, K. Zieba, "End to End Learning for Self-Driving Cars", 2016, [online] Available: https://arxiv.org/abs/1604.07316.

[5] D. N. Kordonowy, "A power assessment of machining tools", Bachelor of Science Thesis, Massachusetts Institute of Technology, USA, 2002.

[6] J. B. Dahmus and T. G. Gutowski, "An environmental analysis of machining", In ASME 2004 International Mechanical Engineering Congress and Exposition, USA, 2004.

[7] M. F. Rajemi, P. T. Mativenga, and A. Aramcharoen, "Sustainable machining: selection of optimum turning conditions based on minimum energy considerations," *J. Clean. Prod.*, vol. 18, no. 10–11, pp. 1059–1065, Jul. 2010.

[8] N. Diaz, E. Redelsheimer, and D. Dornfeld, "Energy Consumption Characterization and Reduction Strategies for Milling Machine Tool Use," in *Glocalized Solutions for Sustainability in Manufacturing*, Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 263–267.

[9] Y. He, F. Liu, T. Wu, F.-P. Zhong, and B. Peng, "Analysis and estimation of energy consumption for numerical control machining," *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.*, vol. 226, no. 2, pp. 255–266, Feb. 2012.

[10] S. Kara, and W. Li, "Unit process energy consumption models for material removal processes," *CIRP Ann.*, vol. 60, no. 1, pp. 37–40, Jan. 2011.

[11] M. U. Uluer, H. Ö. Ünver, K. Akkuş, and S. E. Kılıç, "A Model for Predicting Theoretical Process Energy Consumption of Rotational Parts Using STEP AP224 Features," in *Re-engineering Manufacturing for Sustainability*, Singapore, 2013, pp. 141-146.

[12] M. U. Uluer, H. Ö. Ünver, ."A framework for energy reduction in manufacturing process chains (E-MPC) and a case study from the Turkish household appliance industry," *J. Clean. Prod.*, vol. 112, pp. 3342–3360, Jan. 2016.

[13] R. S. Altıntaş, M. Kahya, and H. Ö. Ünver, K. Akkuş, and S. E. Kılıç, "Modelling and optimization of energy consumption for feature based milling," *Int. J. Adv. Manuf. Technol.*, vol. 86, no. 9–12, pp. 3345–3363, Oct. 2016.

[14] M. Moradnazhad and H. O. Unver, "Energy consumption characteristics of turn-mill

machining," *Int. J. Adv. Manuf. Technol.*, vol. 91, no. 5–8, pp. 1991–2016, Jul. 2017.

[15] R. H. Meyers, and D. C. Montgomery, Response Surface Methodology, John Walley & Sons, New Jersey,4th edition, 2016

[16] B. Yegnanarayana, Artificial Neural Networks, Prentice Hall of India, Private Limited, New Delhi, India, 1st edition, 2004

[17] S. Haykin, Neural Networks a Comprehensive Foundation, Pearson Eduıcation, Canada, 2nd edition, 2001