# NSGA III for CNC End Milling Process Optimization

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**Abstract.** Computer Numerical Controlled (CNC) end milling processes require very complex and expensive experimentations or simulations to measure the overall performance due to the involvement of many process parameters. Such problems are computationally expensive, which could be efficiently solved using surrogate driven evolutionary optimization algorithms. An attempt is made in this paper to use such technique for the end milling process optimization of aluminium block and solved using Non-dominated Sorting Genetic Algorithm (NSGA III). The material removal rate, and surface roughness are considered as the crucial performance criteria. It is shown that the regression driven NSGA III is efficient and effective while obtaining improved process responses for the end milling.

**Keywords:** Parameter Optimization; NSGA III; Regression; CNC End Milling

## 1 Introduction

Metamodel or Surrogate function driven optimization has recently been emerged, which exploits the cheap metamodel/surrogate functions as objective functions and eliminates the requirement of complex mathematical functions or laboratory experiments. Traditional optimization methods could be used for these problems, such as, the exact methods, evolutionary algorithms, and non-evolutionary methods as the solution methodologies. Surrogate/black-box models are useful when less information exists on the problems [1]. Surrogate based approaches can predict correlations among the process variables depending on the data obtained through Design of Experiment (DOE) approaches [2]. Precision of the prediction model would be significant for the training of the models. The Mean Square Error (MSE), Root Mean Square Error (RMSE) etc. are exploited as performance metrics for the surrogate approaches. Once the training of the surrogate model is completed, a suitable optimization technique, such as Genetic Algorithms (GA), Ant Colony Optimization (ACO), Bat Inspired Algorithm (BA), Particle Swarm Optimization (PSO) etc. could be employed as an optimization technique to obtain Pareto optimal front [3]. Surrogate models are substantially prompt and efficient. Therefore, the surrogate-assisted optimization is not expensive in terms of computation.
DOE techniques, e.g. Latin Hypercube Sampling (LHS), Full Factorial Design (FFD), Orthogonal Array Design (OAD) etc. are employed to design the experimental or trial

sample points in the process design space. These could be employed as the training dataset for the surrogate/black-box models. The DOE techniques amplify the process information acquired from the experimental runs [4].

Some of the surrogate-based approaches are heavily practiced in literature. These could be Response Surface Models (RSM), radial basis functions (RBF), Support Vector Machines (SVM), Gaussian Process (GP), Artificial Neural Network (ANN) etc. [5].

Recently surrogate-assisted techniques are being practiced for manufacturing process optimization problems. Ref. [6] portrays a metamodel based process parameter optimisation. In ref. [7], ANN coupled GA is used to find improved process parameters. Ref. [8] [9] introduced surrogate modeling for the optimisation of an injection molding process. Ref. [10] demonstrated the expected improvement, which could select the enhanced solutions in a surrogate-based optimization. Ref. [11] introduced a Model-Based Self-Optimisation (MBSO), which includes machines having the reasoning capabilities. Therefore, automatic parameters adaptation could be done by machines in uncertain conditions. In another work authors introduced surrogate-based optimisation to a composite textile draping process, which is a deep ANN and it could predict the shear angle of many textile elements [5]. It is shown to minimize the number of FEM simulations, which was needed to attain optimal level of parameters.

Computer Numerical Controlled (CNC) milling is an essential metal cutting technique among various machining processes in the modern era of manufacturing. CNC milling not only makes the milling process fully automated, but also enhances the machining time, reduces milling process variations, improves the quality of the machined parts, and enriches the overall productivity of the manufacturing companies [8]. For CNC milling, end mill is one of the most vital tools amongst various milling cutters due to its ability of high-speed cutting of metal with minimum surface roughness in a single pass [12]. CNC end milling is being practiced significantly in different manufacturing sectors, such as aerospace, automotive, electronics, jewellery, bioinstrumentation industries, etc. CNC end milling is used for making different geometrical shapes and holes in a metallic work-piece during milling, profiling, contouring, slotting, counter-boring, drilling, and reaming applications, etc. [13]. Aluminium alloy is mostly explored material for end milling, which has more than 90% pure Aluminium. It has high strength and ductility, corrosion resistance, weldability, machinability, and formability. It is used as an important material for vehicle bodies, refrigerated trucks, cold storage rooms, anti-skid flooring, manufacturing of mobile homes, residential siding, and rain carrying goods, etc. [14]. It is also used in sheet metal work. With optimum settings of end milling parameters, it is possible to achieve good surface quality and high Metal Removal Rate (MRR) for the aluminium alloy. For that matter, Tool Diameter (TD), Spindle Speed (SS), Feed Rate (FR), and Depth of Cut (DOC) could be the most important process variables. The Surface Roughness (Ra) is the primary machining attribute since most of the manufacturing companies try to maintain better surface quality for the machined parts. Therefore, Ra determines the manufacturing cost and quality of the engineered products [15]. Surface texture, fatigue resistance, and heat transmission of manufactured products are greatly influenced by Ra. Surface quality also depends on the abovementioned machining parameters of end milling. On the contrary, MRR is determined by the volume of removed metal and the machining time on the metal work-piece. MRR could affect the cost of manufacturing largely. When the combined effect of MRR and Ra is studied, the cutting process optimization becomes more complicated [16]. The solidity and life of the cutting tools could also be influenced by the cutting forces for the end milling process. Machining errors could be seen if the cutting forces are not considered while optimizing the process [17] [18]. The objective of this study is to determine the ideal parameter settings, which could yield high MRR and low Ra for the end milling of AA3105 alloy in desired range. Data-driven surrogate assisted optimization has rarely been used for machining process optimization [19], which is depicted in this work.

## 2 Material and Method

AA3105 alloy work-piece (90 x 140 x 20 $mm^3$) is used for the testing of end milling operation. AA3105 alloy is primarily used in sheet metal work and manufacture of mobile homes, residential siding, and rain carrying goods in sub-zero temperature. It is perfectly suitable for the climate of Nordic Europe. AA3105 portrays good machinability property. Percentages of weight in chemical composition of the AA5105 are Al - 98.56%, Mn - 0.716%, Fe - 0.38%, Zn - 0.128%, Cu - 0.118%, Cr – 0.081%, and Pb – 0.006%. The experimental set up is depicted in Fig. 1.

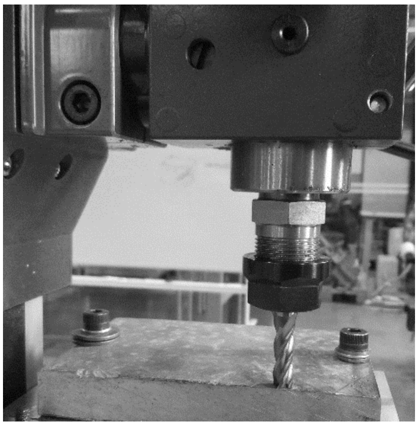

**Fig. 1.** End Milling operation in laboratory

The experiments are carried out on Proxxon FF 500/BL 3-Axes CNC milling machine, manufactured by Proxxon, Germany. It has double roller bearing recirculating ball spindles at all 3-axes. The spindle speed varies in the range of 200 - 4000 rpm. It has large traverse area (X -290mm, Y-100mm, and Z-200 mm). Tools are based on the spiral design according to DIN 844 and made of the high-speed steel (HSS-Co5) 5% cobalt. To measure the surface quality of the machined work-pieces, a ZEISS Handysurf E-35B is used.

## 3 Surrogate Assisted Optimization Method

In this article a novel regression driven NSGA III algorithm is employed. The cutting process is modelled with a popular DOE tool namely, Taguchi's orthogonal design. For carrying out the basic experiments during the cutting of AA3105, the initial settings of the levels of the milling process parameters (Table 1). The responses are determined by conducting trials, which are portrayed in Table 2.

**Table 1.** End milling parameters with their levels

| Factors | Level 1 | Level 2 | Level 3 | Level 4 |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| TD (mm) | 6 | 7 | 8 | 10 |
| SS (rpm) | 1500 | 1750 | 2000 | 2250 |
| FR (mm/s) | 2 | 3 | 4 | 5 |
| DOC (mm) | 0.5 | 1.0 | 1.5 | 2.0 |

**Table 2.** Experimental design space using $L_{16}$ Orthogonal array

| Ex# | TD | SS | FR | DOC | MRR (mm3/s) | Ra (μm) |
|---|---|---|---|---|---|---|
| 1 | 6 | 1500 | 2 | 0.5 | 5.263 | 0.08 |
| 2 | 6 | 1750 | 3 | 1 | 11.080 | 0.06 |
| 3 | 6 | 2000 | 4 | 1.5 | 18.100 | 0.06 |
| 4 | 6 | 2250 | 5 | 2 | 7.299 | 0.05 |
| 5 | 7 | 1500 | 3 | 1.5 | 6.652 | 0.29 |
| 6 | 7 | 1750 | 2 | 2 | 20.690 | 0.25 |
| 7 | 7 | 2000 | 5 | 0.5 | 5.848 | 0.05 |
| 8 | 7 | 2250 | 4 | 1 | 18.018 | 0.04 |
| 9 | 8 | 1500 | 4 | 2 | 41.379 | 0.18 |
| 10 | 8 | 1750 | 5 | 1.5 | 20.000 | 0.22 |
| 11 | 8 | 2000 | 2 | 1 | 13.043 | 0.29 |
| 12 | 8 | 2250 | 3 | 0.5 | 7.477 | 0.62 |
| 13 | 10 | 1500 | 5 | 1 | 25.641 | 0.075 |
| 14 | 10 | 1750 | 4 | 0.5 | 6.390 | 0.27 |
| 15 | 10 | 2000 | 3 | 2 | 40.000 | 0.89 |
| 16 | 10 | 2250 | 2 | 1.5 | 24.390 | 0.72 |

### 3.1 Regression Analysis

Multiple regression mode is obtained for MRR and Ra at 95% confidence level. Regression equations are depicted in Eq. (1)-(2). These equations are used as the fitness functions for the NSGA III algorithm. Table 3 shows the p-values and $R^2$ values of the regression analysis, which states that the MRR is mostly dependent on the DOC and Ra is mostly dependent on the TD.

$$MRR = -18.6 + 3.60 * TD - 0.00464 * SS + 0.12 * FR + 12.73 * DOC \tag{1}$$

$$Ra = -0.885 + 0.1090 * TD + 0.000290 * SS - 0.1036 * FR + 0.0937 * DOC \quad (2)$$

**Table 3.** Regression models with P Values and $R^2$ Values

| | | P-Value | $R^2$-Value |
|---|---|---|---|
| P-Values for regression models and parameters | Regression | 0.015 | 0.002 |
| | TD(mm) | 0.022 | 0.001 |
| | SS(rpm) | 0.530 | 0.055 |
| | FR(mm/s) | 0.947 | 0.011 |
| | DOC(mm) | 0.005 | 0.193 |
| $R^2$ | | 64.69% | 75.66% |

### 3.2 NSGA III Technique

NSGA III is a recently published optimization technique developed in the ref. [20]. NSGA III is extended based on the framework of previously published NSGA-II with a newer selection approach.

NSGA III works on an evenly distributed reference points in the state space. These are further updated using supervised learning technique. Algorithm 1 portrays NSGA III. It starts with a randomly generated initial population POP (size *N*). The set of reference points are assumed as $Z^{ref}$. The NSGA III runs for a fixed number of generations. The tournament selection, binary crossover, and polynomial mutation [21] are used for the NSGA III, which further produce *N* number of child solutions (e.g. $POP_{new}$).

**NSGA III**

1: **Create** the set of reference points $Z^{ref}$ to put on hyper plane
2: **Create** random population *POP*
3: **Create** the Ideal points $Z^{max}$
4: **Calculate** fitness for the generated population
5: **Execute** non-dominated sorting on population
6: **for** i=1 to Iteration No. **do**
    7: **Compute** crossover with $P_c$ probability
    8: **Compute** mutation with $P_m$ probability
    9: **Add** new solutions to obtain NEWPOP = POP ∪ $POP_{new}$
    10: **Execute** non-dominated sorting on NEWPOP
    11: **Normalize** NEWPOP exploiting $Z^{max}$
    12: **Correlate** the NEWPOP solutions with the $Z^{ref}$
    13: **Compute** niche and **Execute** niche preservation
    14: **Send** niche obtained solutions to the next iteration
15: **end for**

The new population is combined with old population and the combined population of size 2*N* is achieved. Further the non-dominated sorting is performed [22], which clubs the solutions of combined population using some ranking method ($F_{i \text{ where } i=1, 2,\dots, n}$). In the next iteration the population is acquired using this ranking method (e.g. initially $F_1$ members are picked, then $F_2$, $F_3$, etc.). Once the population size becomes *N*, this method stops. However, if the $l^{th}$ rank holders are being included in the next population as last set of members, then, rest of the members from $(l+1)^{th}$ are discarded. This could mean that some of the members with $F_l$ rank are counted (restriction of size $N$). To achieve such goal, reference point-driven selection technique is introduced. This method is different than the crowding distance technique of previous version of NSGA [23].

### 3.2.1 Reference Point Generation

A hyper-plane is defined as an inclined plane to the M-objective axes using (M-1)-dimensional unit simplex. The technique suggested in ref. [24] distributes the reference points on this normalized hyper-plane, where the Pareto solutions are mapped with the reference points. The number of segments of each of the objective axes decides the number of the reference points. For P segments, the number of reference points is computed using,

$$H = C_P^{M+P-1} \tag{3}$$

### 3.2.2 Normalization of Population

The normalization procedure proposed by [20] can recognize ideal points $Z^{max}$. This is done with solutions to the computationally expensive linear equations. The basic normalization technique is followed for that ease of computation. If $Z_j^{min} = (z_1^{min}, z_2^{min}, \ldots, z_M^{min})$ with the lowest fitness scores for $j^{th}$ member $\forall j \in [1, N]$. $z_i^{min}$ is the $i^{th}$ minimum fitness score $f_i$ $\forall i \in [1, M]$. The $z_i^{max} \in Z^{max}$ is worst point for the $i^{th}$ objective. The normalized fitness score $fi^*(x_j)$ is computed as,

$$f_i^*(x_j) = \frac{z_i^{max} - f_i(x_j)}{z_i^{max} - z_i^{min}} \quad \forall i \in [1, M] \; and \; \forall j \in [1, N] \tag{4}$$

### 3.2.3 Mapping the Population Members and Reference Points

After obtaining the normalized fitness scores, each solution is linked to a corresponding reference point. To facilitates that, reference lines are derived from reference points to hyper-plane origin and the perpendicular distance between each solution and each reference line is calculated. The solution is mapped to reference point based on this lowest perpendicular distance.

### 3.2.4 Niche Preservation

Niches are paired with reference points using the linked solution. Niche preservation is executed to decide, which candidates of rank $F_l$ would be opted. First, the set of reference points is chosen with lowest niche counts. If there is more than one reference point in such situation, a random reference point is chosen from the set. However, the solution is chosen based on the smallest perpendicular distance when niche count is zero. If niche count ≥ 1, the solution selection is random from $F_l$ front. In next iteration the niche count is amplified. The reference point is removed once the operation is finished for it. This procedure is iterated for the $N - |POP|$ counts until the new population of size $N$ is achieved. The proposed algorithm framework is depicted in Fig. 2.

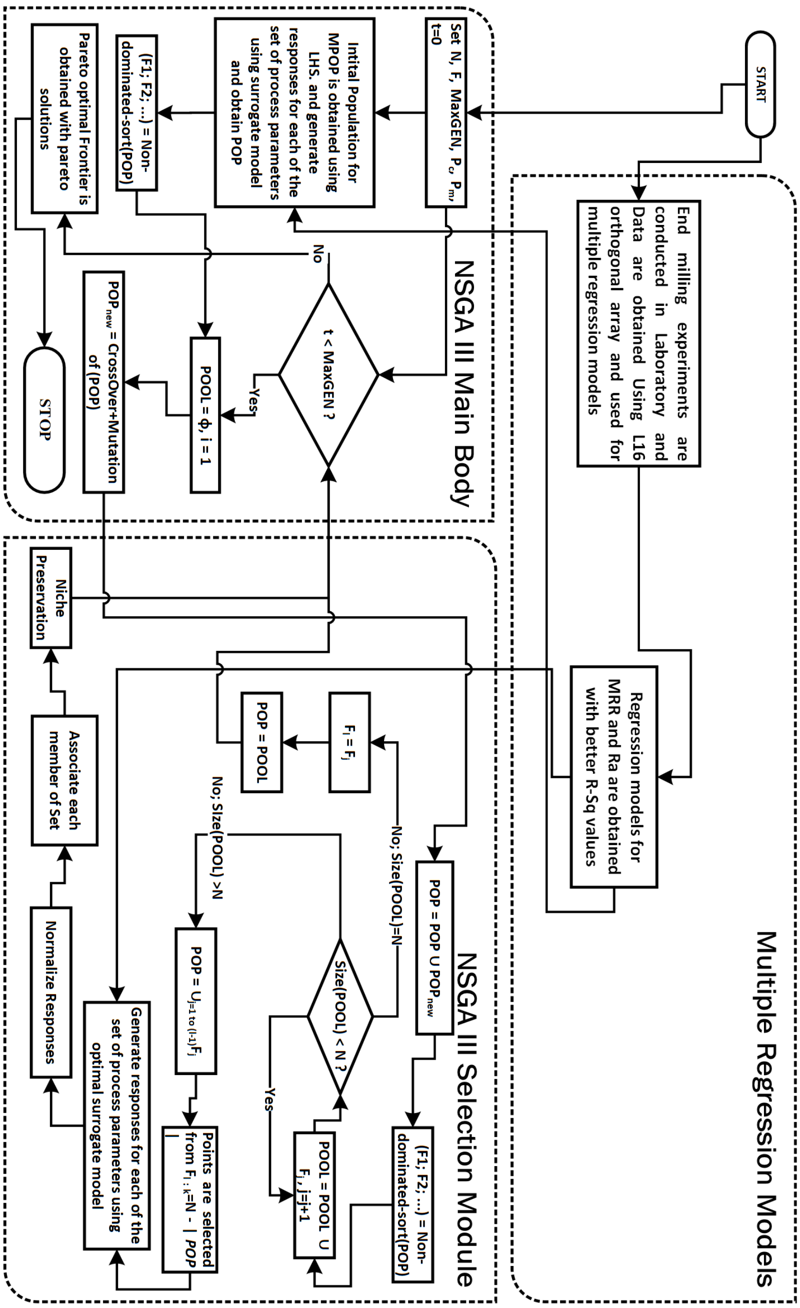


**Fig. 2.** Data-Driven Surrogate-Assisted NSGA III framework

## 4 Results and Discussions

The regression-assisted NSGA III technique is coded with MATLAB functions on an Intel i7 laptop with 16GB RAM. Since it is a multi-objective optimization problem, Pareto solutions are recorded. These are near-optimal solutions with trade-offs among the fitness scores (Fig. 3). Total 13 Pareto solutions are depicted in Table 4. The best solution is chosen for the confirmatory experiment (Table 5).

**Table 4.** Total 13 Pareto solutions obtained by regression driven NSGA III

| TD | SS | FR | DOC | MRR | Ra |
|---|---|---|---|---|---|
| 8.319 | 1565.011 | 4.548 | 1.403 | 22.489 | 0.136 |
| 6.077 | 1993.653 | 4.394 | 1.486 | 13.475 | 0.040 |
| 6.221 | 1829.457 | 4.095 | 1.685 | 17.252 | 0.057 |
| 8.323 | 1629.146 | 4.884 | 1.729 | 26.399 | 0.151 |
| 6.888 | 1835.224 | 4.660 | 1.531 | 17.731 | 0.059 |
| 7.527 | 1609.844 | 4.236 | 1.305 | 18.150 | 0.086 |
| 8.495 | 1580.086 | 4.131 | 1.736 | 27.245 | 0.234 |
| 9.813 | 2079.163 | 4.863 | 1.847 | 31.169 | 0.457 |
| 6.772 | 1519.991 | 3.408 | 1.749 | 21.404 | 0.105 |
| 6.543 | 1595.130 | 3.503 | 1.556 | 17.778 | 0.074 |
| 9.788 | 2176.137 | 3.233 | 1.970 | 32.009 | 0.663 |
| 9.481 | 1620.140 | 3.631 | 1.745 | 30.666 | 0.406 |
| 9.252 | 1874.775 | 4.840 | 1.856 | 30.213 | 0.340 |

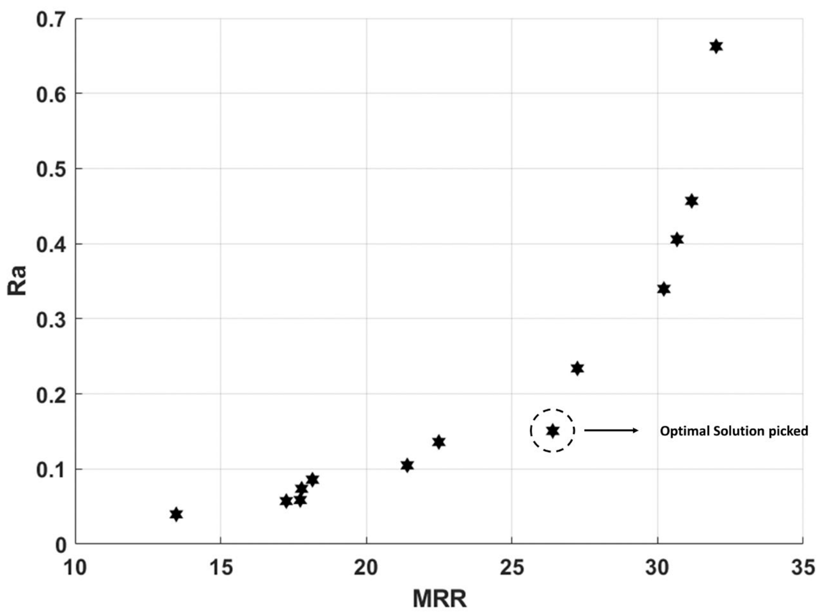


**Fig. 3.** Pareto solutions obtained by regression driven NSGA III

### 4.1 Confirmatory Test

Once the optimal levels of the control factors are identified, confirmatory test is performed. Total 10 experimental run are performed using the obtained set of parameters. The parameter values are rounded off to the nearest real values. The average MRR, and Ra scores are shown in Table 5. The confirmatory test results are compared with the model output, which are substantially close to each other with deviation of 10.66% and 3.22% for the Ra and MRR respectively, which are in the acceptable range. Therefore, the confirmatory test indicates that the selection of the optimal levels of the parameters could produce the best and accurate process responses for the end milling process.

**Table 5.** Confirmatory test result

| End milling Parameters | Predicted Responses | Experimental Responses | Errors |
|---|---|---|---|
| TD=8, SS=1629, FR=4.88, DOC=1.73 | MRR=26.4, Ra=0.15 | MRR=27.25, Ra=0.166 | MRR=3.22%, Ra=10.66% |

## 5 Conclusions

In this study, a novel regression driven NSGA III algorithm is employed for the end mill cutting problem. This technique exploits multiple regression equations as the surrogate fitness functions. This regression driven NSGA III technique can attain Pareto optimal solutions. Four process parameters for the end milling process are considered, TD, SS, FR, DOC and two process responses are considered, MRR, and Ra. The experimental design space is obtained using $L_{16}$ orthogonal array method with a total of 16 experimental runs. The proposed NSGA III obtains accurate results, which indicate the optimal parameter settings. This choice of settings based on our intuition and experience showed very promising results within the desired parametric range. Obtained results are successfully validated with a small number of confirmatory test runs, which recommends the proposed technique as an effective optimizer for the end milling process.

## 6 Acknowledgement

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