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PREDICTION OF SOLIDIFICATION MODE IN SUPER AUSTENITIC STAINLESS STEEL WELDS

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Abstract: - *Super Austenitic OR Nickel alloy. Group of stainless steels having Fe- Ni-Cr-Mo alloys contents. The best known material : 904L (20Cr,25Ni,4.5Mo) offers Superior corrosion resistance providing they are welded carefully with low heat input (less than 1 KJ/mm recommended) and fast travel speeds with no waving.[1](3)(5) This is because of the reason that fusion welding of SASS often destroy the chemical homogeneity of the weld metal composition by developing unavoidable micro segregation of the tramped elements in the solidified weld structure. Which leads to poor corrosion & Mechanical properties[1]. This has been discovered through a research study. Source [1] done about the influence of Molybdenum on the solidification mode of high Mo bearing, Fe- Ni-Cr-Mo alloys, although SASS fusion welding best practices recommending, each run of weld , not to be started until the metal temperature falls below 100ºC. But a non-uniform distribution of alloying elements always remains a possibility. As It has been already discovered by the researchers[1] that various solidification mode (A, F, AF, FA) and solid state phase transformations will not be a only function of Cr eq/Nieq but also Mo concentration, specifically due to the transformation of ferrite into eutectoid $\gamma + \sigma$ in high-Mo alloys. So, it becomes very necessary to understand the possible solidification mode and the very effect of various elements on various solidification modes.*

This problem can be overcome by Neural Network analysis, as through well trained model, it is also possible to establish the relationships between the elements & the different transformation products. The Neural Network classification method has been approached to solve this problem. The database collected from the research paper has been used to develop & train the Probabilistic generalized classification Neural Network (PNN) model to meet the overall objective of prediction of the multifaceted solidification mode of SASS alloys in appropriate welding process as a function of chemical composition, in order to understand the mechanical and corrosive properties of the weld material for use in service applications.

Key Words : *Super Austenitic stainless steel (SASS), Probabilistic Neural Network , Solidification mode ,Austenite ,Martensite, Ferrite content, Alloy composition, Constitution Diagram*

Introduction

1.1 Fusion welding of super austenitic stainless steel

Super austenitic stainless steels (SASS), Group of stainless steels having Fe- Ni-Cr-Mo alloys exhibit superior corrosion resistance and toughness compared to the low alloy steels that are currently used in marine applications. However, conventional welding processes destroy the chemical homogeneity of the material, leaving solute depleted regions of the microstructure susceptible to preferential corrosive attack. Laser processing provides a unique opportunity to improve the corrosion performance of SASS welds by potentially producing segregation-free microstructures with extended solubility through the imposition of rapid solidification conditions within the weld pool. In addition, these laser welds can be produced without the need for Ni-base filler metals, thereby providing a cost benefit.[1]

Super Austenitic Stainless Steel alloys can often pose difficulties during fusion welding due to the unavoidable micro segregation of Mo and tramp elements, which lead to the loss of corrosion resistance and solidification cracking, respectively. Four solidification modes (A, AF, FA, F) and three solid-state transformations ($\delta \rightarrow \gamma$, $\delta \rightarrow (\sigma+\gamma)$, and $\gamma \rightarrow$ martensite) were observed in these alloys system that produced a wide variety of microstructures[1]

The Schaeffler weld constitution diagram accurately predicted the presence of martensite in low-Mo alloys. The high microsegregation of Mo led to martensite forming in high-Mo alloys that exceeded Schaeffler's martensite boundary. For the same reasoning, several high-Mo alloys containing martensite exceed the martensite boundary proposed by Kotecki[21] on the WRC-1992 diagram.[1]

A massive transformation of $\delta \rightarrow \gamma$ can produce fully austenitic microstructures with uniform distributions of Mo at the nominal concentration. The transformation is seen to occur in primary ferrite alloys that are near the eutectic composition.[1]
So there has been creating much uncertainty particularly in predicting the mode of solidification as the relations among compositional variations and solid state transformation products (different solidification modes) are very complex.

1.2 Factors affecting the solidification mode.

The phenomena like the relative % dilution of the the filler metal and the base metal, Gas-metal reactions, Slag-metal reactions, fluid flow in weld pools, Metal evaporation, Rate of heat transfer, Rate of metal transfer and Segregation of alloying elements all lead to complexity in the final microstructure.

1.3 Solidification Structures.

The hot cracking sensitivity depends fundamentally on the solidification mode, which results from the relationship between chromium equivalent and nickel equivalent. Increasing Cr eq./Ni eq. ratios produce successively the following solidification structures :[25][26]

a) Single phase austenite (A).
b) mixed-mode with primary austenite (AF).
c) mixed-mode with primary ferrite (FA).
d) Single phase ferrite (F)

Reduced hot cracking sensitivity results from a FA solidification. The ferritic solidification mode will minimize micro segregation during solidification due to elevated diffusion rates, while a subsequent solid-state transformation of ferrite into austenite will create the austenitic matrix that is desired for good toughness.[1] During the cooling, the great part of the ferrite transforms to austenite in the solid state. Except for the ferritic-austenitic types, the only use of the ferrite retained at room temperature is more often to give an estimation of the solidification mode

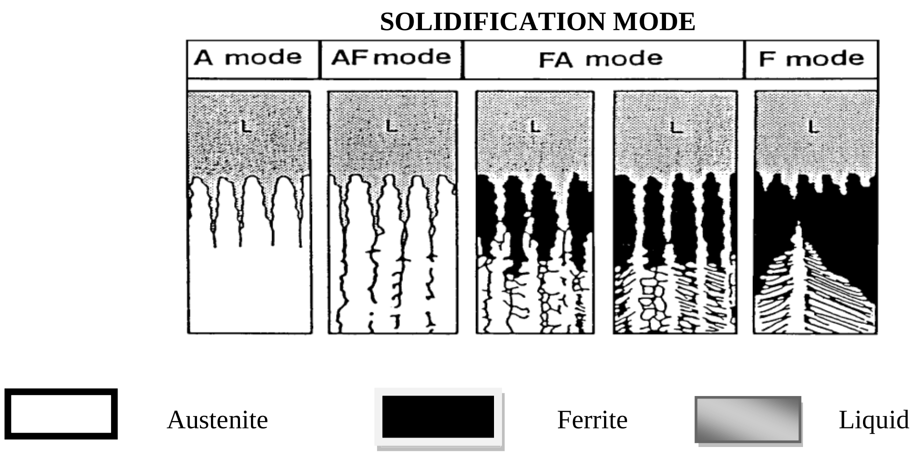

Fig. 1 Solidification mode source (2)(3)

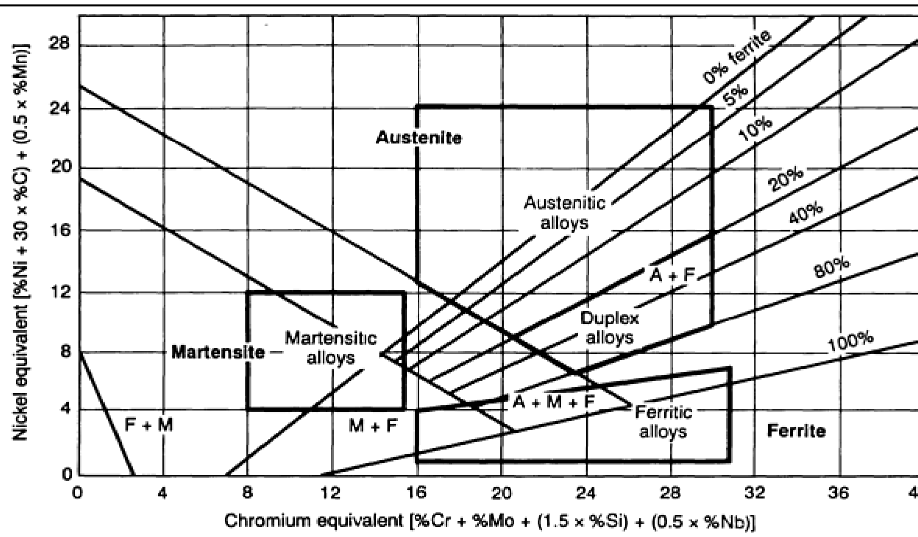

Fig. 2 (a) Schaffler diagram Source [16]

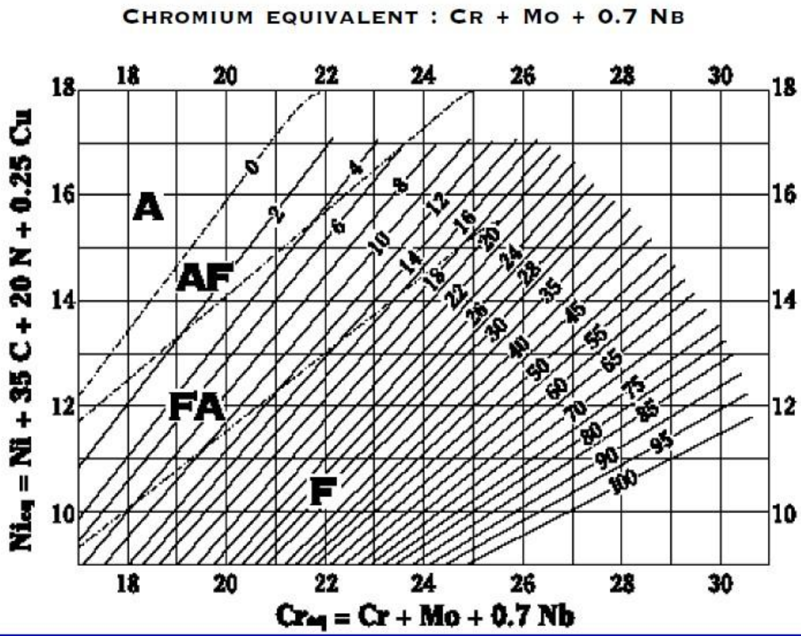

Fig. 2(b) WRC-1992 DIAGRAM source [25]

The aim of this paper is to explain the usefulness of the Classification Neural network modeling technique as an optimum tool for recognizing the pattern among many complex weld deposits variables & to establish some relationship between input & output variables. The purpose of using the classification type Neural Network is to determine, to which of a number of discrete classes a given input case belongs. Here, we have attempted - Probabilistic Neural Network (PNN) architecture to build the model and PN (Probabilistic Network) as a training algorithm to train the model. The trained model shows good conformity between the predicted and reported values of the belonging class, i.e. Solidification Mode.

2.0 Modeling work

2.1 Database

An experimental Austenitic welds data base containing different fusion zone compositions and subsequent solidification mode and weight % ferrite, has been collected from source [1]. That exhibits different solidification mode and subsequent solid-state transformations. See Table 1.

Table 1 A portion of the data base of Ni-Cr-Mo alloy. Source [1]

Alloy composition	Fe	Ni	Cr	Mo	SM	Wt% Ferrite
4Mo-13Cr-12Ni	72.58	11.99	12.55	2.68	AF	1.397
4Mo-17Cr-8Ni	72.99	7.8	15.85	3.13	F	50.52
4Mo-13Cr-17Ni	67.28	16.82	12.43	3.27	A	0
4Mo-15Cr-15Ni	67.9	14.83	14.46	2.58	AF	0.375
4Mo-17Cr-13Ni	66.59	12.51	16.57	3.95	FA	7.321
4Mo-19Cr-11Ni	66.42	10.88	18.98	3.42	F	17.835
4Mo-16Cr-19Ni	61.08	19.05	15.68	3.95	A	0
4Mo-18Cr-17Ni	61.58	16.88	17.6	3.67	AF	0.7245
4Mo-20Cr-15Ni	59.91	14.75	20.63	4.26	FA	9.815
4Mo-22Cr-13Ni	62.91	12.31	20.62	3.79	F	17.42
6Mo-4Cr-16Ni	73.57	16.2	4.02	5.98	M	0
6Mo-8Cr-12Ni	73.88	12.02	8.01	5.84	M	0
6Mo-10Cr-10Ni	73.6	10.21	10.64	5.27	M	0
6Mo-14Cr-6Ni	74.41	5.95	13.59	5.72	M	0

6Mo-9Cr-16Ni	68.73	16.33	9.18	5.58	A	0
6Mo-11Cr-14Ni	68.66	14.57	11.2	5.29	AF	0.184
6Mo-13Cr-12Ni	68.06	12.23	13.53	5.87	FA	5.33
6Mo-15Cr-10Ni	69.01	10.31	14.83	5.48	F	13.025
6Mo-12Cr-18Ni	63.37	18.64	12.2	5.48	A	0
6Mo-14Cr-16Ni	63.55	16.4	14.37	5.36	AF	0.148
6Mo-4Cr-16Ni	62.25	14.37	17.19	5.75	FA	6.475
6Mo-18Cr-12Ni	62.93	12.31	18.97	5.44	F	14.385
6Mo-16Cr-19Ni	58.52	19.31	16.08	5.74	AF	0
6Mo-18Cr-17Ni	57.39	17.57	19.26	5.41	AF	0.5125
6Mo-20Cr-15Ni	58.77	15.18	19.7	5.95	F	12.18
6Mo-22Cr-13Ni	57.05	13.41	23.17	5.94	F	38.92

The data has been statistically analyzed as Maximum, Minimum, Mean and Standard deviation as shown in Table 2. The analyzed data will show the (range) limiting values of the input parameters, about which the NN model can be trained to obtain the optimized predictions for the given input values falling in these range.

Table 2 Data analysis

Elements	Max	Min	Mean	S.D.
Fe	80.37	53.08	68.3218	6.590013
Ni	20.9	3.85	13.1632	3.9525
Cr	23.3	1.92	13.871	4.772
Mo	10.95	0.01	4.3986	3.163541
Wt% Ferrite	14.385	0.148	5.906056	13.45225

2.2 Optimization of the Classification model using PNN

A useful interpretation of network outputs was as estimates of probability of class membership, in which case the network was actually learning to estimate a probability density function (p.d.f.). A similar useful interpretation can be made in regression problems if the output of the network is regarded as the expected value of the model at a given point in input-space. This expected value is related to the joint probability density function of the output and inputs.(1)(6)(8)

In the PNN, there are at least three layers: input, radial, and output layers. The radial units are copied directly from the training data, one per case. Each models a Gaussian function centered at the training case. There is one output unit per class. Each is connected to all the radial units belonging to its class, with zero connections from all other radial units. Hence, the output units simply add up the responses of the units belonging to their own class. The outputs are each proportional to the kernel-based estimates of the p.d.f.s of the various classes, and by normalizing these to sum to 1.0 estimates of class probability are produced. (1)(6)(8) see Parzen, 1962; Speckt, 1990; Speckt, 1991; Bishop, 1995, Patterson, 1996.
The Probability Neural Network model (PNN) has been optimized with 4 numbers of input units (Fe, Ni Cr and Mo) and 49 numbers of radial (Hidden) units & 5 numbers of output units as Solidification mode (SM). 17 Numbers of classification PNN models were trained, out of them, the best is PNN:4-49-5. Which gives accurate prediction of the solidification mode.

Table 3 model summary report.

Model Summary Report (Superausenitic SS.sta)										
Index	profile	Train Perf.	select Perf.	Test Perf.	Training Error	Selection Error	Test Error	Input	Hidden (Radial)	Output
34	PNN:4-49-5	1	0.608696	0.652174	0.065564	0.318935	0.295285	4	49	5

2.3 Performance of the model.

The Table 4 below shows an unseen data base (i.e. the data base Not Used in the training of the network) pertaining to varying compositions of Fe-Ni-Cr –Mo. that has been tested with the trained PNN:4-49-5 model.

Table 4 Unseen data base (For the PNN MODEL)

Case Number	Fe	Ni	Cr	Mo
1	69.12	9.3	13.71	7.61
2	62.57	18.66	10.39	8.18
3	61.13	13.01	17.38	7.83
4	58.1	14.32	19.4	7.85
5	70.48	16.59	4.06	8.73
6	70.36	11.69	7.71	10.06
7	62.92	20.02	9.63	7.22
8	61.1	14.82	13.59	9.86
9	54.8	18.88	15.84	10.18
10	56.66	14.69	19.72	8.51
11	70.86	11.45	17.43	0.02
12	70.14	10.02	19.59	0.02
13	70.77	7.89	21.06	0.01
14	62.17	15.02	20.33	2.12
15	62.44	12.65	22.6	1.97

In the context of a classification problem, if we can construct estimates of the p.d.f.s of the possible classes, we can compare the probabilities of the various classes, and select the most-probable. This is effectively what we ask a neural network to do when it learns a classification problem - the network attempts to learn (an approximation to) the p.d.f.

The table 5 shows the prediction obtained for the unseen data base pertaining to the varying composition of Fe-Ni-Cr -Mo alloy.

Table 5 Prediction by PNN: 4 -49-5

Case Number	(SUPERAU_UNSEEN
1	F
2	AF
3	F
4	F
5	M
6	M
7	AF
8	FA
9	AF
10	F
11	AF
12	F
13	F
14	FA
15	F

The database shown in Table 5. Used to test to obtain the prediction of the possible solidification mode has already been experimentally discovered and reported in the research article [1] and as shown in table 6.
The above result/prediction of different 15 numbers of cases can be compared with the table 7. While it can be observed that trained PNN model shows very accurate approximation with the experimentally (Physically verified) reported values.

Table 6 Comparison of the prediction with the "known" test data sheet

Case Number	Alloy composition	Fe	Ni	Cr	Mo	SM	Wt % Ferrite
1	8Mo-15Cr-10Ni	69.12	9.3	13.71	7.61	F	26.89
2	8Mo-11Cr-19Ni	62.57	18.66	10.39	8.18	AF	0
3	8Mo-17Cr-13Ni	61.3	13.01	17.38	7.83	F	14.51
4	8Mo-20Cr-15Ni	58.1	14.32	19.4	7.85	F	13.17
5	10Mo-4Cr-16Ni	70.48	16.59	4.06	8.73	M	0
6	10Mo-8Cr-12Ni	70.36	11.69	7.71	10.06	F	8.025
7	10Mo-10Cr-20Ni	62.92	20.02	9.63	7.22	AF	0
8	10Mo-14Cr-16Ni	61.1	14.82	13.59	9.86	FA	0.3995
9	10Mo-16Cr-19Ni	54.8	18.88	15.84	10.18	AF	0
10	10Mo-20Cr-15Ni	56.66	14.69	19.72	8.51	F	8.355
11	0Mo-18Cr-14Ni	70.86	11.45	17.43	0.02	AF	2.289
12	0Mo-20Cr-12Ni	70.14	10.02	19.59	0.02	F	10.53
13	0Mo-22Cr-8Ni	70.77	7.89	21.06	0.01	F	55.13
14	2Mo-20Cr-15Ni	62.17	15.02	20.33	2.12	FA	5.395
15	2Mo-22Cr-13Ni	62.44	12.65	22.6	1.97	F	14.17

Good agreement can be observed between experiment results and ANN model in the prediction of solidification mode

3.0 Results & Discussion

During the phase transformations, it has also become very necessary to identify the influence of the alloying elements on the transformation product(s). Although, the potent austenite stabilizer Ni, and ferrite stabilizers like Cr ,Mo, are well known among us but the interactions between them and their tendency to support or suppress any transformation as a function of concentration and their Effect in single and in "combined" can only be predicted by NN analysis. The Fig. 3 to 6 shows the same.
Several alloys have been identified that solidify in the FA mode and have an Austenite matrix with a more uniform distribution of Mo than that exhibited by primary austenite solidification. These alloys should have improved resistance to solidification cracking and localized corrosion [1] by using such "smart" NN predictive tool, weld joint with desired microstructure can be developed.

3.1 RESPONSE CURVE

The observations from the fig. No. 2,4 5 & 6 are as under:-

1) Fig. 3. Effect of Fe content between 56-58%wt promotes AF mode, then between 60 – 66%wt. reduces the tendency (green curve). Between 60 to 70 wt. sharp variation in FA mode.(black curve)
2) Fig. 4. Effect of Ni content, being potent austenite stabilizer, suppresses the ferrite content (pink curve), increases A mode formation tendency beyond 12%wt. and more steeply after > 18% wt. (red curve). Between 10 – 16 % wt. show variation over FA mode (Black curve) and Steeply increases tendency for AF mode with probability of 70 % apprx. from 10% wt minimum to 18% wt. up to. (Green curve).
3) Fig. 5. Cr. Being strong ferrite stabilizer reduces tendency for A mode solidification (red curve). Tendency for FA mode is apprx. 90%. With between 16 to 29 % wt. Cr.
4) Fig. 6. Mo. Being Cr, equivalent, steeply increases the F mode tendency up to 98%, between 7 to 9 % wt. of addition. (Pink curve). Composition variation between 2.5 to 5 %wt. favours FA solidification mode, whereas, same range dis favours AF solidification mode.

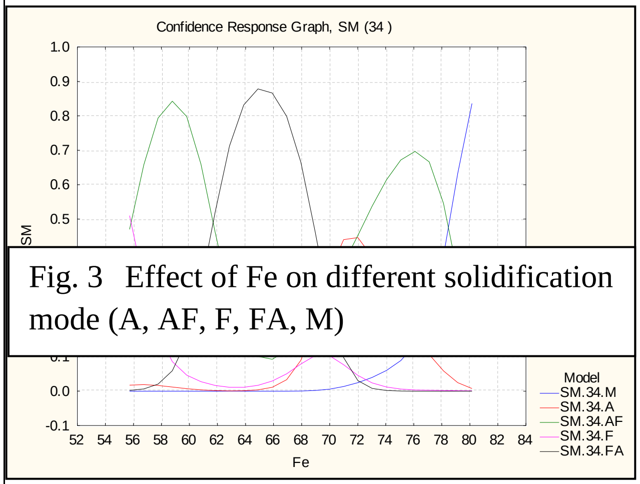

Fig. 3 Effect of Fe on different solidification mode (A, AF, F, FA, M)

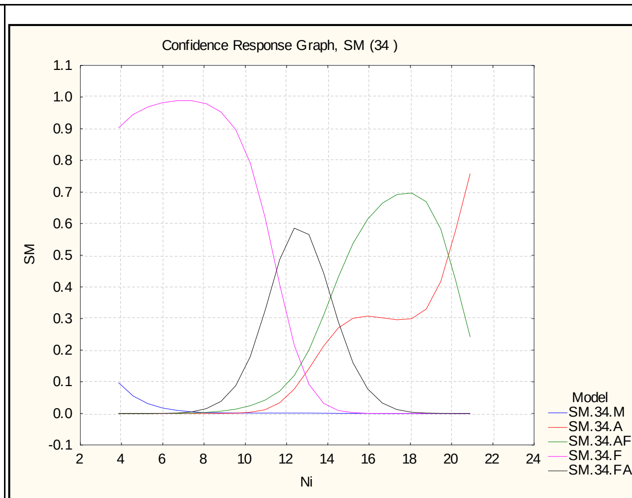

Fig. 4 Effect of Ni on different solidification mode (A, AF, F, FA, M)

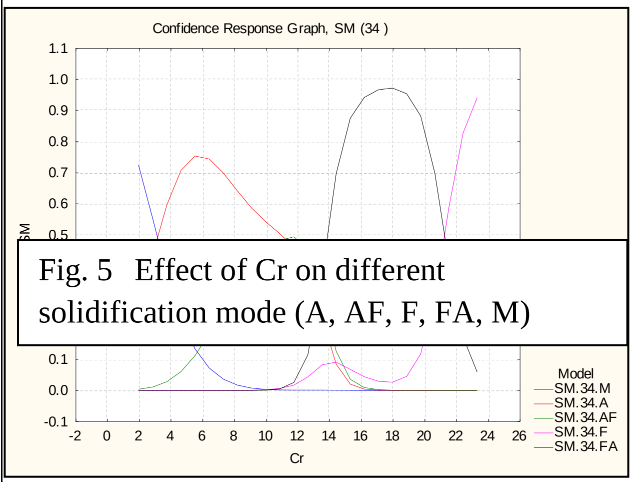

Fig. 5 Effect of Cr on different solidification mode (A, AF, F, FA, M)

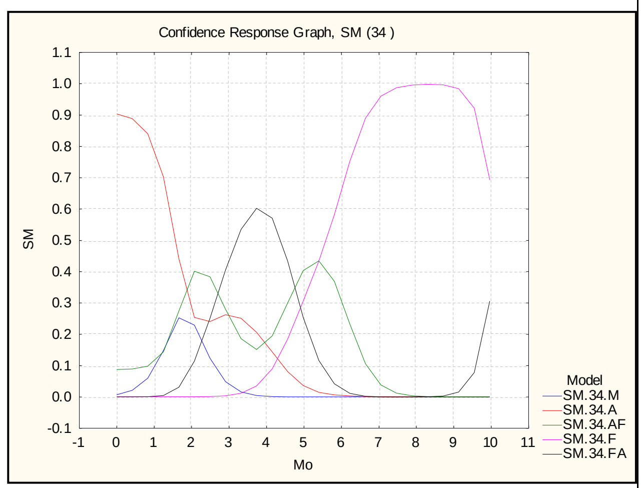

Fig. 6 Effect of Mo on different solidification mode (A, AF, F, FA, M)

Conclusions

- With the help of one of the features –RESPONSE CURVE of this model, it is possible to identify the potential probable effect of individual alloying elements (Ni, Cr and Mo) on different solidification modes and transformation product ((F, AF,FA, A and M). Thereby it is possible to design different weld metal compositions by controlling the appropriate chemistry of the filler metal.
- The PNN based model used to predict the Super Austenitic Stainless Steel (SASS) material system and serves as an important tool to establish the relation between the composition and the microstructural development. Having known the mechanism of the uniform solute redistribution in desired mode of solidification, such a “difficult-to-join” metals can be welded successfully with superior quality and enhanced productivity.

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