PROCESS PARAMETER OPTIMIZATION FOR STEEL RECYCLING PROCESS BY
PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

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Abstract

In this paper optimization of parameters for recycling of steel process by using Particle Swarm Optimization (PSO) algorithm was used. For analysis five significant affecting input process parameters were considered with three objective functions. The material selected for experimentation was steel rod of diameter 16 mm manufactured by secondary steel manufacturing process. The three objective functions were maximization of Tensile strength (N/mm²), Hardness number value (No.) and minimization of Energy consumption (Kw-H). By Taguchi’s design of experiment optimal combination of 46 input parameters at various levels were generated and experiments are conducted and responses were noted for each corresponding level. Mathematical model for the given problem was formed and Regression equation was generated by using Response Surface Methodology. PSO, a modern heuristic algorithm was used to solve the regression equation. The optimum results obtained by applying above algorithm were tested experimentally and results were compared. Significant improvement was observed in the objective function and the same was presented in a systematic manner.

Keywords: global, population, pso, steel, recycling.

1. INTRODUCTION

Steel is used as a main material in many engineering fields. There is a significant difference in tensile strength and hardness number values from one manufacturer to another. Hence in this paper modern optimization technique called as particle swarm optimization algorithm is used to enhance the objective function along with
minimum energy consumption per ton of steel. From the available literature this gap was observed and the same has been addressed to meet the desired goal.

2. PROCESS PARAMETERS

It is observed that there was a significant variation in tensile strength and hardness number values for different secondary steel manufacturers. Based on literature and consultation with experts from secondary steel manufacturing industries five significant affecting input process parameters were identified with their levels. They were Furnace temperature (Ft in °C)), Sponge steel addition (SS in %), Scrap steel composition (SCS in %), TDS number of water used (TDS in No.) and Quenching temperature of steel (Qw in °C)). Input parameters with their levels were shown in Table.1. For analysis of objective function, steel rod (diameter 16 mm) of 2 feet length was used on universal testing machine (UTM), and for hardness number value steel rod of 1 cm length with its flat face polished with emery paper of different grades was used on Brinell hardness testing machine. The process parameters involved are interdependent and the entire process of secondary steel making is complex. Only prime influencing parameters are considered for analysis starting scrap sorting to storing of final steel bars at the store yard. Minutely the process is observed, weaknesses are identified and the same is incorporated in the process. The main objective functions are to maximize tensile strength and hardness number value with minimum consumption of energy in the entire process. The input parameters with their levels are shown in Ref Table.1 below.

3. MODEL FORMULATION

The optimization model for the given steel recycling problem is formulated as shown below in equation (1).

\[
\text{Find } X = \begin{bmatrix} \text{Ft} \\ \text{SS} \\ \text{SCS} \\ \text{TDS} \\ \text{Qw} \end{bmatrix}
\]

\[
\text{Max. T.S} = -12105+13.37 \text{Ft} + 82.0 \text{ SS} - 3.2 \text{SCS} + 8.7 \text{TDS} + 1.72 \text{Qw} - 0.00377 \text{Ft}^2 - 0.017 \text{SS}^2 - 0.0042 \text{SCS}^2 - 0.0142 \text{TDS}^2 - 0.00137 \text{Qw}^2
\]
0.0400 $Ft^*SS^+ + 0.0060 \, Ft^*SCS^-$
$0.0020 \, Ft^*TDS^+ + 0.0000\, Ft^*Qw^-$

$0.280 \, SS^*SCS^+ + 0.100 \, SS^*TDS^+ \, 0.0160 \, S^*Qw - 0.0200 \, SCS^*TDS^-$
$0.0040 \, SCS^*Qw^-$

$0.0080 \, TDS^*Qw\geq 580$

Such That

Hardness number value must be high and
Energy consumption rate should be low and
Corresponding regression equations were

used.

1. Method: Particle Swarm Optimization (PSO) Algorithm

Particle swarm optimization method was
proposed for the first time by Dr. Kennedy
and Dr. Eberhart in 1995. It was a nature
inspired modern heuristic technique used
for solving optimization problems in
manufacturing industries will less
computational complexity. The main
characteristic of Particle Swarm
Optimization is, it is best suitable for multi
objective optimization function, easy to
implement and converges quickly when
compared to other modern optimization
techniques. It conducts search using a
population (swarm) of individuals
particles) that are updated with each
iteration. Each particle in the swarm is
described by position and velocity. It helps
to find the particle best position that results
in the best evaluation of a given fitness
function.

3.1 Algorithm Process for Particle
Swarm Optimization with sample
calculation

The main objective was to maximize tensile
strength and hardness number with
minimum consumption of energy. The
objective function is solved by using
particle swarm optimization algorithm. The
algorithm flow with sample calculation is
represented below:
Input:
Number of particles in population
(population size) = 5,
Number of iterations=1.
Step 1. Generate initial population.
Initial population =
$\begin{bmatrix}
1675 & 15 & 80 & 40 & 525 \\
1675 & 12.5 & 75 & 30 & 500 \\
1700 & 15 & 80 & 30 & 525 \\
1675 & 12.5 & 80 & 35 & 550 \\
1675 & 15 & 85 & 35 & 500
\end{bmatrix}$

Step 2. Find fitness values (Tensile
Strength) of all particles.
Step 3. Generate initial velocity (Old velocity) matrix randomly which has size same as population.

Initial velocity =

\[
\begin{bmatrix}
3.2261 & 0.8329 & 3.4097 & -3.0644 & -1.2736 \\
-3.7062 & 0.3070 & 1.8979 & -2.5502 & -0.5900 \\
-3.2147 & -1.5742 & 2.2410 & 0.2957 & 2.1526 \\
1.1115 & 3.1452 & -3.5145 & -2.5938 & -0.6693 \\
1.9183 & 3.1436 & -3.7932 & -2.8995 & -0.6073 \\
\end{bmatrix}
\]


Assign each particle to its P best. Particle best =

\[
\begin{bmatrix}
1675 & 15 & 80 & 40 & 525 \\
1675 & 12.5 & 75 & 30 & 500 \\
1700 & 15 & 80 & 30 & 525 \\
1675 & 12.5 & 80 & 35 & 550 \\
1675 & 15 & 85 & 35 & 500 \\
\end{bmatrix}
\]

Step 5. Calculate new velocity for each particle i by using equation (2)

\[
V_{\text{new}} = \omega * V_i + C_p * \text{rand} \left( 0,1 \right) \ast (P_{\text{best}} - X_i) + C_g * \text{rand} \left( 0,1 \right) \ast (G_{\text{best}} - X_i)
\]

New velocity =

\[
\begin{bmatrix}
3.1910 & 0.1666 & 0.6819 & -4.0000 & -0.2547 \\
2.0636 & 3.4877 & 3.6969 & -0.5100 & 4.0000 \\
-0.6429 & -0.3148 & 0.4482 & 0.0591 & 0.4305 \\
4.0000 & 4.0000 & -0.7029 & -4.0000 & -4.0000 \\
4.0000 & 0.6287 & -4.0000 & -4.0000 & 4.0000 \\
\end{bmatrix}
\]

Step 6. Prepare new population as follows.

New population =

\[
\begin{bmatrix}
1675 & 15 & 80 & 40 & 525 \\
1700 & 15 & 80 & 30 & 525 \\
1675 & 12.5 & 85 & 35 & 550 \\
1700 & 15 & 75 & 30 & 525 \\
1700 & 15 & 80 & 30 & 525 \\
\end{bmatrix}
\]

Make adjustments to satisfy all constraints. If new Tensile strength value is better than earlier, replace earlier Tensile strength with new one. Evaluate new population.
Fitness = \[
\begin{bmatrix}
621.5125 \\
632.6088 \\
606.4725 \\
635.3638 \\
632.6088
\end{bmatrix},
\]

**Step 7.** Find new particle best ($P_{\text{best}}$) and new global best ($G_{\text{best}}$) for new population.

**Step 8.** Update particle best and global best. If new particle is better than particle best, replace particle best with new particle. Find the best particle of new population. If it is better than $G_{\text{best}}$, replace $G_{\text{best}}$ with best particle of new population.

Updated $P_{\text{best}}$ = \[
\begin{bmatrix}
1675 & 15 & 80 & 40 & 525 \\
1700 & 15 & 80 & 30 & 525 \\
1700 & 15 & 75 & 30 & 525 \\
1700 & 15 & 80 & 30 & 525
\end{bmatrix},
\]

Updated Fitness = \[
\begin{bmatrix}
621.5125 \\
632.6088 \\
632.6088 \\
635.3638 \\
632.6088
\end{bmatrix},
\]

Updated $G_{\text{best}}$ = \[
\begin{bmatrix}
1700 & 15 & 75 & 35 & 500
\end{bmatrix},
\]

Maximum tensile strength = 635.36 N/mm$^2$,
Hardness Number value = 104.38,
Energy consumption / Ton = 366.12Kw-H.

**Step 9.** Assign new velocity to old velocity.

**Step 10.** If termination condition is satisfied go to

**Step 11.** Otherwise go to step 5.

**Step 12.** Finalize the maximum tensile strength.

2. RESULTS
(Ref Figure-1) shows graph of Tensile strength versus number of iterations, it was observed that Tensile strength increases in the initial stage, reaches maximum and remains constant for the remaining iterations. In similar way as shown in fig.1, number of iterations is carried out and the best possible parameter setting level was obtained. The algorithm converges at Furnace temperature of 1700°C, Sponge steel addition of 15%, Scrap steel composition of 75%, TDS number of water used at 35 and Quenching temperature of steel was at 500°C. The output responses obtained by PSO algorithm are shown as below.

[1700 15 35 500] as input parameters with output as:
Maximum tensile strength = 636.8550 N/mm$^2$
Hardness Number = 105.1055
Energy Consumption = 367 kWh.
5. EXPERIMENTATION
The parameter setting [1700, 15, 75, 35, 500] obtained by applying Particle Swarm Optimization algorithm is considered for experimentation. The optimized input parameters obtained were set and experiment was conducted for a steel rod of 16 mm diameter. A sample from the above lot is picked and tested for Tensile strength, Hardness number value and Energy consumption rate. The experimental results obtained are as shown below:
- Maximum Tensile strength = 652.382 N/mm²
- Hardness Number value = 105.89
- Energy Consumption /Ton of steel = 361.372 kWh.

The comparison of output values by PSO algorithm and experiment are shown in Table 2 below. (Ref Figure 2) below shows graph for the comparison of algorithm values with experimental values for tensile strength, hardness number value and energy consumption / ton of steel.

6. CONCLUSION
Quality of steel like its tensile strength and hardness number value play an important role in any civil structures. Optimization of process parameters to manufacture steel from secondary steel manufacturing is challenging task. Particle swarm optimization algorithm was applied to experimental results obtained from secondary steel manufacturing process, with an aim to increase tensile strength along with hardness number value and to decrease energy consumption rate. Regression equation obtained by response surface methodology was solved by the above stated technique and optimum input parameter levels were identified with corresponding output responses. The optimum input parameter levels obtained by particle swarm optimization were analyzed by conducting experiment in a secondary steel recycling industry. The output responses for Tensile strength and Energy consumption rate/ton of steel show significant improvement, where as Hardness number value remains nearly same. The limitation of the work is only 16 mm rod is considered for experimentation and the results are valid for the same, where as there are steel rods of 5 mm, 8mm, 10 mm, 20 mm etc., also needs to be investigated. By using these results the mechanical properties definitely increases makes structures safer.
7. REFERENCES


LIST OF FIGURES

Figure- 1
Fig. 1. Graph showing Tensile strength variation with No. of Iterations

Fig. 2. Graph showing Comparison of algorithm values with experimental values for output responses
LIST OF TABLES

Table- 1

<table>
<thead>
<tr>
<th>Input Parameter</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ft (°C)</td>
<td>1650</td>
<td>1675</td>
<td>1700</td>
</tr>
<tr>
<td>SS (%)</td>
<td>10</td>
<td>12.5</td>
<td>15</td>
</tr>
<tr>
<td>SCS (%)</td>
<td>75</td>
<td>80</td>
<td>85</td>
</tr>
<tr>
<td>TDS (No.)</td>
<td>30</td>
<td>35</td>
<td>40</td>
</tr>
<tr>
<td>Qw (°C)</td>
<td>500</td>
<td>525</td>
<td>550</td>
</tr>
</tbody>
</table>

**TABLE 1.** Process parameters with their values at 3 levels

Table- 2

<table>
<thead>
<tr>
<th>Description</th>
<th>Output values - PSO Algorithm</th>
<th>Output values- experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input Parameters obtained by PSO Algorithm [1700, 15, 75, 35, 500]</td>
<td>Ts = 636.855 N/mm²</td>
<td>Ts = 652.382 N/mm²</td>
</tr>
<tr>
<td></td>
<td>Hs = 105.11</td>
<td>Hs = 105.89</td>
</tr>
<tr>
<td></td>
<td>En.con.= 367.29 Kw-H</td>
<td>En.con. = 361.372 Kw-H</td>
</tr>
</tbody>
</table>

**TABLE 2.** Comparison of output values by PSO algorithm with experimental values