Parameter Prediction through Soft PIN System in a Plasma Ion Nitriding Steel Hardening Unit

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ABSTRACT
This paper introduces an excellent merge of Soft computing techniques from Computer Science Engineering, Plasma Technology and Material Surface Engineering. The paper is mainly focused on the Case Based Reasoning (CBR) approach for plasma nitriding process in the prediction of the values of the process parameters for different alloyed steels based on the actual data available from number of high-cost processing experiments. For different grade alloying steel-materials a number of process parameters have to be adjusted to get requisite surface hardness and case depth in the plasma nitriding process, which includes sample temperature, process time, working gas pressure, gas composition etc needed to be maintained in the optimal conditions. In practice, in the laboratory, it is usually achieved through hit-and-trial method and intuition, which becomes difficult for large-volume and large-scale plasma nitriding experiments to bear the cost. It is demonstrated that the CBR based computational reasoning can minimize the monitory losses and physical efforts in identifying the process parameters for those steel-materials for which such parameters are not currently available. The utility and implementation of CBR for the surface hardening of steel in a Plasma Nitriding process is justified. It is expected that the suggested methodology would prove a successful achievement in the plasma nitriding technology and also on the other emerging trends and technologies of industrial relevance.

General Terms
Plasma Technology, Material Surface Engineering. Process parameters, K- Nearest Neighbor Algorithm

Keywords
Soft Computing, Case based reasoning, plasma ion nitriding (PIN), Soft Plasma Ion Nitriding System

1. INTRODUCTION
The plasma nitriding (PN) or plasma ion nitriding (PIN) process is a thermo chemical process to improve the surface properties of different grades of alloying steels, such as surface hardness, wear resistance, corrosion resistance and fatigue strength of various industrial steel components [1,2]. It may be possible through plasma nitriding we can enhance the wear resistance, surface hardness and service period of the different steels. In a plasma nitriding process, the work tools and a variety of steels are processed within a high capacity furnace to achieve a specific hardness of the steel material as per the demand of the industries. During the hardening process, a specific temperature and the ratio of the gases (e.g., Nitrogen and Hydrogen) are required to be maintained within the plasma system for fixed process duration. For number of different types of steel materials, the corresponding values of sample temperature, process time and gas compositions have to be maintained within optimal limits to get the desired results. At present around 23 grades of steels have been plasma nitrided and process parameters have been established as per industrial requirements.

We do have a large volume plasma nitriding facility available with us. Around 500 kg steel can be loaded at time in this large volume plasma system. A large number of steels from the readily mentioned 23 grades of steels have been tested on this system and services are provided to the local industries. There are many more new steels with different alloying compositions used in the industries, and plasma nitriding is essentially required for increased life under service condition. Nevertheless, a specific steel require specified plasma process parameters in the nitriding system, which requires an extensive exercise to test various steels and establish the basic process parameters. In general, the process parameters data i.e. temperature, time, gas composition etc are not readily available for many steels. Situation becomes even worse cost wise when one is trying to identify the process parameters by hit and trail method on such larger volume systems with an aim of a specific hardness value with some specified case depth that is demanded by an industry. Obviously it becomes difficult as well as costly to determine the process parameters required to be maintained in the PIN system for a specific new application with different configurations.

The problem in hand demands an easy and appropriate computational technique for identifications of the desired process parameters based on the information already available. There exist a few computational techniques –like, Neural Network, Genetic Algorithm and Fuzzy Logic that can be used for such problems. However, these methods are complex and time consuming. In contrast the Case-based reasoning (CBR) is another easy and suitable computational technique. The CBR, broadly construed, is the computer-based reasoning that can be used for solving new problems based on the solutions of the similar past problems [4]. In this paper an effort has been made to develop and implement a CBR technique to determine the values of the process parameters computationally –like, temperature, time and gas compositions which are very much required to be maintained within the PIN system for specific process conditions. The major standards and procedure necessary to solve the proposed problem and the justification of the implemented solution are presented in the next subsequent sections.

The formulation of the problem is discussed in section 2. The results and discussion is provided in section 3 whereas the conclusion is presented in the section 4.

2. PROBLEM FORMULATION
To determine the process parameter in PIN system, we have introduced Case Based Reasoning. In fact, we have certain known process parameter like temperature, process time, and gas composition collected from literature for about 23 grades of different steels along with the available knowledge of their chemical compositions. The information is collected for the

following steels: 1040, En8, 4137,En19, 58CrV4, 4340, En24, En41B, H11, H13, D2, HCHC, P20, SS420, SS440B, SS410, SS304, SS316, SS201, 17-4PH, M2 in the present study.

Case based reasoning (CBR), cooperates, as the process of finding unknown parameters in a real physical system, based on the solutions of similar past problems [3]. The case based reasoning is generally formalized as a four-step process for the purpose of computer based reasoning:

1. **Retrieve:** Given a target problem, retrieve cases from memory those are relevant to solving it. A case consists of a problem, its solution, and, typically, annotations about how the solution was derived. Let us suppose, we wanted to run PIN process for a specific steel. It will require process parameters that we don't have for new steel to be used in PIN system. This is the current problem. To do so, the CBR system tries to explore knowledge, which is stored in Case Base in terms of Cases. The CBR system will act intelligently on the problem and based on the past information, CBR would retrieve the similar past cases from case base and hence on the basis of solutions strategy, system suggest the solution of current PIN problem.

2. **Reuse:** Map the solution from the previous case to the target problem. This may involve adapting the solution as needed to fit the new situation. For example targeted PIN process is matched with previous similar problem then, solution/ solution strategy of past problem can be reused for current PIN process.

3. **Revise:** Having mapped the previous solution to the target situation, one should test the new solution in the real world (or a simulation) and, if necessary, one should revise. In our case for targeted PIN process, if there is new solution in the real world, then system revise case base accordingly.

4. **Retain:** After the solution has been successfully adapted to the target problem, store the resulting experience as a new case in memory. After alteration of the case base, the new case (solution of the targeted PIN process) is retained in case base.

Hence Case-based reasoning (CBR) can solves new problems of PIN process of specific steel by adapting previously successful known solutions to similar problems. For adapting successful solutions to similar new problems the basic steps of the algorithm are:

1. Input parameters of the PIN process.

2. Find out the cases similar to the targeted PIN process current problem (i.e. characterize the input problem, retrieve cases with matching features, and pick the best match (es)),

3. Adapt a previous solution to fit the current problem.

Based on the known process parameters and weights specified for them, a similarity coefficient for the new steel is determined. Similarly, similarity coefficients have been determined for each PIN process of specific steel in the case base (previous cases) using weights specified and corresponding process parameters of the PIN process. Based on these similarity coefficients, the nearest *n (may be three or more)* cases have been identified. Figure 1 Elaborates flow the flow chart of the algorithmic steps.

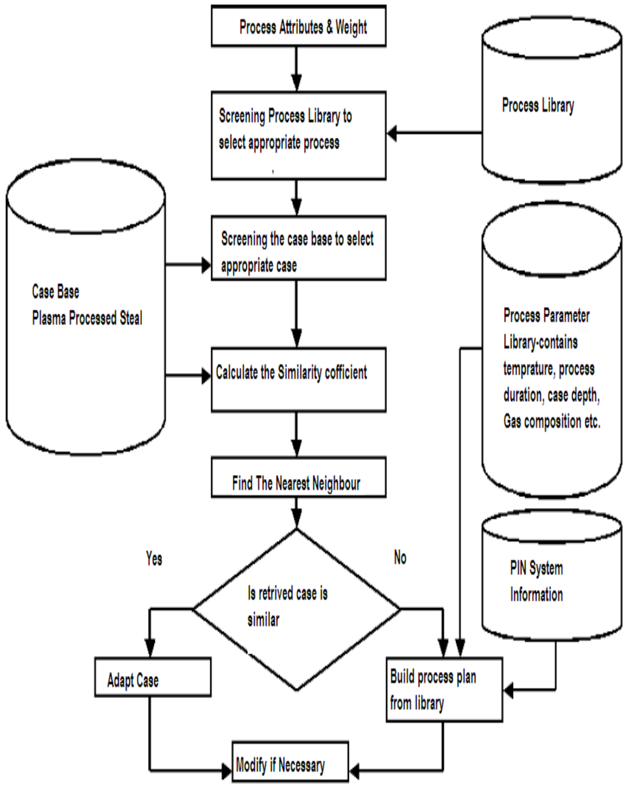

Fig 1: CBR based PIN process flow

3. ALGORITHM FOR FINDING PIN PROCESS PARAMETERS FOR THE STEEL HARDENING

The following methodology has been applied to find the process parameters using CBR. The basic steps of the CBR methodology traced in terms of algorithm are explained below:

Step 1 (a) Retrieve the components percentage and all the associated process parameters of 23 grade steels as the cases

(b) Read the new steel components percentage

Step 2 (a) Compare the names of the new steel case with all the available cases

(b) If name matches then go to step2(c) Else go to step3 (c)

(c) Find the difference in the percentage composition of matched case and the new steel case

(d) If difference=0 then go to step 3(a) Else go to step 3(b)

Step 3 (a) Values of process parameters of the new steel case are same as the matched case, go to step 4(a)

(b) Predict process parameters of the new steel using k Nearest Neighbor algorithm as knn (matched case, new case), go to step 4(b)

(c) Predict process parameters of the new steel using k Nearest Neighbor algorithm as knn (allcases, new case), go to step 4(b)

Step 4 (a) Do not store the new steel case as a new case

(b) Store the new steel case as a new case

Step 5 End

4. RESULTS AND DISCUSSION

On the basis of available literature, experiments and documented data, a collection of 23 steels with the associated components percentage and hardening process parametric values has been traced. Now, to instantiate the process of prediction, these sets of steel are considered as the cases which provide a crucial platform, required to implement the case based reasoning model to solve the problem in hand. A specific steel could be considered as a new case if its hardening process parameters are yet to be determined. As per the industrial demands and our requirement, the steel En32 is found appropriate to be considered as a new case for the purpose of the conceptualization of the solution.

The prediction paradigm defined here, involves the K-Nearest Neighbor (KNN) algorithmic approach, a supervised learning algorithm, where the result for a new case can be interpolated on the basis of values of the k nearest neighbors. For interpolation through KNN algorithm, the input data chosen here is the collection of 22 steels and a new steel En32. These 23 cases (Case1, Case2, Case3……Case23) consist of multivariate attributes like name of the steel, percentage composition of the alloying elements, temperature, time, gas, surface hardness and case depth with the their values, whereas, the new steel case also consists the values of all the attributes except the parameters temperature, time and gas composition which are to be predicted. To impose KNN algorithm on the target problem, these 22 cases are considered as the training data with the coordinates ($P_{1,}$ P_2 P_3 P_4 $P_{5\ldots\ldots}P_n$, SH, CD) and (T_1, T_2, G) where, $P_{1,}$ P_2 P_3 P_4 $P_{5\ldots\ldots}$ P_n represents the percentage of alloying elements, SH represents the surface hardness and CD represents the case depth, T_1 represents the temperature, T_2 represents the time and G represents the gas composition. Considering the new steel case as the query instance with the given values of coordinates ($P_{1,}$ P_2 P_3 P_4 $P_{5\ldots\ldots}P_n$, SH, CD), we want to predict T_1, T_2 and G. Let us consider K (number of nearest neighbors to the query instance) as the parameter of KNN and its value as 10. Since we are dealing with the quantitative data, we could use the Euclidean distance method to calculate the distance between the coordinates of training samples and the query instance.

Now, if the coordinates of Case1 are (0.37, 0.6, 0) and the coordinates of query instance are (0.15, 0.8, 0.25), then the Euclidean distance, d_{1q} between Case1 and the query instance is calculated as: $d_{1q} = (0.37 - 0.15)^2 + (0.6 - 0.8)^2 + (0 - 0.25)^2 = 0.0484 + 0.4 + 0.625 = 0.5109$

Similarly, the distance for all the 22 cases is calculated and results are tabulated in the table 1.

After calculating distances, the cases are sorted in ascending order as shown in table 2 and then first K=10 data cases are included in the set of nearest neighbors, as shown in table 3 along with their process parameters.

Table 1. Euclidean distance for all the cases

Case Name	C	Mn	P	S	Si	Cr	Ni	Mo	Ti	Other	Query Distance (d_{iq})	Temp	Time	Gas Composition	Surface Hardness	Case Depth
Case1	0.37	0.6	0.04	0.05	0	0	0	0	0	0	0.155	550-570	15-20	35:65	500-700	0.3-0.6
Case2	0.4	0.8	0.02	0.02	0.25	0	0	0	0	0	0.06295	550-570	15-20	35:65	500-700	0.3-0.5
Case3	0.35	0.7	0.04	0.04	0.15	0.8	0	0.2	0	0	0.725325	510-530	20-24	20:80	500-700	0.3-0.5
Case4	0.4	0.7	0	0	0.25	1.2	0	0.3	0	0	1.6025	510-530	20-24	20:80	500-700	0.3-0.5
Case5	0.58	0.95	0	0	0.25	1.1	0	0	0	0.12	1.4318	500-520	12-16	20:80	600-700	0.3-0.5
Case6	0.5	0.75	0	0	0	1	0	0	0	0.15	1.21	500-520	12-16	20:80	600-700	0.3-0.5
Case7	0.38	0.6	0.04	0.04	0.15	0.7	1.7	0.2	0	0	3.358225	530-550	14-16	35:65	600-800	0.3-0.5
Case8	0.4	0.6	0	0	0.3	1.2	1.5	0.3	0	0	3.8575	530-550	14-16	35:65	600-800	0.3-0.5
Case9	0.4	0.5	0	0	0.25	1.6	0	0.2	0	1.2	4.1925	520-540	40-45	20:80	900-1200	0.3-0.5
Case10	0.33	0	0	0	0.8	4.8	0	1.1	0	0.3	24.8374	510-530	16-18	20:80	900-1300	0.2-0.3
Case11	0.37	0.2	0.03	0.05	0.8	5	0	0	0	0.8	26.354025	510-530	16-18	20:80	900-1500	0.2-0.3
Case12	1.5	0	0	0	0	12	0	0.8	0	0.8	135.9775	470-490	40-50	20:80	900-1300	0.1-0.15
Case13	0.98	0.15	0.03	0.03	0.15	1.3	0	0	0	0	2.81265	470-490	40-50	20:80	900-1300	0.1-0.15
Case14	0.28	0.6	0.03	0.03	0.2	1.4	0	0.3	0	0	2.1112	520-540	14-18	20:80	700-900	0.3-0.5
Case15	0.14	1	0.04	0.03	1	11	1	0.3	0	0	122.6951	520-540	15-20	20:80	1000-1300	0.05-0.1
Case16	0.75	1	0.04	0.03	1	18	0	0.8	0	0	325.5275	560-580	15-20	20:80	1000-1300	0.15-0.2
Case17	0.15	1	0.04	0.03	1	12	0.8	0	0	0	133.4175	540-550	24-30	20:80	900-1200	0.1-0.15
Case18	0.08	2	0.05	0.03	1	18	8	0	0	0	390.010325	560-570	10-15.	20:80	1000-1300	0.05-1.0
Case19	0.08	2	0.05	0.03	1	16	10	2	0	0	362.0108	560-570	15-24	20:80	900-1200	0.05-1.0
Case20	0.15	5.5	0.06	0.03	1	16	3.5	0	0	0.25	290.9695	560-570	15-24	20:80	900-1500	0.05-1.0
Case21	0.07	1	0.04	0.03	1	15	3-5	0	0	3	1678786964	460-480	35-50	20:80	1200-1400	0.05-1.0
Case22	0.83	0	0	0	0	4.1	0	5	0	6.4	83.9349	500-510	5-10.	20:80	800-1000	0.05-1.0
Query Instance	**0.15**	**0.8**	**0**	**0**	**0.25**	**0**	**0**	**0**	**0**	**0**	**0**					

Table 2. Euclidean distance for all the cases

Case Name	C	Mn	P	S	Si	Cr	Ni	Mo	Ti	Other	Query Distance (d_{iq})	Temp	Time	Gas Composition	Surface Hardness	Case Depth
Case2	0.4	0.8	0.02	0.02	0.25	0	0	0	0	0	0.06295	550-570	15-20	35:65	500-700	0.3-0.5
Case1	0.37	0.6	0.04	0.05	0	0	0	0	0	0	0.155	550-570	15-20	35:65	500-700	0.3-0.6
Case3	0.35	0.7	0.04	0.04	0.15	0.8	0	0.2	0	0	0.725325	510-530	20-24	20:80	500-700	0.3-0.5
Case6	0.5	0.75	0	0	0	1	0	0	0	0.15	1.21	500-520	12-16	20:80	600-700	0.3-0.5
Case5	0.58	0.95	0	0	0.25	1.1	0	0	0	0.12	1.4318	500-520	12-16	20:80	600-700	0.3-0.5
Case4	0.4	0.7	0	0	0.25	1.2	0	0.3	0	0	1.6025	510-530	20-24	20:80	500-700	0.3-0.5
Case14	0.28	0.6	0.03	0.03	0.2	1.4	0	0.3	0	0	2.1112	520-540	14-18	20:80	700-900	0.3-0.5
Case13	0.98	0.15	0.03	0.03	0.15	1.3	0	0	0	0	2.81265	470-490	40-50	20:80	900-1300	0.1-0.15
Case7	0.38	0.6	0.04	0.04	0.15	0.7	1.7	0.2	0	0	3.358225	530-550	14-16	35:65	600-800	0.3-0.5
Case8	0.4	0.6	0	0	0.3	1.2	1.5	0.3	0	0	3.8575	530-550	14-16	35:65	600-800	0.3-0.5
Case9	0.4	0.5	0	0	0.25	1.6	0	0.2	0	1.2	4.1925	520-540	40-45	20:80	900-1200	0.3-0.5
Case10	0.33	0	0	0	0.8	4.8	0	1.1	0	0.3	24.8374	510-530	16-18	20:80	900-1300	0.2-0.3
Case11	0.37	0.2	0.03	0.05	0.8	5	0	0	0	0.8	26.354025	510-530	16-18	20:80	900-1500	0.2-0.3
Case22	0.83	0	0	0	0	4.1	0	5	0	6.4	83.9349	500-510	5-10.	20:80	800-1000	0.05-1.0
Case15	0.14	1	0.04	0.03	1	11	1	0.3	0	0	122.6951	520-540	15-20	20:80	1000-1300	0.05-0.1
Case17	0.15	1	0.04	0.03	1	12	0.8	0	0	0	133.4175	540-550	24-30	20:80	900-1200	0.1-0.15
Case12	1.5	0	0	0	0	12	0	0.8	0	0.8	135.9775	470-490	40-50	20:80	900-1300	0.1-0.15
Case20	0.15	5.5	0.06	0.03	1	16	3.5	0	0	0.25	290.9695	560-570	15-24	20:80	900-1500	0.05-1.0
Case16	0.75	1	0.04	0.03	1	18	0	0.8	0	0	325.5275	560-580	15-20	20:80	1000-1300	0.15-0.2
Case19	0.08	2	0.05	0.03	1	16	10	2	0	0	362.0108	560-570	15-24	20:80	900-1200	0.05-1.0
Case18	0.08	2	0.05	0.03	1	18	8	0	0	0	390.010325	560-570	10-15.	20:80	1000-1300	0.05-1.0
Case21	0.07	1	0.04	0.03	1	15	3-5	0	0	3	1678786964	460-480	35-50	20:80	1200-1400	0.05-1.0
Query Instance	0.15	0.8	0	0	0.25	0	0	0	0	0	0					

Table 3. Selected K Nearest Neighbors

	Case Name	Temp	Time	Gas Composition	Surface Hardness	Case Depth
1	Case2	550-570	15-20	35:65	500-700	0.3-0.5
2	Case1	550-570	15-20	35:65	500-700	0.3-0.6
3	Case3	510-530	20-24	20:80	500-700	0.3-0.5
4	Case6	500-520	12-16	20:80	600-700	0.3-0.5
5	Case5	500-520	12-16	20:80	600-700	0.3-0.5
6	Case4	510-530	20-24	20:80	500-700	0.3-0.5
7	Case14	520-540	14-18	20:80	700-900	0.3-0.5
8	Case13	470-490	40-50	20:80	900-1300	0.1-0.15
9	Case7	530-550	14-16	35:65	600-800	0.3-0.5
10	Case8	530-550	14-16	35:65	600-800	0.3-0.5

Then the average of the gathered process parametric values of the selected cases is calculated to predict the process parameters for the Query Instance En32 as follows:

Temp_range1= (550+550+510+500+500+510+520+470+530+530)/10 = 517^{0}C

Temp_range2= (570+570+530+520+520+530+540+490+550+550)/10 = 537^{0}C

Time_range1= (15+15+20+12+12+20+14+40+14+14)/10= 17.6 = ~ 18 hrs

Time_range2= (20+20+24+16+16+24+18+50+16+16)/10 = 22 hrs

GascompositionN= (35+35+20+20+20+20+20+20+20+35+35)/10 = 26

GascompositionH= (65+65+80+80+80+80+80+80+80+65+65)/10 = 74

Surfacehardness_range1= (500+500+500+600+600+500+700+900+600+600)/10 = 600 HV

Surfacehardness_range2= (700+700+700+700+700+700+900+1300+800+800)/10 = 800 HV

Casedepth_range1= (0.3+0.3+0.3+0.3+0.3+0.3+0.3+0.1+0.3+0.3)/10 = 0.28 mm

Casedepth_range2= (0.5+0.6+0.5+0.5+0.5+0.5+0.5+0.15+0.5+0.5)/10= 0.475 mm

Thus, the final values found for unknown steel En32 are as follows: the process temperature (in ^{0}C) is 517-537, the process time (in hrs) is 18-22, Gas composition of N2:H2 is 26:74. For these process parameters, the surface hardness and cased depth is also calculated by the proposed CBR system. The surface hardness for the same steel (in HV) is found to be 600-800 and case depth (in mm) as 0.28-0.475. The preliminary results could be verified through experimentations. Thus, it could be estimated that the system analysis of the proposed system could be done in due course of time and more related parameters could be identified for other unknown steels. Our claim here is to implement CBR techniques for the identification of suitable process parameter in PIN system.

A further scope exists to verify the results experimentally and solve the problem targeting the derivation of the interdependence relations between the parameters viz. temperature, time duration, gas composition, percentage composition of the components, surface hardness and case depth for more accurate results. Consequently, we expect the mathematical formulation of the targeted relation along with the predetermined conceptual background would help in refining the desired results and hence contribute for the development of an efficient CBR based PIN system in an effective manner. Thus, to point up the usability of the proposed methodology, the conceptual CBR system have been implemented and now would be practically verified in the PIN system to provide an easy solution for a set of process parameters of certain steels of industrial interest.

The case based reasoning is applied and handled for the 23 grade steels, with the necessary process parameters and chemical compositions as listed in table 1. Based on the available information of cases from this table, the CBR and the NN algorithm has been applied to find the PIN process parameters for unknown steel En32 in which the composition percentage of Carbon, Magnesium and Silicon is 0.15, 0.8 and 0.25. The PIN process parameters are then calculated using CBR based technique and found process parameter are as follows: the process temperature ~ 520-530, process time in hour ~ 18-20 and gas composition of N_2:H_2 ~ 20:80. For these process parameters the surface hardness and case depth is also calculated by the CBR based system. The surface hardness is found to be ~ 900-1000 and case depth ~ 0.15-0.20 for En32 steel. Then preliminary results are verified with the experiment and are found to be approximately similar. Further analysis could be done in due course of time and more parameters for different steels could be identified.

5. CONCLUSION AND FUTURE WORK

We here can conclude till today application of soft computing techniques has been applied and successful model formulation and their implementation has been notified in a variety of Material engineering procedures, but the Case Based Reasoning has also now gripped its position in the field of commercial industrial applications. All the evidences and results also indicates that there is a range of promising future directions for the solution of other similar kind of industrial and commercial problems.

Future work under this research will focus on the following issues:

1) The impact of alloying percentages of the elements after their compound formation or their integration within the steel

2) Complete design of a predictor application model module

3) To prove and justify the proposed solution through experiments

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