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Multi-Objective Optimization of Milling Parameters for Machining Cast Iron on Machining Centre

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Abstract

This paper presents an approach for determination of the best cutting parameters leading to minimum surface roughness and maximum Material Removal Rate in machining Cast Iron on Machining Centre. A feed forward neural network model is developed exploiting experimental values. The neural network model is trained and tested in MATLAB. Multi objective Genetic algorithm coupled with neural network is employed to find optimum cutting parameters leading to minimum surface roughness and maximum Material Removal Rate.

Keywords: Machining Centre, Artificial Neural network, genetic algorithm, multi-objective optimization.

Introduction

The main challenge of the manufactures are to increase the production and to decrease the production cost without effecting the quality for which selection of machining parameters place a important role. Optimum machining parameters can be done by considering a single objective function like desired surface finish, maximum material removal rate or maximum tool life. Optimum machining parameters achieved for a objective function may not be suited for another objective function. Efficient machining parameters can be achieved by considering multi objective optimization. Using traditional algorithms it is very difficult to solve multi objective functions. Evolutionary algorithms like genetic algorithm, ant colony optimization and swarm particle optimization are used to solve multi objective optimization.

In metal cutting operation cutting parameters are the dominant factors in determining cutting parameters there is a conflict between metal removal rate and minimizing surface roughness. Increasing cutting speed or feed rate will increase MRR but results in poor surface finish. Optimum machining parameters are to be evolved for maximum material removal rate and minimum surface roughness.

Optimization of machining parameters, surface roughness in end milling of mold surface of an ortez part by coupling neural network and genetic algorithm was studied by Hason Oktem[1].

While machining hardened steel AISI H13 with TiN coated carbide insert at high speed optimal machining parameters for semi finishing and finishing are optimized by J.A.Ghani[2] using taguchi optimization methodology.

Experiments were conducted according to the principles of taguchi method, design of experiments for different factors like cutting speed, feed, depth of cut, use of cutting fluid, wear of cutting tool and three cutting forces Benardos and Vasia Kos[3] ANN network was created for prediction of surface roughness. By considering factors like cutting speed, feed, depth of cut Sharma et.al[4] predicted cutting force and surface roughness in hard turning.

Many researches use objective function in the form of equation and tried to optimize the process parameters. Evolution of this equation is based on many assumptions which may not be representing for actual process.

In this work, Experiments were conducted on CNC vertical machining centre for four levels of machining parameters on cast iron with carbide tipped tool. The machining parameters selected are speed, feed and depth of cut are shown in table 2. Surface roughness was measured by using talysurf and material removal rate is calculated. A neural network is generated with speed, feed and depth of cut as input parameters and surface roughness as target values. The network is properly trained and tested for accuracy. This neural network generated is used to predict the surface roughness values, and is exported optimization programs used to optimize the machining parameters.

Methodology

In this paper milling operation is performed on CNC Vertical Machining Centre by considering different levels of cutting parameters. The work piece material is Cast Iron and the cutting tool used is Carbide tipped tool, the composition of cast iron is shown in table1. The cutting parameters considered are cutting speed, feed and depth of cut as shown in table2. Experiments were conducted at four levels of machining parameters. 64 experiments were conducted and Surface Roughness and surface roughness was measured. The Material Removal Rate is calculated by MRR = f x n x z× d × D. Results are tabulated in table 3

Table-1
Composition of cast iron

	Carbon	Silicon	Manganese	Phosphorous	Sulphur
%	3.4	2.1-2.3	$0.5^{\pm 1}$	0.1	0.07

Table-2
Machining parameters and their levels

Machining Parameters	Unit	Symbol	Levels			
			1	2	3	4
Cutting Speed	rpm	n	396	496	595	674
Feed	mm/teeth	f	0.1	0.15	0.17	0.2
Depth Of cut	mm	d	0.75	1	1.25	1.5

Table-3
Experimental results to Train the ANN Model

	Speed (rpm)	Feed (mm/teeth)	Depth (mm)	Ra (µm)	Material Removal Rate(mm^3/min)
1	496	0.1	1	2.900	23808
2	496	0.1	0.75	2.960	17856
3	496	0.1	1.25	2.845	29760
4	496	0.1	1.5	2.683	0.112
5	496	0.15	1	2.840	0.112
6	496	0.15	0.75	2.950	26784
7	496	0.15	1.25	2.713	44640
8	496	0.15	1.5	2.576	53568
9	496	0.17	1	3.160	40472
10	496	0.17	0.75	3.220	30354
11	496	0.17	1.25	2.860	50590
12	496	0.17	1.5	2.780	60708
13	496	0.2	1	3.430	47616
14	496	0.2	0.75	3.260	0.112
15	496	0.2	1.25	3.100	83328
16	496	0.2	1.5	3.030	0.224
17	396	0.1	1	2.980	19008
18	396	0.1	0.75	2.860	14256
19	396	0.1	1.25	2.633	23760
20	396	0.1	1.5	2.730	28512
21	396	0.15	1	2.890	28512
22	396	0.15	0.75	2.830	21384
23	396	0.15	1.25	2.650	35640
24	396	0.15	1.5	2.555	42768
25	396	0.17	1	3.180	32312
26	396	0.17	0.75	3.120	24234
27	396	0.17	1.25	2.757	40390
28	396	0.17	1.5	2.840	48468
29	396	0.2	1	3.310	38016
30	396	0.2	0.75	3.250	28512
31	396	0.2	1.25	2.940	47520
32	396	0.2	1.5	2.913	57024
33	595	0.1	1	3.100	28560
34	595	0.1	0.75	2.980	21420
35	595	0.1	1.25	2.740	0.100
36	595	0.1	1.5	2.613	42840
37	595	0.15	1	2.900	42840
38	595	0.15	0.75	2.920	32130
39	595	0.15	1.25	2.660	53550
40	595	0.15	1.5	2.596	64260
41	595	0.17	1	3.060	48552
42	595	0.17	0.75	3.070	36414
43	595	0.17	1.25	2.780	60690
44	595	0.17	1.5	2.68	72828
45	595	0.2	1	3.286	57120
46	595	0.2	0.75	3.220	42840
47	595	0.2	1.25	2.966	0.200
48	595	0.2	1.5	3.010	85680
49	674	0.1	1	3.080	32352
50	674	0.1	0.75	2.920	24264
51	674	0.1	1.25	3.45	40440
52	674	0.1	1.5	3.663	48528
53	674	0.15	1	2.866	48528
54	674	0.15	0.75	3.173	36396
55	674	0.15	1.25	2.956	60660
56	674	0.15	1.5	2.86	72792
57	674	0.17	1	3.296	55000
58	674	0.17	0.75	3.44	41250
59	674	0.17	1.25	3.353	68750
60	674	0.17	1.5	3.326	82500
61	674	0.2	1	3.113	64704
62	674	0.2	0.75	3.505	48528
63	674	0.2	1.25	3.680	80880
64	674	0.2	1.5	3.400	97056

Artificial Neural Networks: An artificial neural network is created for predicting surface finish in Mat lab using results shown in table 3 Machining parameters are input parameters and surface roughness is the target value. The network architecture consists of one input, 5 hidden layer, and one output layer. The hidden layer consists of twenty neurons. The network shown in fig1 is feed forward back propagation network transfer function is TRANSIG and training function is TRAINLM adoption learning function is LEARNDGM performance function is mean square error. The network created is exported to the multi objective genetic algorithm program written in

MATLAB software. The generated machining parameters i.e. cutting speed, feed rate and depth of cut are input to the network and output is surface finish. To have an accurate and reliable model, surface roughness is estimated by using a perceptron neural network. Several network architectures, which are not presented in this study, are tested. Regression plot for training test and validation for the network is shown in figure 2.

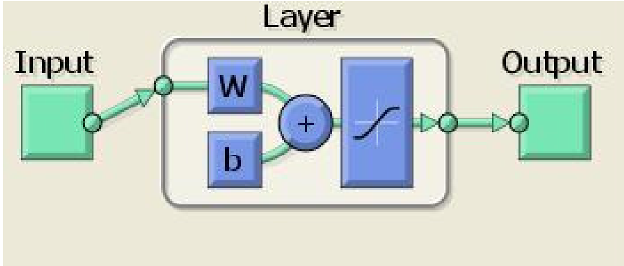

Figure-1
ANN Feed Forward Back Propagation Network

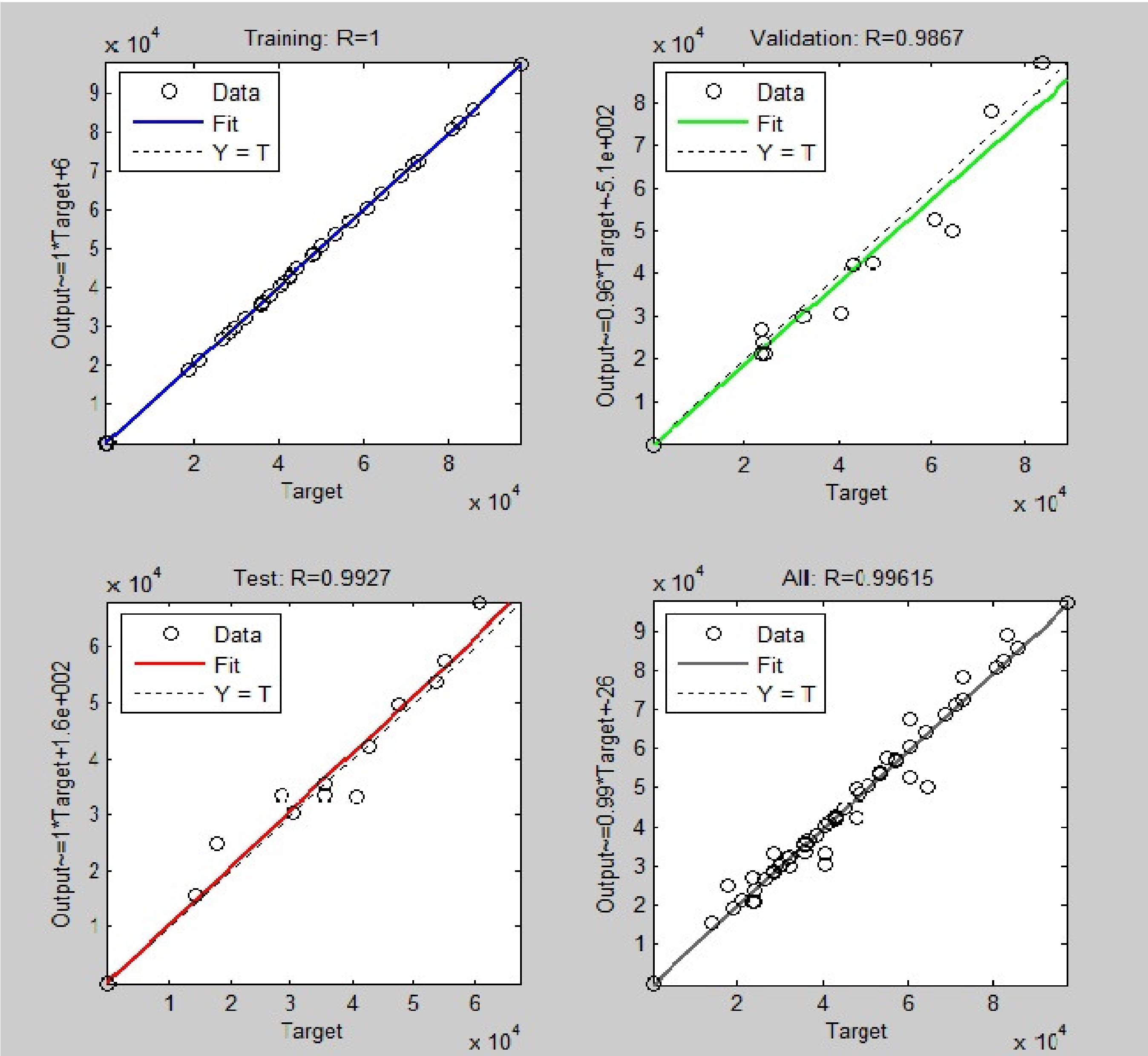

Figure-2
Regression plot in Artificial Neural Network for surface finish

The network created is exported to the multi objective genetic algorithm program written in MATLAB software. The generated machining parameters i.e. cutting speed, feed rate and depth of cut are input to the network and output is surface finish. Flow Chart for the procedure of Multi Objective Genetic Algorithm is shown in figure 3

Multi Objective Genetic Algorithm: MOGA is used for the solving of problems with two or more objectives to be satisfied simultaneously. The objective may be conflict to each other and expressed in different units. The multi-objective optimization problem general formulation consists of a number of objectives with a number of inequality and equality constraints. The maximize objective function is to be converted into minimization type by multiplying negative one without loss of generality. A perfect objective solution that simultaneously optimizes each objective function is almost impossible. A reasonable solution to multi objective problems is to investigate a set of solutions. Each set satisfies the objectives at an acceptable level without being dominated by any other solution. MOGA is differing from the classical GA in the way the fitness is assigned to each solution in the population. In MOGA first each solution is checked for its domination in the population. To a solution i a rank equal to one plus the number of solutions n_i that dominates solution i is assigned.

$$R_i = 1+n_i$$

Non dominated solutions are assigned a rank equal to 1 so that no solution dominates a non dominated solution. A raw fitness to a solution is assigned based on the rank. A raw fitness is assigned to each solution by using linear mapping function. Solutions of each rank are considered at a time and their raw fitness is averaged. The averaged fitness is called assigned fitness. The total allocated raw fitness and total assigned fitness to each rank remains identical. The mapping and averaging procedure ensured that the better ranked solution have a higher assigned fitness. In MOGA niching is introduced among solution of each rank. A shared fitness value is calculated by dividing the fitness of the solution by niche count. The assigned fitness values are divided by the niche count so that fitness of each solution is reduced. This procedure is continues until all ranks are processed. Stochastic universal solution (SUS) the single point cross over and the bit wise mutation operations are applied to create a new population. The procedure is repeated until the objective function criterion is satisfied.

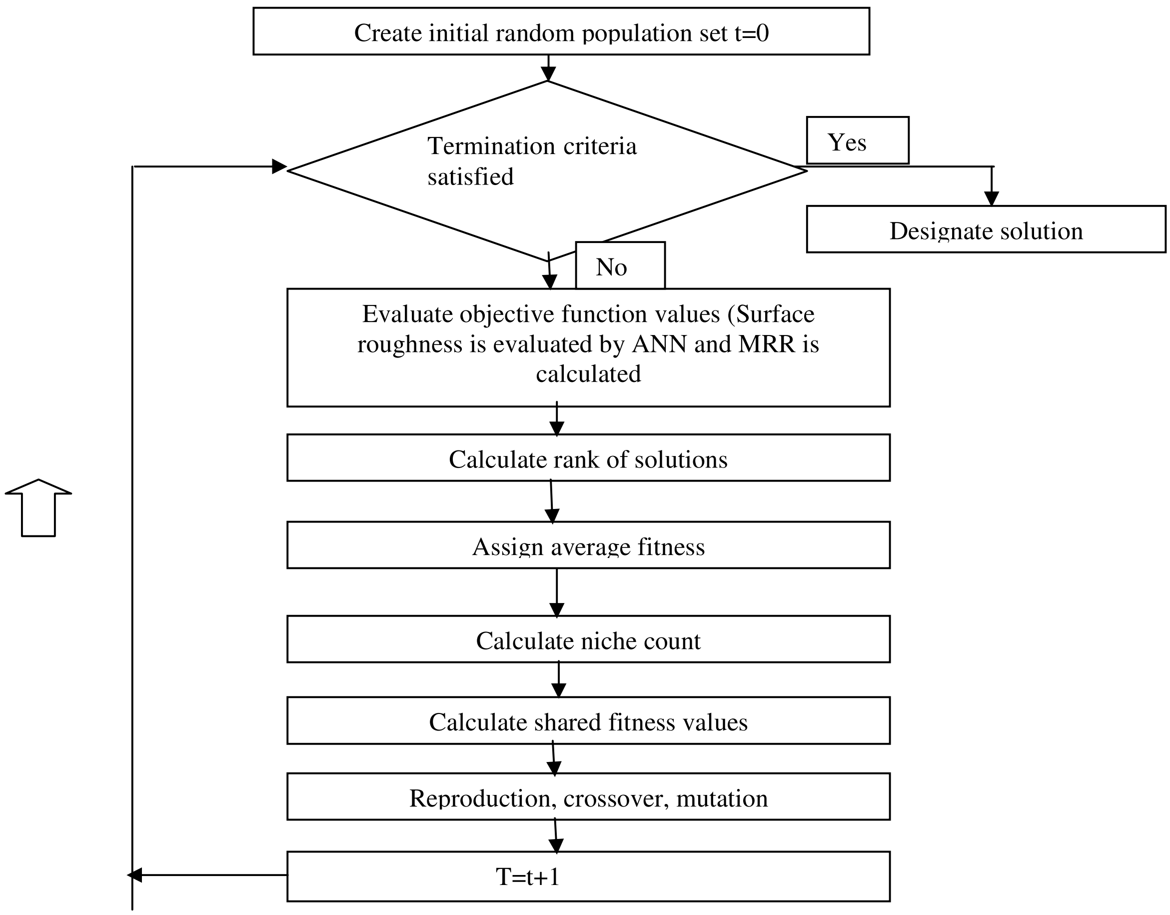

Figure-3
Flow Chart for the procedure of Multi Objective Genetic Algorithm

Results and Discussion

By exporting ANN to Genetic algorithm optimum machining parameters for surface roughness are evaluated. The values are
Optimum speed = 457.4 rpm
Optimum feed = 0.16 mm/teeth
Optimum depth of cut = 1.33mm
Minimized surface roughness = 2.3457 µm
Metal Removal Rate = 46720.6656 mm^3/min

By exporting ANN to MOGA optimum machining parameters are obtained for minimum surface roughness and maximum metal removal rate are
Optimum speed = 614
Optimum feed = 0.1714 mm/teeth
Optimum depth of cut = 1.3414
Minimum surface roughness = 2.82 µm
Maximum material removal rate = 67760.83 mm^3/min

By generating ANN by using surface roughness as input value and machining parameters as target value surface roughness can be predicted.

For surface roughness, machining parameters are predicted and experiments were conducted at these values of machining parameters. The values of surface roughness found are in agreement with predicted values

Conclusion

Artificial Neural Network coupled Genetic Algorithm and Multi Objective Genetic Algorithm are proved to useful techniques in the optimization of machining parameters. Properly trained Artificial neural network can be used as an useful tool for predicting the surface roughness at the given machining parameters and machining parameters for given surface roughness.

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