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Radial Basis Neural Network Models: Model Development and Validation

M. H. Gadallah[1], K. El-Sayed[2], and K. Hekman[3]
Department of Mechanical Engineering
School of Science and Engineering
The American University in Cairo, Egypt
Corresponding Author E-mail:
Mohamed@aucegypt.edu

Abstract
A supervised neural network using radial basis network (RBN) is developed. The RBN uses error back-propagation algorithm (EBP) as predictive tools for the modelling process. Since NN based models are expensive techniques, Design of Experiments and statistical techniques have been employed to offset this expense. A comparison between several experimental based models on predictive capability and number of training patterns is given. Very often, the designer is faced with a difficult situation that sometimes information is not available. In such a case, the process modeller can compromise accuracy information for the experimental cost. Several 2-levels, 3-levels, 4-levels, and 5-levels OAs are used. These are L8 OA, L9 OA, L27 OA, L32 OA, and L25 OA respectively. Results show that each individual model has a potential for approximation if used by itself. Besides an attempt to combine the models in a sequence and the resulting composed models are used and compared for approximation. Results of constructing different composed models indicate that using a certain sequence leads to a better model with faster convergence and less predictive error.

Keywords: Radial Basis Network, Neural Networks, Modelling.

1 Introduction
Neural networks are modelling techniques used to abstract human knowledge and output the prediction outside any system operating range. This is done through expensive training. Generally, a NN is composed of a group of connected neurons. A neuron can be connected to many other neurons, so that the overall structure of the network can be very complex. Back-

[1] TO WHOM CORRESPONDENCE SHOULD BE DIRECTED. Associate Professor, Operations Research Group, Institute of Statistical Studies & Research, Cairo University, Egypt 12613.
[2] M.Sc. Student, Department of Mechanical Engineering, The American University in Cairo, Egypt

[3]Associate Professor, Department of Mechanical Engineering, The American University in Cairo, Egypt

propagation and Radial basis networks are some kinds of supervised learning. This means that input/ output data is required during the training phase. Learning in systems involves adjustments to the synaptic connections that exist among neurons. A trained neural model can be looked at as an expert in this field of knowledge and can be used to extrapolate outside knowledge domains. An adaptation is to introduce the use of design of experiments to plan and design experimentation for two reasons; the first, without DOE, the user will have to carry one-at-a time variable changes. Given the fact that any realistic process has several hundred variables, the problem becomes intractable. Second, the DOE allows multi-variables to be changed simultaneously; a kind of complex analysis allowing full considerations of process variables and their mutual interactions. Neural networks are used in several different applications such as investment analysis, signature analysis, process control, monitor and marketing analysis for sales prediction and change of customer tastes (Leslie Smith, 1996). The science of soft computing has developed at a faster pace lately. In this paper, a neural based network model is developed using radial basis network. without the inclusion of DOE, several hundred milling experiments are needed to be performed over several ranges of feasible input parameters to feed the neural model. Overall, roughly 150 experiments were conducted for the need of training and testing the used neural model. The resulting neural models are valid for cutting force prediction inside and outside the variables domains. Besides, Using the DOE along a certain neural network design can compensate to a good extent, the limitation of experimentation. This paper is made of five sections. The first section introduces the problem and importance of neural network as modelling tool. In section 2, the radial basis network is given together with the concept of design of experiments. Several different force components are used to evaluate the efficiency of modelling. Experimental results are given in section 4 due to space limitations. Several detailed results are referred to briefly. Discussions of results together with conclusions are shown in section 5.

2 Modeling Process Using Neural Networks

The ANN is used here as tool for mapping input vector received (P) by input neurons to output vector (Y) resultant from output neurons. The mapping process tries to approximate the input function F (P) to another unknown function F (P, W), where W is a parameter vector called weight function. This mapping process is achieved by designing an ANN and training it with a number of input vectors and their corresponding output vectors. The task of training is to adjust W at every training pattern to find the best achievable mapping between input and output. Therefore, the weight values represent knowledge learned through the training patterns. In the training phase, the fractional factorial design (FFD) is used as a systematic way to reduce the number of training experiments. This study started by comparing every model by itself. Several possible combinations are then studied for their approximation capacity. Several process variables are included in this study. These variables are depth of cut, spindle speed, feed rate, and tool diameter. The output vector contains six force components: F max., F min., F mean, F std., Fm-max, Fm-min. The modelling process used is summarized in Figure 1.

3 Radial Basis Network (RBN)

Radial basis networks consist of two layers. The first layer is a hidden radial basis layer of S^1 neurons, uses the Gaussian function for mapping, and the second layer is an output linear layer of S^2 neurons. The algorithm of radial basis NN depends on adding neurons to the hidden layer of a radial basis network until it meets the specified mean squared error goal or until the size of neurons reach the maximum allowable number. The design of radial basis NN depends on two main parameters. The first parameter is called spread. The second parameter deals with the stopping criteria. This parameter is very important to avoid over-training. Adding too much training results can cause the network to learn noise in the data and the model to stop when the training performance reaches the goal. In this paper, the general procedure for neural modelling is shown in Figure 2.

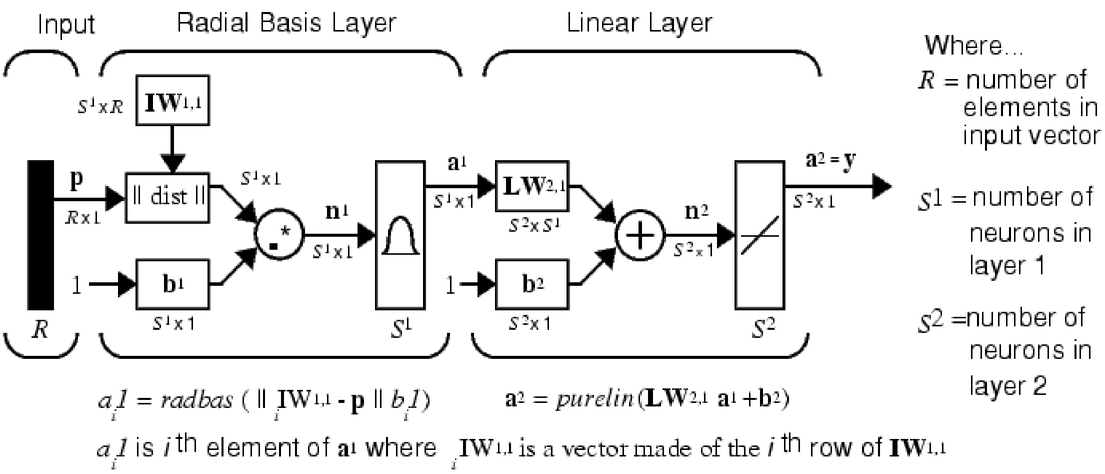

Figure 1: Basic Elements of Radial Basis Neural Network.

4 RBN Process Modelling

Feeding the neural model with "enough information" is not an easy task. We try to reach the minimum predictive error through use of certain experimental models for training. The spread value is very important parameter and a study was carried to scale the input/output values between -1 and +1. Results indicate that the best spread lies within 0.8-0.95. The radial basis neural network depends on the number of hidden layers, the number of neurons and the spread value. Overtraining and under-training are two significant effects. Adding too much information will lead the model to learn noise in data. Under-training, also, means a model with insufficient information or a model not fully covering the whole space.

Figure 3 gives a plot between the predictive error and the training error. The graph can be divided into three regions: overtraining, best stopping time and lastly a region where the model requires further training information. The least error is observed where both training and validation error coincide. Figure 4 gives a plot of the predictive error as a function of neurons. Again, both the training and validation errors converge together in the range 23-35 neurons. In the first region (0-22 neurons), the error converges at a high rate. Above 35 neurons, the 2 sets diverge to higher levels of predictive error.

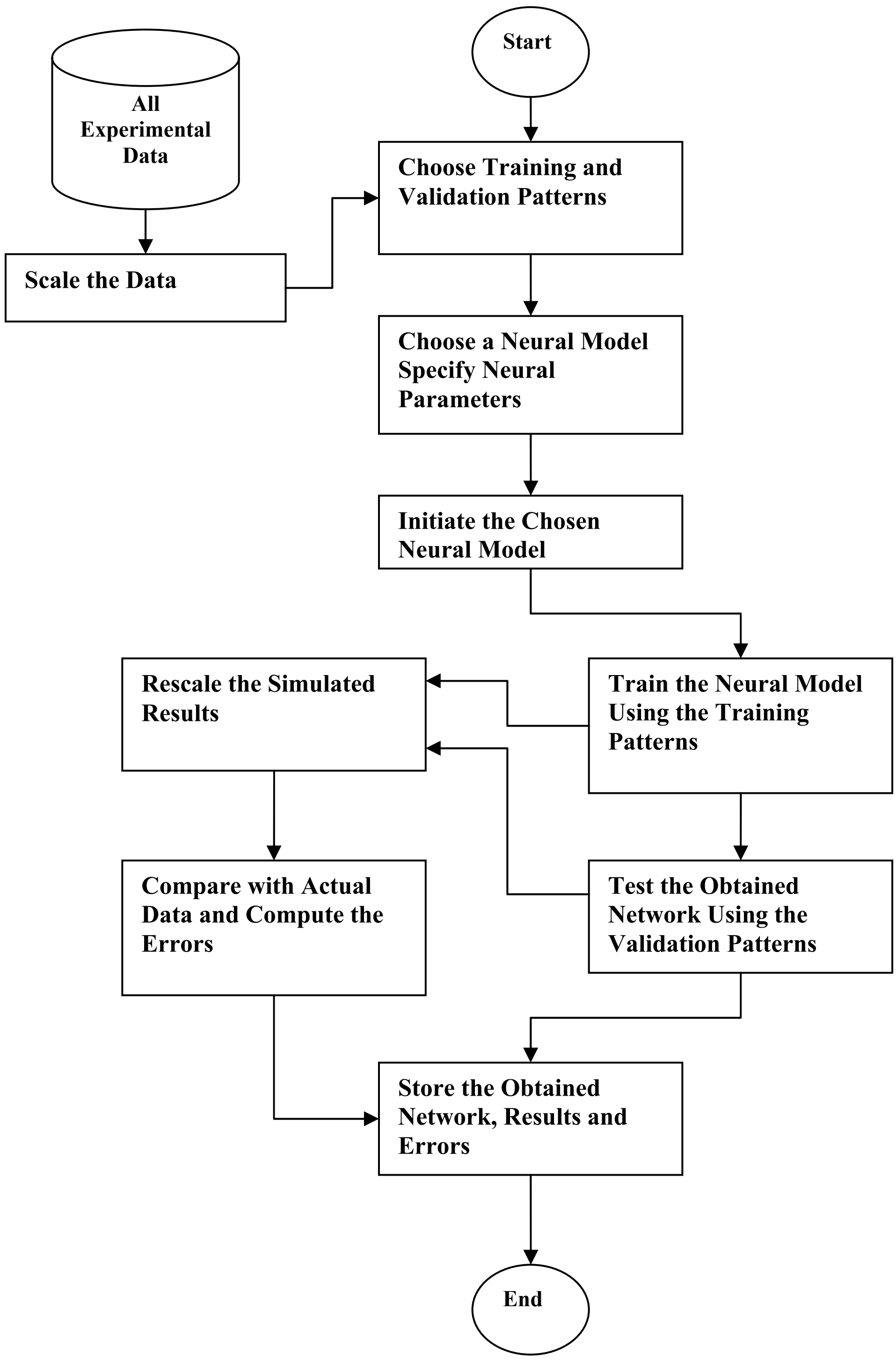

Figure 2: General Procedure for Neural Modeling Process.

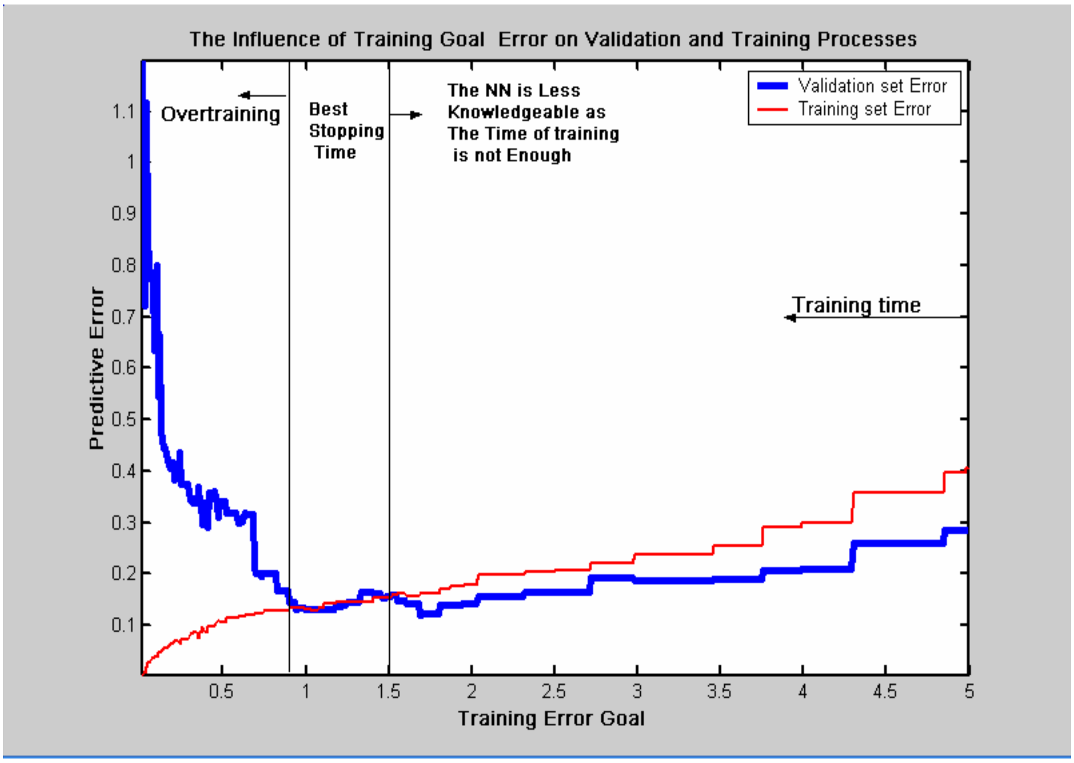

Figure 3. The Influence of Training Goal Error on Validation and Training Processes

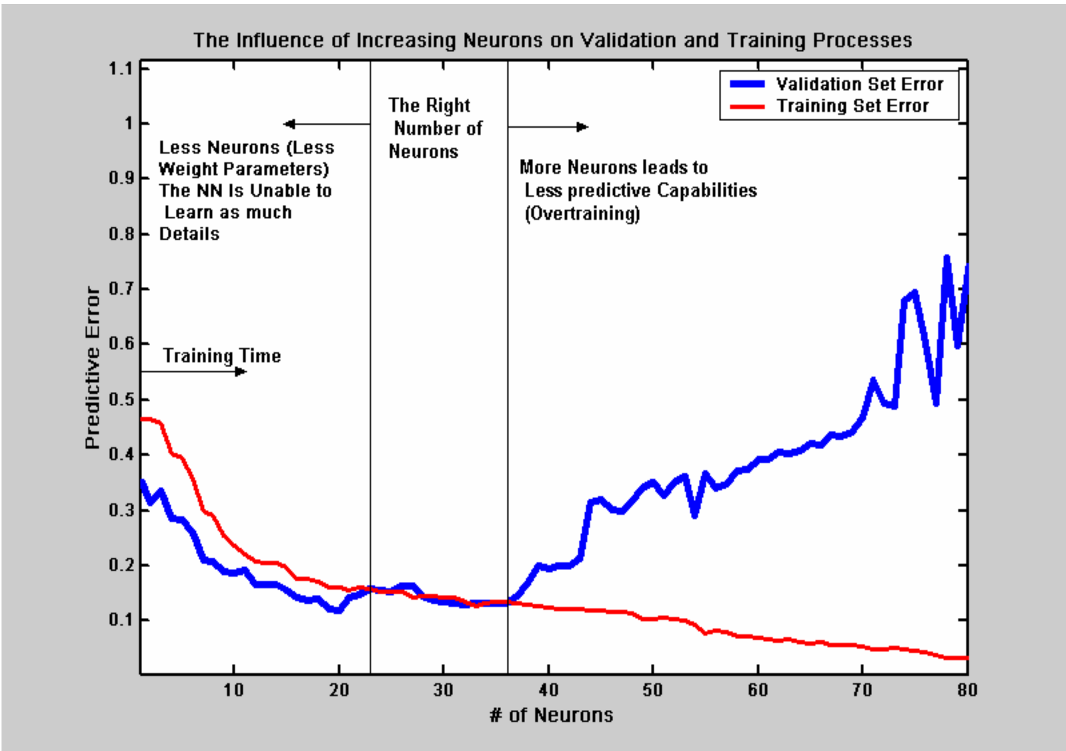

Figure 4. Influence of Increasing Neurons on Validation and Training Processes.

4.1 Experimental Work & 2 Composed Models

Table 1 gives the six force components for the seven developed models. For instance, Fmax ranges from 0.28 (for UL 27-1) to 0.46 (for UL9). Different trends for the other force components are shown. The mean and standard error of the forces are given. Again, the UL27-1 has the smallest mean error; whilst the UL9 has the highest mean error. On the other hand, the standard deviation shows that UL27-2 has the smallest error, whilst the UL32 has the highest error.

An attempt to combine 2 models using a basic model, UL27-1 and the 7 models referred to before. For instance, when UL8-1, with UL27-1, the resulting composed model is UL35-1. Several other composed models are developed; these are UL35-2, UL36, UL54, UL59 and UL52 respectively. Generally speaking, the composed models reduce the predictive errors from 38% ~ 56% (for UL8-2 ~ UL32) for Fmax. Similar reductions are noticed for Fmean, Fstd., Fm-max. and Fm-min respectively. These results are not shown for brevity. This validates our hypothesis that composing more than one model results in drastic reduction in error predictions. Figure 5 shows a sample predictive force errors versus experiment number using UL59. Both the mean and standard deviation for error converge with experiment number.

4.2 Experimental Work & 3 Composed Models

The UL59 previously developed is used here as a basic model to combine with several models to form the new composed model. For instance, when UL59 is added to UL8-1, the resulting composed model becomes UL67-1. Table 3 shows the predictive force errors for various developed models. Again, the predictive errors reduce by 64% ~ 70% for Fmax. Similar trends have been observed for other force components.

4.3 Experimental Work & 4 Composed Models

The UL84 previously developed is used here as a basic model to combine with several models to form the new composed model. For instance, when UL84 is added to UL8-1, the resulting composed model becomes UL92-1. Sometimes, one or two separate experiments are added to cover a certain domain. Again, Tables 1 & 4 are compared together based on the predictive force errors. The difference between UL86-1 and UL92-1 lies in the fact that when we added UL8-1 to UL84, we recognized that there are repetitive experiments. The predictive error based on Fmax. reduce by 60% ~ 74%. Similar trends have been observed for other force components.

4.4 Experimental Work & 2-Final Models

Two models are refined after all experimentation measurements; these are UL90 and UL136 respectively. Table 5 gives the predictive force errors for various force components for the UL90 and UL136 models. A comparison is also graphed in Figure 8 showing good convergence to reasonable error. It is clear that UL90 converges faster than UL136. This requires further study. We attempted to adjust the spread values which positively impacted the predictive errors by 8.9% ~ 13.2% for UL136 and UL90 respectively (using Fmax. for example).

Table 1. Predictive Force Errors Result From Training Basic Models

Model Name	Predictive Force Errors						Excluding F min., F m-min.	
	F max.	F min.	F mean	F std.	F m-max.	F m-min.	E mean	E std.
UL8-1	0.43	2.48	0.46	0.46	0.46	0.47	0.45	0.09
UL8-2	0.44	2.60	0.55	0.46	0.45	0.92	0.47	0.08
UL9	0.46	3.48	0.53	0.49	0.49	0.81	0.49	0.08
UL27-1	0.28	8.72	0.28	0.34	0.31	0.74	0.30	0.08
UL27-2	0.38	4.11	0.45	0.40	0.40	0.71	0.41	0.07
UL32	0.41	3.86	0.51	0.44	0.43	0.93	0.45	0.11
UL25	0.43	4.25	0.60	0.44	0.47	0.89	0.48	0.10

Table 2. Predictive Force Errors for 2-composed models.

Basic models with UL27-1	Model Name	Predictive Force Errors						Excluding F min., F m-min.	
		F max.	F min.	F mean	F std.	F m-max.	F m-min.	E mean	E std.
UL8-1	**UL35-1**	0.21	6.26	0.18	0.28	0.23	0.43	0.23	0.09
UL8-2	**UL35-2**	0.27	7.53	0.30	0.32	0.29	0.85	0.29	0.08
UL9	**UL36**	0.24	4.21	0.24	0.28	0.26	0.53	0.25	0.08
UL27-2	**UL54**	0.17	4.52	0.13	0.22	0.17	0.58	0.17	0.07
UL32	**UL59**	0.18	3.64	0.13	0.17	0.16	0.64	0.16	0.07
UL25	**UL52**	0.19	4.18	0.23	0.17	0.17	0.65	0.19	0.06

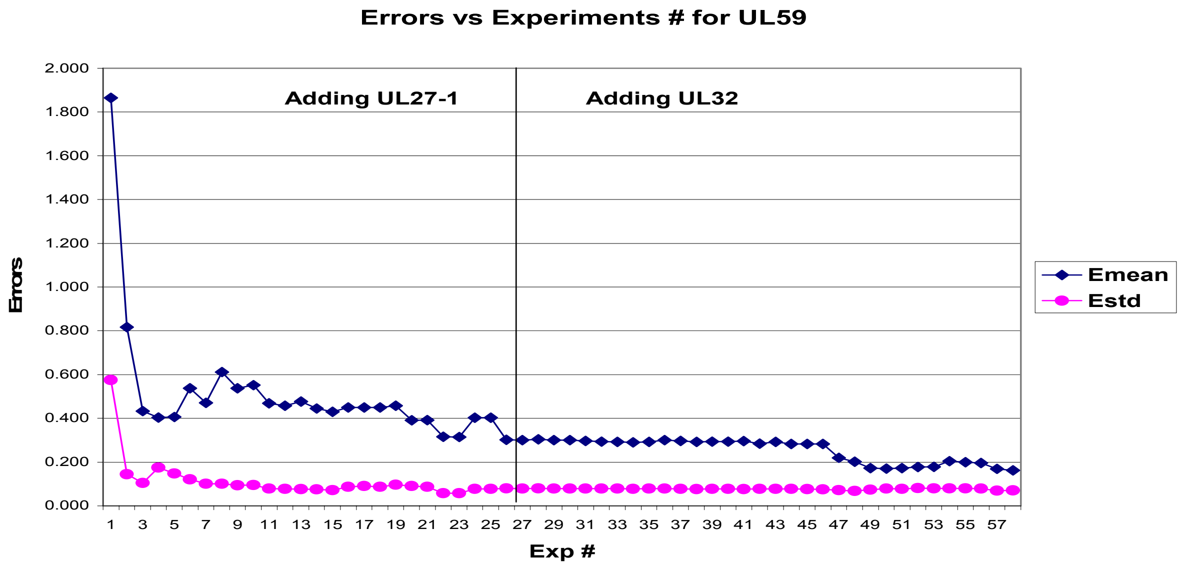

Figure 5. Predictive Force Errors vs. Experiment Number for using UL59.

Table 3. Predictive Force Errors for 3-composed model.

Basic models with UL59	Model Name	Predictive Force Errors						Excluding F min., F m-min.	
		F max.	F min.	F mean	F std.	F m-max.	F m-min.	E mean	E std
UL8-1	UL67-1	0.132	3.054	0.173	0.146	0.138	0.552	0.147	0.068
UL8-2	UL67-2	0.156	4.726	0.177	0.163	0.171	0.614	0.167	0.082
UL9	UL68	0.159	3.007	0.170	0.170	0.147	0.412	0.162	0.064
UL27-2	UL86	0.133	3.568	0.171	0.156	0.135	0.561	0.149	0.060
UL25	UL84	0.127	4.319	0.138	0.133	0.115	0.625	0.128	0.055

Table 4. Predictive Force Errors for 4-composed models and effective points.

Basic models with UL84	Exp. Added	Model Name	Predictive Force Errors					Excluding F min., F m-min.	
			F max.	F min.	F mean	F std.	F m-max.	F m-min.	E mean, Estd
UL8-1	1 to 8	UL92-1	0.17	3.13	0.17	0.16	0.15	0.6	0.16, 0.07
	7	UL86-1	0.123	4.754	0.153	0.107	0.095	0.698	0.119, 0.056
UL8-2	1 to 8	UL92-2	0.127	4.64	0.147	0.145	0.127	0.543	0.136, 0.054
	6	UL85	0.12	4.897	0.148	0.106	0.098	0.676	0.118, 0.059
UL9	1 to 9	UL93	0.168	2.731	0.153	0.145	0.129	0.377	0.149, 0.053
	2	UL86-2	0.119	4.522	0.138	0.106	0.099	0.59	0.116, 0.056
UL27-2	1 to 27	UL111	0.138	2.275	0.117	0.134	0.101	0.563	0.123, 0.056
	10 to12	UL87	0.145	3.254	0.105	0.13	0.105	0.531	0.121, 0.06
Adding all Effective points		UL90	0.107	4.063	0.103	0.095	0.077	0.552	0.095, 0.053

Table 5. Predictive Force Errors after using all experimental models.

Model	Predicted Force Errors						Excluding Fmin, Fm-min	
	Fmax	Fmin	Fmean	Fstd	Fm-Max	Fm-min	Emean	Estd
UL136	0.1	0.87	0.09	0.11	0.10	0.33	0.10	0.05
Ul90	0.107	4.063	0.103	0.095	0.077	0.552	0.095	0.053

Adjusted spread values (0.97 for UL90, 0.97 for UL136)

Model	Predicted Force Errors						Excluding Fmin, Fm-min	
	Fmax	Fmin	Fmean	Fstd	Fm-Max	Fm-min	Emean	Estd
UL136	0.0911	1.552	0.1049	0.094	0.0803	0.324	0.092	0.052
Ul90	0.0928	4.142	0.1236	0.069	0.0735	0.589	0.089	0.055

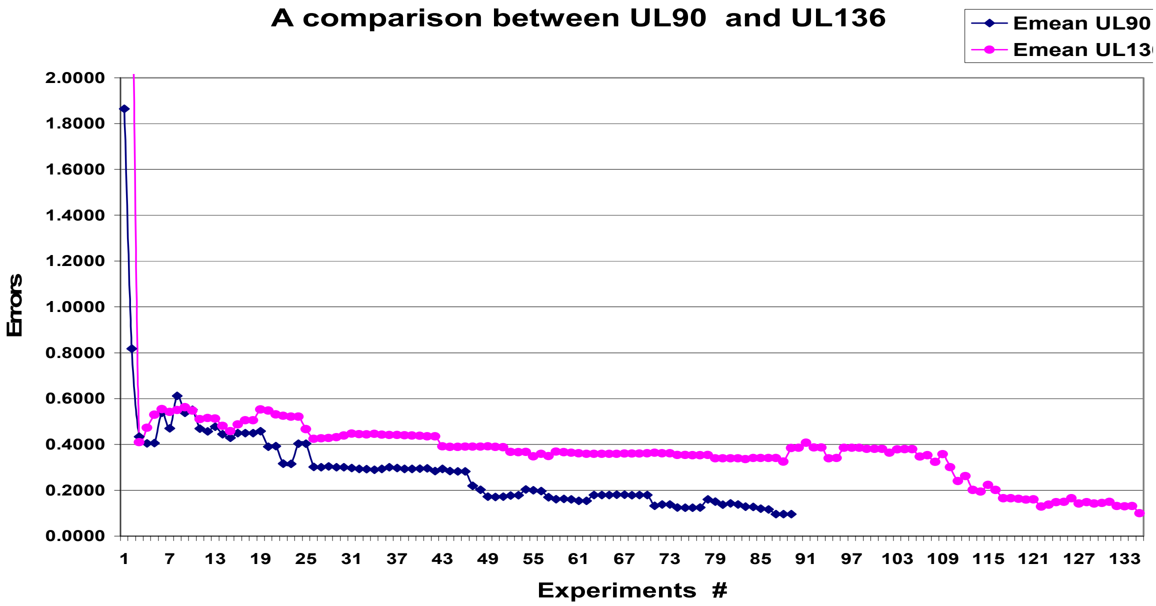

Figure 8. A comparison between UL90 and UL136.

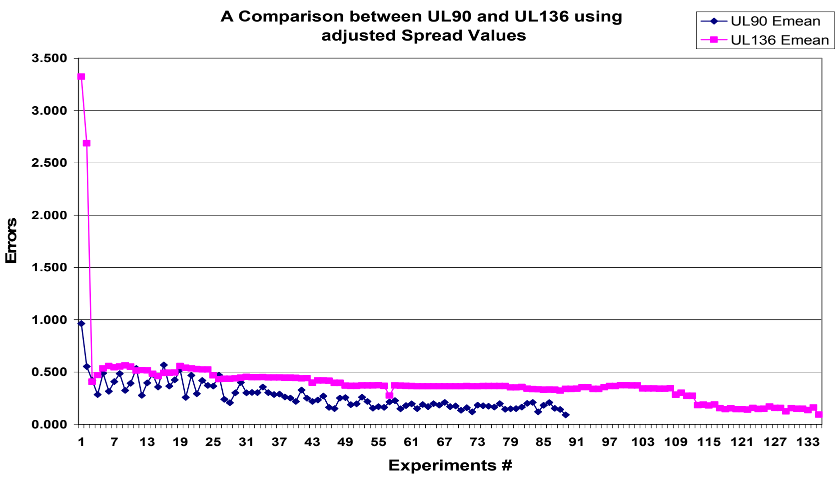

Figure 9: A comparison between UL90 and UL136 using the new spread Values

5 Discussion & Conclusion

A radial basis neural network is combined with orthogonal arrays as approximation means to model end milling. The problem of overtraining and sufficiency of information is dealt with by adding models in sequence. Several conclusions can be drawn:

1. The radial basis network could have been developed without the use of orthogonal arrays. This, would have required, huge number of experimentation.

2. In this work, 2-, 3-, 4-, 5-, levels orthogonal arrays have been used; other high level arrays could have been employed. It is expected that the higher the number of levels, the better the model error convergence.
3. The idea of composed models is new. It has been used to avoid overtraining and unnecessary experimentation. It is true that spread value could improve the situation as shown. A comparative study could be done to verify this statement. Due to page limitations, past literature was briefly referenced in the reference section without inclusion in the body of the paper.

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