Machine Learning based Heuristic Technique for Multi-Response Machining Process

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Abstract. Manufacturing process variables influence the quality of products substantially. It is unquestionably difficult to model the manufacturing processes that include a large number of variables and responses. Development of the multi-objective surrogate models for the manufacturing processes could be computationally and economically expensive. In this article, a generic multi-objective surrogate-coupled heuristic algorithm is employed that needs small amount of experimental data as input, and predicts precise responses with quick Pareto solutions. The proposed algorithm is verified with different cases collected from the literature based on the CNC turning, centreless cylindrical grinding, and micro milling machining and shown to produce some interesting results.

Keywords: Manufacturing Process Optimization, Surrogate Models, Heuristic Algorithm, Multi-Objective Optimization.

1 Introduction

Manufacturing process optimization has gained substantial interest from the researchers since decades. In reality, it is difficult to optimize the process of manufacturing due to the association of a large number of design parameters and multiple objectives or performance indicators. Multidisciplinary collaborative approaches are required to manufacture complex engineering components. It also requires complicated design space due to the nonlinear relationships among various dependent and independent design variables to manufacture these optimally. Due to the above fact, it is substantially difficult to formulate these relationships mathematically [1]. Precision of manufacturing process largely depends on the empirical process data, which is expensive in terms of the machining costs, labor costs, overhead costs, and scrap costs. Data-driven models, machine-learning techniques, meta-model or surrogate modeling techniques could be appropriate in such scenarios [2].

The complexity of engineering product increases with the number of design variables, performance indicators and specifications or tolerance levels defined for the products. This problem is termed as combinatorial problem, which could have many near optimal solutions within boundary conditions. For an example, the milling machining is associated with various design parameters such as the spindle speed, feed rate, depth of cut, tool diameter, etc. while minimizing the surface roughness, applied cutting forces, tool wear, which in turn improve the material removal rate and tool life. However, this optimization could be very complex due to the nonlinear relationships among the input and output variables. Moreover, this kind of optimization approach is substantially process specific and generic formulations or models are not prominently available in the literature [3]. Hence, the aim of this study is to portray a suitable multi-objective process modeling to solve the above problem promptly.

To cater the purpose, an Artificial Neural Network (ANN) and Gaussian Kernel Regression (GKR) techniques are considered to construct efficient surrogate models, which take various design parameters as the inputs. Once the surrogates are trained, these are capable of predicting process responses with good accuracy. Both the surrogates studied here, are compared with each other based on the Normalized Mean Square Error (NMSE) and the best one is selected.

In general, Design of Experiment (DOE) is used to define the design space for the machining or manufacturing processes [4]. For that purpose, the Latin hypercube sampling (LHS) [5] is used, which uniformly generates the set of values for design parameters within the predefined range. Thereafter a heuristic method is employed to select optimal sets of these parameters, which could fine-tune the process responses.

2 Manufacturing Process Optimization

CNC (Computerized Numerical Control) machining has transformed the manufacturing industries drastically since past few decades, which precisely removes excess materials with precision and accuracy while improving the tool life and the quality of the manufactured products with reduced manufacturing cost. This includes the turning, grinding, milling, welding, lathe, which effectively obtain flat or curved shaped components with smooth finishing [6]. In this paper, three cases are considered based on the CNC turning, grinding, and milling operations. In CNC turning, design parameters such as the cutting tool geometry and materials, the depth of cut, feed rates, cutting speeds as well as the use of cutting fluids could influence the material removal rates and the other performance indicators, such as the surface roughness, roundness of circular and dimensional deviations of the product [7]. Whereas, the cylindrical grinding is employed to finish parts with circular symmetry and projections, variations in shapes, varying diameters etc. In in-feed method, the shape variations are accommodated in the form of the grinding wheel aiming to form various part diameters and lengths to meet the part geometry [8]. In this process, the part is fed to the wheels from the above with no lateral movement of the piece while it is being on ground. However, in milling process, machining at the top speeds usually attains better surface roughness, material removal rate, and improved tool wear rate. The effect of the input parameters such as the cutting speed, feed per tooth and depth of cut for milling could be decisive factors for the product quality in a big way [9].

For manufacturing process optimization, the experimental design approaches are heavily practiced in literature, which are active statistical method. The design space is formed with a DOE tool, which makes small changes in one or more inputs to analyze the corresponding influences in the response patterns. This analysis could essentially points out the complex correlations among the process parameters and responses, which further reduces the process variabilities [6]. This experimental design space could be useful for evaluating the nature of the manufacturing process and considered as the input to the process optimization models. Various methods are available in the literature, which are categorized as the DOE techniques. These are full factorial method, fractional factorial method, Taguchi's method, LHS etc. Various applications of the DOE based approaches to the manufacturing process optimizations could be found in the literature for the single or multiple performance indicators [10]. In this study, three different cases are collected from the literature [7] [8] [9], which are used as the training data for the proposed iterative heuristic optimizer. The cases are discussed in the following subsections.

2.1 CNC Turning Case Study

The experimental data for CNC turning are collected from the literature and presented in **Table 1**. A rigid CNC turning center with a 7.5kW spindle motor at 4200rpm (machine type of Vtum||–20, manufactured by VICTOR Taichung Machinery Works Co. in Taiwan) is used to perform machining [7].

Table 1. CNC turning process data [7]

No.	CS	FR	DC	CFMR	Ra	Rt	phi
1	125	0.12	0.5	4	3.27	28.76	4.7
2	125	0.16	0.65	8	1.92	15.91	2.9
3	125	0.2	0.8	12	1.8	11.04	1.9
4	155	0.12	0.65	12	1.11	6.626	0.85
5	155	0.16	0.8	4	1.78	7.861	1.1
6	155	0.2	0.5	8	2.73	10.84	1.95
7	185	0.12	0.8	8	1.04	5.698	0.75
8	185	0.16	0.5	12	2.87	11.19	2.1
9	185	0.20	0.65	4	3.91	15.71	2.55

The cutting length of the work piece is 40mm. The cutting tool is made of carbide and coated with titanium nitride (TiN) manufactured by Sumitomo Electric Industries, Ltd., Japan with a part number of TNMG160408-UG. In this case, the cutting speed (CS) (100 -200m/min), feed rate (FR) (0.1 - 0.25 mm/rev), depth of cut (DC) (0.1 – 1.0 mm) and the cutting fluids mixture ratio (CFMR) (2 – 15%) are considered as most influential parameters of turning operations and average surface roughness (Ra), maximum surface roughness (Rt) and roundness of circumference surface (RCS) are considered as process responses. The material considered is SKD11 (JIS) alloy tool steel with high carbon high chromium. This is used in the production of dies, plastic injection molding dies, precision gauge, spindle, jigs and fixtures, etc. The composition of the SKD11 is 1.55 wt.% C–11.5 wt.% Cr–0.70 wt.% Mo–1.00 wt.% V–0.30 wt.% Mn–0.25 wt.% Si. The yielding stress of raw SKD11 is 330MPa, the Young's modulus is 200 GPa and hardness is 25 HRC. The diameter for the work pieces has been fixed to 20mm.

2.2 Centerless Cylindrical Grinding Case Study

An in-feed centerless cylindrical grinding machine is considered for the experiments [8]. The material considered for the experiments is made of EN52 for an internal combustion (IC) engine valve stem with 79.6 mm dia. An A80N5V45 grinding wheel rotating at 1440 rpm (giving a surface speed of 45 m/s) and an A80RR control wheel were utilized for this process. The centreless cylindrical grinding process was carried out over a length of 98 mm of valve stem with a job height of 212 mm above the blade. The chemical composition of the EN52 is given as, C (0.40–0.50%) Si (2.70–3.30%) Mn (0.8% max) P (0.04% max) S (0.03% max) Cr (8-10%). For centreless cylindrical grinding process, surface roughness (Ra), out of cylindricity (OC) and diametral tolerance (Dt) were selected as response variables whereas dressing feed (DF) (2-15 mm/min), grinding feed (GF) (1-12 mm/min), dwell time (DT) (1-5 Sec.) and cycle time (CT) (5-15 Sec.) are considered as experimental design parameters. **Table 2** presents the experimental data for the cylindrical grinding process.

Table 2. Cylindrical grinding process data [8]

No.	DF	GF	DT	CT	Ra	OC	Dt
1	5	2	1.5	10	0.432	0.67	0.001
2	5	6	2.5	11	0.439	0.67	-0.001
3	5	10	3.0	12	0.427	1	-0.002
4	8	2	2.5	12	0.578	1.67	0.001
5	8	6	3.0	10	0.613	1	0.001
6	8	10	1.5	11	0.763	1.33	0.001
7	10	2	3.0	11	0.505	3.33	0.004
8	10	6	1.5	12	0.517	3	0.004
9	10	10	2.5	10	0.554	3.67	0.003

2.3 CNC Micro-Milling Case Study

The micro-milling experimental data are collected from the published paper and portrayed in **Table 3**. The experiments were carried out using a DECKEL MAHO DMU 60 PCNC milling machine [9].

Table 3. Taguchi's Design sets for micro milling process [9]

No.	SS	FPT	DC	TW	Fx	Fy	Ra
1	10000	0.5	50	5.41	1.33	0.71	0.33
2	10000	1.0	75	13.51	1.63	0.86	0.47
3	10000	1.5	100	16.22	2.02	1.02	0.71
4	11000	0.5	75	27.02	1.62	1.08	0.32
5	11000	1.0	100	32.43	2.03	1.49	0.59
6	11000	1.5	50	14.86	2.65	1.52	0.58
7	12000	0.5	100	45.95	2.10	1.36	0.27
8	12000	1.0	50	27.03	2.99	1.66	0.35
9	12000	1.5	75	32.43	3.55	1.81	0.58

Al7075 material is used (Vickers hardness of 139) as a work piece material, which had a dimension of $15\times10\times20$ mm^3. The chemical compositions of material are given as, Li < 0.0002 wt%, Si 0.92 wt %, Mn 0.348 wt%, P <0.001 wt%, Sr <0.0001 wt%, Cr 0.093

wt%, Ni 0.057 wt%, Na 0.003 wt%, Al 89.0 wt%, Cu 1.71 wt%, Co <0.001 wt%, Ti 0.048 wt%, Be 0.0003 wt%, V 0.009 wt%, Fe 0.55, Pb wt%, 0.018 wt%, Mg 2.00 wt%, B 0.0017 wt%, Sn 0.008 wt%, Zn 5.22wt%, Ag 0.0022 wt %, Bi 0.0018 wt%, Ca 0.0027 wt%, Cd 0.0031 wt%, and Zr 0.0078 wt%. In this case, Spindle speed (SS) (5000-15000 rpm), feed per tooth (FPT) (0.5-1.5 µm/tooth) and depth of cut (DC) (50-100 µm) were considered as design parameters and tool wear (TW), cutting forces (Fx, Fy), and surface roughness (Ra) were selected as process responses.

3 Iterative Surrogate-Assisted Heuristic

The Taguchi's design based data sets are employed for the training of the surrogate functions for the proposed heuristics. All these data contain the input data and output responses. Following surrogate functions are used in this work,

3.1 Artificial Neural Network (ANN)

In order to construct the ANN based surrogate model, a Cascade-Forward Neural Network (CFNN) is considered, which consists of the input layer, hidden layer, and output layer [11]. The number of neurons in the input layer and the output layer depends on the number of design parameters and the performance indicators. The CFNN has some direct connections among the inputs and outputs on top of the multi-layer feed forward perceptron architecture. The response equation for the CFNN is given in Eq. (1) as,

$$y_i = \sum_{k=1}^{n} Z_i^k \times w_j^k x_k + Z_i^{oa}\left(\sum_{j=1}^{m} w_{ji}^{oa} \times Z_k^{ha}\left(\sum_{k=1}^{n} w_{jk}^{ha} x_k\right)\right) \tag{1}$$

$$y_i = \sum_{k=1}^{n} Z_i^k \times w_j^k x_k + Z_i^{oa}\left(\beta_i + \sum_{j=1}^{m} w_{ji}^{oa} \times Z_k^{ha}\left(\beta_j + \sum_{k=1}^{n} w_{jk}^{ha} x_k\right)\right) \tag{2}$$

Where Z_i^{oa} is denoted as the activation function for i^{th} output y_i, w_{ji}^{oa} is the weight from j^{th} hidden layer neuron to i^{th} output node, Z_k^{ha} is the activation function for j^{th} hidden layer neuron, w_{jk}^{ha} is the weight from k^{th} input to j^{th} hidden layer neuron, and x_k is the k^{th} input signal. Further, if some bias is added to input layer, the Eq. (1) becomes Eq. (2), Z_i^k is the activation function and w_j^k is the weight from the inputs to outputs. The network weight in the CFNN is approximated based on the neurons in the input layer.

3.2. Gaussian Kernel Regression (GKR)

The GKR is based on the data mapping from the low-dimensional space to high-dimensional space. This linear regression model in high-dimensional space is equivalent to the Gaussian regression in the low-dimensional space. The linear regression learner is based on the Support Vector Machine (SVM) regression. In this approach, the input parameters x are mapped onto an m-dimensional attribute space using the nonlinear mapping, which further converts it to a linear model in the same attribute space. The linear model is,

$$f(x,\omega)=\sum_{j=1}^{m}\omega_j g_j(x)+\beta \tag{3}$$

Where $g_j(x)$ $(j=1\ldots m)$ is a non-linear transformation function and β is the bias. The performance of regression is analyzed using the ε-insensitive loss function [12],

$$L\big(y,f(x,\omega)\big)=\begin{cases}0 & if\ |y-f(x,\omega)|\le\varepsilon\\ |y-f(x,\omega)|-\varepsilon & Otherwise\end{cases} \tag{4}$$

The abovementioned regression model can be transformed into an optimization problem using,

$$\min Z=\frac{1}{2}\|\omega^2\|+C\sum_{k=1}^{n}(\gamma_i+\gamma_i^*) \tag{5}$$

Subject to,

$$\begin{cases}y_i-f(x_i,\omega)\le\varepsilon+\gamma_i^*\\ f(x_i,\omega)-y_i\le\varepsilon+\gamma_i\\ \gamma_i,\gamma_i^*\ge 0, i=1\ldots n\end{cases} \tag{6}$$

Where γ_i and γ_i^* ($i=1\ldots n$) are positive slack variables, which can calculate the deviation of the input parameters beyond the ε-insensitive neighborhood. This optimization problem is known as the *primal*. It could be transformed into a *dual* and an exact SVM kernel is required to solve this. Whereas, in SVM assisted GKR, the *primal* is solved using the high-dimensional attribute space [13].

3.3. Normalized Mean Square Error (NMSE)

In this study, the NMSE is employed for the performance evaluations of the surrogates. The NMSE is a metric that measures the overall deviations between the predicted and measured values. It is defined as,

$$NMSE=\frac{1}{N}\sum_i\frac{(P_i-M_i)^2}{\overrightarrow{P}\ \overrightarrow{M}} \tag{7}$$

$$\overrightarrow{P}=\frac{1}{N}\sum_i P_i \tag{8}$$

$$\overrightarrow{M}=\frac{1}{N}\sum_i M_i \tag{9}$$

Where P is the predicted output, M is the measured output and N is the number of observations. In NMSE computation, the deviations (absolute values) are summed instead of the differences. Due to that fact, the NMSE generally shows the most striking differences among the models. If a model has a very low NMSE score, then it is an optimal model in the space and time.

Once both the surrogates are trained, the comparison is done based on the obtained NMSE scores and R-values obtained for the regression error. From **Table 4**, it can be stated that the GKR based approach outperforms the ANN model for all the training data. Therefore, the GKR surrogate model is selected, which is further used as a fitness function to the proposed heuristic. **Fig. 1** depicts the ANN based regression plots for the case data with promising R-values.

Table 4. ANN vs GKR: Comparison based on NMSE values

Cases	GKR		ANN	
	NMSE	R-Value	NMSE	R-Value
CNC Turning Operation	**0.0487**	**0.93704**	0.8444	0.84361
Cylindrical Grinding	**0.0474**	**0.96721**	0.3079	0.87762
CNC Micro-Milling	**0.0124**	**0.98418**	0.8701	0.95655

3.4. Heuristic Algorithm

The proposed search technique is an improvement heuristic, which is population based and iterative in nature. The steps of the proposed algorithm are as follows,

Step 1. It generates a new population at the initial iteration using the LHS based algorithm, which uniformly generates the design space for the input parameters. Every row of the population table is an experimental setup. The size of the initial population is set to 100. Maximum number of iterations are set to 100.

Step 2. The GKR based fitness function is used for functional evaluation, which predicts the output for each of the experiment setup (population member) obtained in last step. Since the fitness space has multiple responses or objective values, therefore, it is required to obtain the Pareto fronts for the solutions.

Step 3. To obtain the Pareto fronts, a non-dominated sorting method is applied and each of the members of the population are ranked based on the domination.

Step 4. For every iteration of the heuristic, it generates a new population, evaluates the solutions, add them with initial population set, and rank them using the non-dominated sorting. Hence, each new population has now 200 members.

Step 5. Only the top 100 members are selected based on the ranks and crowding distances and passed on to the next iterations.

The heuristic stops, once it reaches the maximum number of iteration count.

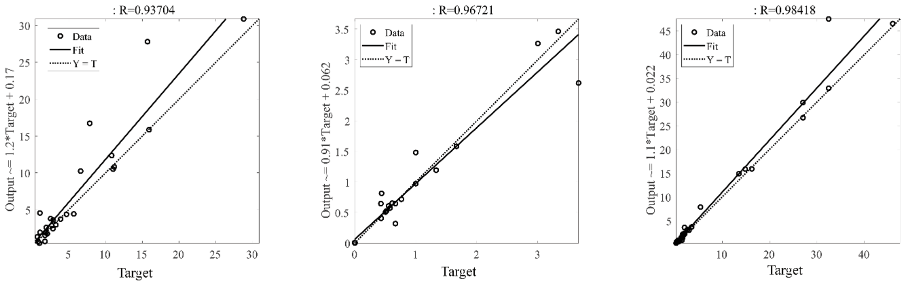

Fig. 1. Regression plots for three cases

4. Results and Discussions

The proposed algorithm is coded in Matlab. The obtained Pareto fronts for each of the test problems are displayed in **Fig. 2**, **Fig. 3**, and **Fig. 4**.

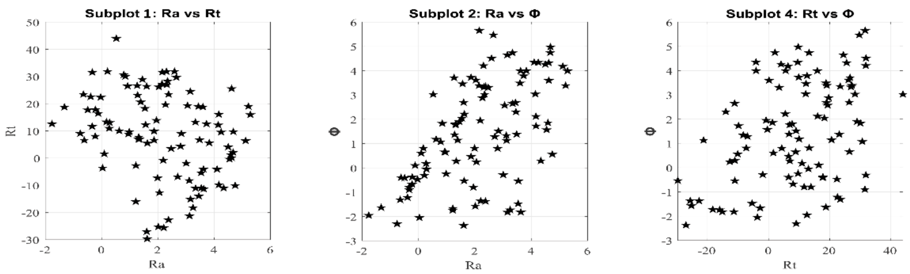

Fig. 2. Pareto Solutions for CNC Turing Case study

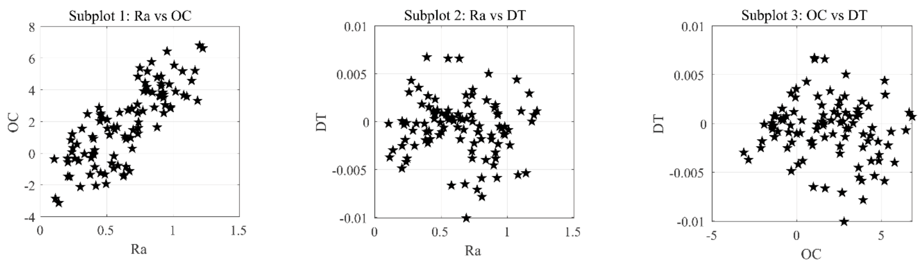

Fig. 3. Pareto Solutions for Centerless Cylindrical Grinding Case study

The turning operation has three responses *Ra*, *Rt*, and φ; the grinding operation has three responses *Ra*, *OC*, and *DT*; and the milling operation has four responses, *TW*, *Fx*, *Fy*, and *Ra*. The computing time is an important factor for the optimization algorithms. This proposed technique consumes 12.14 seconds, 12.11 seconds, and 10.17 seconds to produce the optimal results, and the obtained results are better than the published results. For the CNC turning, the optimal published result is *CF=155, FR=0.12,* *DC=0.8, CFMR=12, and Ra=0.484, Rt=17.762, φ=0.067*. In this study, the most suitably picked results are, *(1) CF=131.08, FR=0.14, DC=0.9, CFMR=13.47, and Ra=0.269, Rt=10.934, φ=0.177 and (2) CF=161.7, FR=0.144, DC=0.913, CFMR=12.355, and Ra=0.094, Rt=1.552, φ=0.604*. For the centerless cylindrical grinding, the optimal published result is the experimental run# 2 in Table 2. In this study two most promising solutions are picked up from the Pareto frontier, *(1) DF= 4.075, GF= 10.920, DT= 4.327, CT= 9.230 and Ra= 0.244, OC= 0.344, Dt = -0.004 and (2) DF= 4.260, GF= 5.959, DT= 2.894, CT= 9.958 and Ra= 0.229, OC= 0.830, Dt = -0.002*. For the micro milling, the optimal published result is the experimental run# 1 in Table 3. In this study, the most promising Pareto solutions obtained are, *(1) SS= 9373.596, FPT= 1.219, DC= 57.163, TW= 4.040, Fx= 2.799, Fy= 1.723, Ra= 0.198 and (2) SS= 11257.000, FPT= 0.153, DC= 86.430, TW= 4.494, Fx= 2.047, Fy= 1.863, Ra= 0.181*.

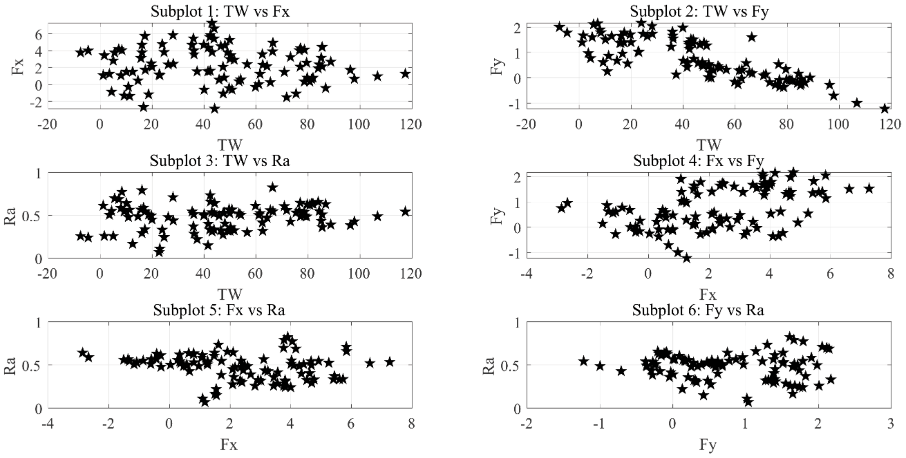

Fig. 4. Pareto Solutions for Micro-Milling Case study

The surface roughness is the most exploited process response for all the cases, which determines the quality of the products. Therefore, the objective of this study is to find those Pareto solutions with the lowest surface roughness scores. Similarly, the Pareto solutions obtained using the proposed technique demonstrates better tool wear score for the CNC milling.

5. Conclusions

This paper proposes a generic surrogate-assisted heuristic algorithm for manufacturing process optimization problems. The proposed technique exploits the GKR surrogate, which is shown to outperform another surrogate based on the neural network. Both the surrogate functions need small amount of manufacturing process data for the training and obtain very accurate output responses with low NMSE scores. The proposed technique is successfully tested on three different cases from past literature. This study shows that the surrogate-assisted heuristic algorithm can obtain realistic solutions within boundary conditions. This study requires further validation tests for the reliability. The proposed surrogate-assisted approach could be extended further with standing optimization algorithms such as Nondominated Sorting Genetic Algorithm (NSGA), Multi-Objective Evolutionary Algorithm (MOEA) etc. This work is a work-in-progress of a project based on multi-response CNC milling operation and process monitoring.

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