The yearly production of a manufacturing plant studied by DES combined with RSM high level designs and neural networks

Lucia Cassettari, Marco Mosca, Roberto Mosca, Fabio Rolando

Abstract — Authors present a study over the target function of a stochastic discrete event simulator of a manufacturing plant. They decided to test some balanced user defined designs as 4^2,5^2,7^2, and 9^2, in order to describe the existing relationship between dependent variables (efficiency of two types of machines of production line) and the independent variable (yearly production). Through this kind of design it was expected to avoid problems of robustness of adopted meta-models like those emerged in a previous work they did in which unbalanced designs based on central composite designs had been used. Eventually it has been possible to put in evidence the bound between regression meta-models and neural networks in this type of research.

Keywords — Discrete Event Simulation, Neural Networks, Regression Meta-models, Response Surface Methodology, User Defined Designs.

I. Introduction and Background

MOTIVATIONS leading authors to carry on the research described in this paper lie in conclusions they drew up in their previous work [23].

In that work Authors studied the influence of the experimental error (Mean Square Pure Error) on the "quality" of the regression meta-models obtained by the Response Surface Methodology (RSM) [2], [4], [16], [20], [21], applied to a DES model of a production shop floor. The aim of the study was the research of the relashionship existing between the yearly production and the efficiency of two types of machines, multi-step grinding machines (factor A) and dimensional check machines (factor B).

Thanks to the MSPE methodology applied on time evolving systems [11], [22], the yearly production of a manufacturing plant (Fig.1) could put in evidence that increasing the simulation run duration means to obtain significant reduction of the MS_{PE} quantity, which quantity, according to Cochran [1], [11], [21], [22], is a correct evaluator of the experimental error variance.

R.Mosca is with the DIME department of University of Genoa, Via all'Opera Pia 15, 16154, Genoa, Italy (phone: +39.019.219.45127; e-mail: mosca@diptem.unige.it).

L.Cassettari, M.Mosca, F.Rolando are with the DIME department of University of Genoa, Via all'Opera Pia 15, 16154, Genoa, Italy (e-mail: cassettari@diptem.unige.it,rolando@diptem.unige.it, marcotulliomosca@gmail.com).

Being MS_{PE} linked to Mean Square Error (σ^2_E), which is a regression variance evaluator, for every its reduction we obtain a size decrease of both confidence and prediction intervals on the average response, thus an error interval reduction on the actual simulator response (σ^2_{PE}) [23].

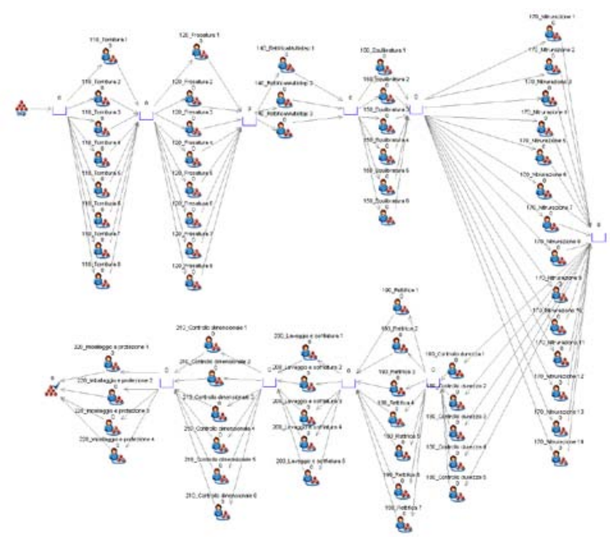


Fig.1

The analysis had been conducted applying the RSM at three different MS_{PE} levels (as shown in Fig.2): 30, 1000, 3650 days respectively.

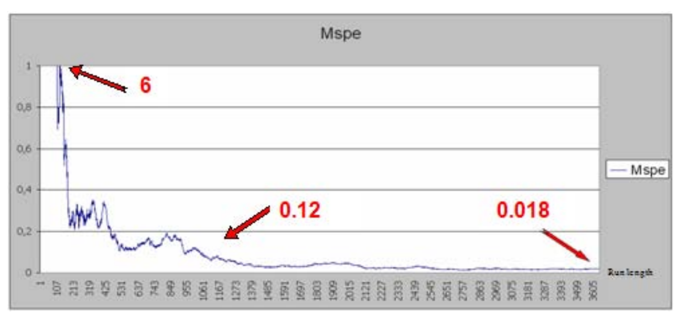


Fig.2

Let's start by saying that act on 30-days-lenght runs, as many researchers who don't know the methodology actually do, could be very dangerous because, at that time, the curve does not get to the stabilization zone yet [4], [11], [24].

The evolution of a set of MS_{PE} curves (Fig.3), built in a same domain point of the target function, must be observed in order to better understand this last statement.

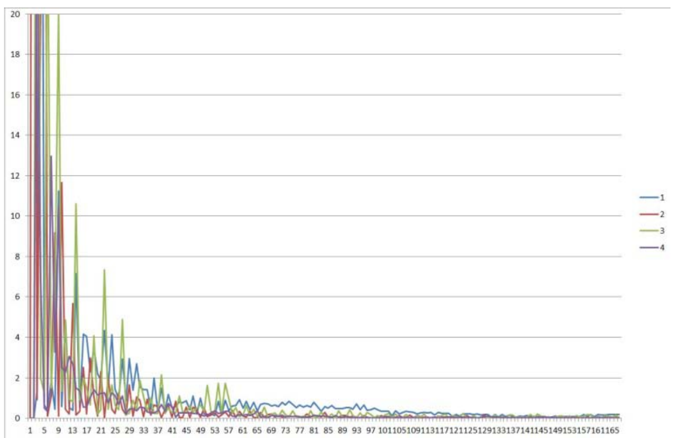


Fig.3

Before converging progressively to a same stabilization value, the three curves had quite different punctual trends.

This behavior depends on the simulation run-time which is affecting the number of samples drawn from the statistical distributions running in the simulated reality. It is well know indeed that, due to the Monte Carlo method's way of act, values from both tails (right and left) of the statistical PDF in the model could be drawn during earlier simulated-time. As direct consequence the related value of the target function at those times will be higher or lower than expected affecting the value of MS_{PE}. For such a reason the evolution of the MS_{PE} curve during simulated-time is initially subject to substantial punctual variations and so different curves outcoming from the same simulation model would never completely overlap. As the simulated-time goes by, data from model's statistical distributions gradually cover them, and so the MS_{PE} punctual oscillations will tend to smooth. When finally the total cover of the initial distribution is done by the extracted (and re-sampled) data, all the curves get to the stabilization phase and so tend to overlap each other.

When this value of the simulated-time is reached, the experimenter can be confident to have a MS_{PE} value depending only on the system noise, and completely unaffected by inadequate experimental phases on the model.

Finally recalling that the experimental error is assumed to be a NID(0, σ^2_{PE}) and that E(MS_{PE}) = σ^2_{PE}, the confidence interval on the result at time equal t is:

$$\bar{y}(t) \pm 3\sqrt{MS_{PE}(t)}$$

For such a reason the quality of the result, given by the simulator when *t* is inadequate, can be strongly affected by the error, and so this could lead the experimenter to very different value of the target function on every simulation run.

After these considerations, by observing Fig.3 it can be seen that a different regression meta-model could be obtained in each different simulation-length scenario: a quadratic model for 30 days simulation, a cubic for 1000 days simulation, and a quartic one in the last 3650 days simulation.

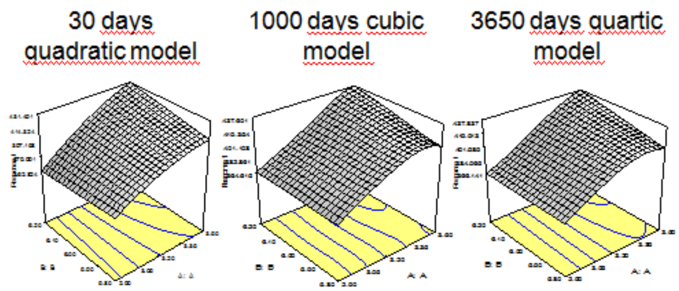


Fig.3

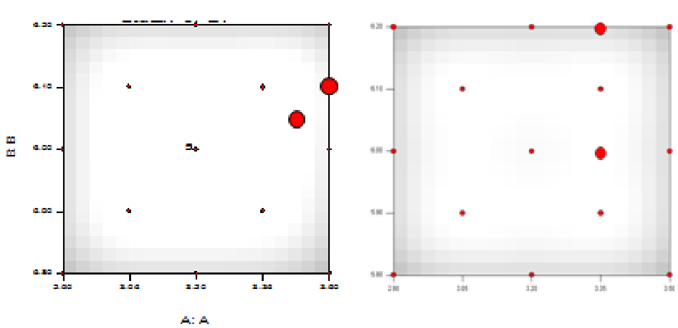
Longer simulation durations, thus, bring to smaller MS_{PE} values.

$$F_0 = \frac{MS_{LOF}}{MS_{PE}} \leq F_{\alpha,\upsilon_1,\upsilon_2} \tag{1}$$

Considering the effect of the Fisher's Lack of Fit test (1) the experimenter needs to obtain a smaller MS_{LOF} and so meta models more fitting to the experimental points.

Another consequence is the greater stability of the simulation responses obtained through narrower confidence and prediction intervals calculated through small MS_{PE} values [23], [24].

Let's analyze the 4th order meta-model construction (3650 days simulation run). Figure 4 (**a**) shows the domain points in which the 19 simulation runs had been carried out in order to find a suitable design. There are 8 vertex points needed for a central composite design (in this case a face-centered kind), 5 central points in order to measure the MS_{PE}, 4 additional internal points located in a symmetric way in order to keep the design balanced, and finally 2 extra points. These two points are necessary to define the 4th order model in a correct way even though they unbalance the design (user defined design).



a) 1st quartic model – experimental points in the domain

b) 2nd quartic model – experimental points in the domain

Fig.4

The quartic model shape, as it can be seen, is representing the evolution, in terms of surface fitting the experimental points, of previous models (2^{nd} and 3^{rd} order models). The issue leading authors to proceed with this second work came out when they, aiming to investigate the robustness of the solution, tried to change the two extra points position (Fig.4-**b**).

That new meta-model, still a 4^{th} order one, though validated by the Fisher's LOF test, showed a punctual trend quite different than the previous one and thus very unrealistic for the case studied (Fig.5).

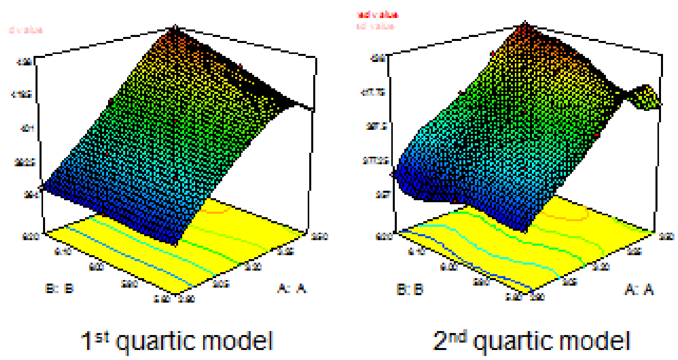


Fig.5

Then authors gathered that a regression meta-model, for its own nature, is like a stiff metal shell. The presence of particular points, main feature of unbalanced designs, could generate attractive forces that cause distortions all over the shell, thus turning it into the waving shape shown in Fig.5 [23].

Trying to avoid such a gap, authors decide to test the opportunity to adopt balanced factorial designs (4^2,5^2,7^2, and 9^2 designs) with an information content equally spread in the domain (uniform precision designs Fig.6).

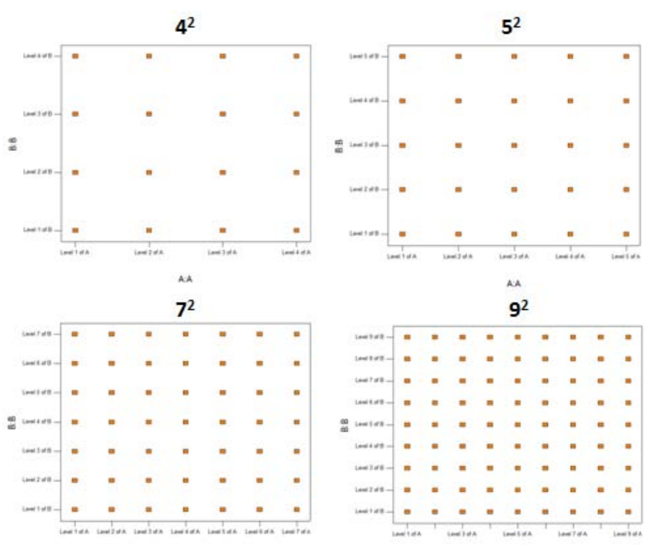


Fig.6

Going toward a greater cost in terms of growing number of factors levels (32, 50, 48, 162 replications respectively, since every design must be replicated in order to measure the experimental error), and keeping the same run length (and thus the same order of MS_{PE}) it has to be expected that a significantly increased robustness of the response surface could be achieved.

II. FOUR–LEVEL FACTORIAL DESIGN

The experiment was carried out by dividing the two factors under analysis into 4 levels in order to obtain a grid of 16 survey points, which were then replicated to allow the software to carry out the Fisher's "Lack of Fit" test. The 32 survey points were obtained by performing simulations having a run length of 10 years (3650 days) in order to ensure an adequate size of experimental error, as shown in Figure 2 [2][4][11][13][18][22].

The results of the regression obtained by entering experimental responses in the Design Expert statistical analysis tool are illustrated in detail below.

The software suggests adapting a cubic model, which, as shown in Fig.7, does not pass the "Lack of Fit" test, with a F_0 value of 4689.61, thus removing the non-significant factors from the model: B^3 and AB^2. It should be noted that the experimental error is very low, thus confirming the robustness of the data output from the model.

ANOVA for Response Surface Reduced Cubic Model

Analysis of variance table [Partial sum of squares]

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Model	16951.26	7	2421.61	1999.24	< 0.0001	significant
A	*1844.03*	*1*	*1844.03*	*1522.39*	*< 0.0001*	
B	*6.27*	*1*	*6.27*	*5.17*	*0.0322*	
A^2	*548.46*	*1*	*548.46*	*452.80*	*< 0.0001*	
B^2	*8.52*	*1*	*8.52*	*7.03*	*0.0140*	
AB	*451.44*	*1*	*451.44*	*372.70*	*< 0.0001*	
A^3	*70.87*	*1*	*70.87*	*58.51*	*< 0.0001*	
A^2B	*131.74*	*1*	*131.74*	*108.76*	*< 0.0001*	
Residual	29.07	24	1.21			
Lack of Fit	*29.06*	*8*	*3.63*	*4689.61*	*< 0.0001*	*significant*
Pure Error	*0.012*	*16*	*7.745E-004*			
Cor Total	16980.33	31				

Fig.7

An analysis of the residuals of the 32 survey points shows that in some of these points the model has difficulties in adapting the initial experimental data: this is the case when the residual value exceeds the unit (Fig.8) . In the design under consideration, there are residuals that take the values of 2.38 and 2.34, both referred to the point (3.30 – 5.93). This means that in that domain zone the response surface is forcibly distorted in an anomalous manner, which is further confirmed by the magnitude of the residuals that are recorded in the neighboring points (3.30 – 5.93). The model does not show any outlier though.

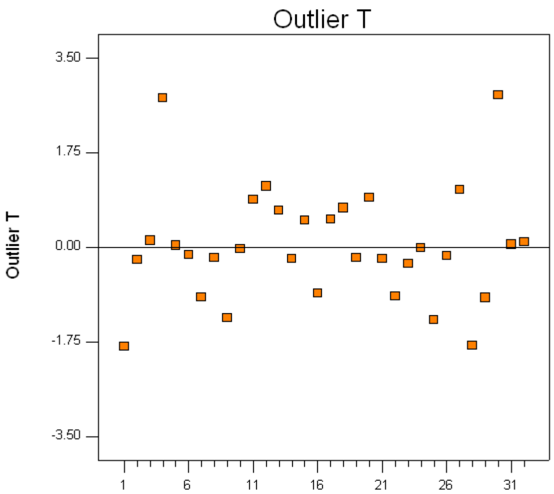


Fig.8

Figure 9 shows the fit surface of the regression meta-model. The surface shows that the critical part highlighted also by the residuals, is the area where the surface no longer has a planar trend, particularly in the section A=3.35.

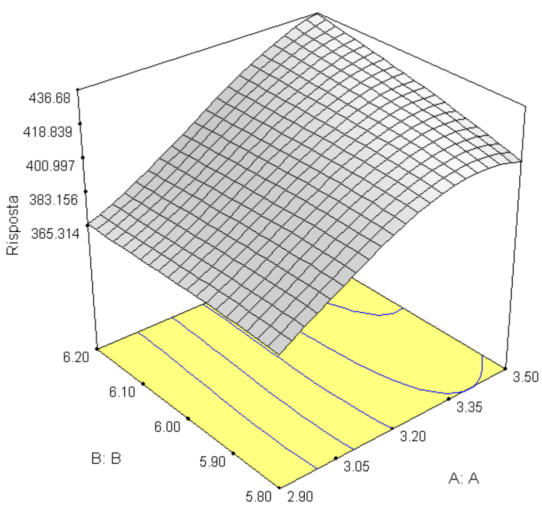


Fig.9

Here below the surface equation is shown:

$$\hat{y} = 413.77 + 26.76\,A + 0.60\,B - 7.15\,A^2 - 1.22\,B^2 + 5.20\,AB - 5.50\,A^3 + 4.90\,A^2B \quad (2)$$

III. FIVE-LEVELS FACTORIAL DESIGN

Considering the unsatisfactory performance of 4^2, the attempt was made to assign 5 levels to each factor in the effort to obtain a better description of the target function. Therefore, an experimental plane of 25 processing combinations is built (Fig.6). In this case as well, two replications of the experimental plane were used for the reasons already expounded for the previous design. The experimental responses are the result of simulations run over a chronological horizon of 10 years. This chronological horizon was used to obtain production values affected by a Mean Square Pure Error in the order of 10^{-3}. The results obtained with the Design Expert application are illustrated below.

Starting from the variance analysis (Fig. 10), it is self-evident that the model does not pass the “Lack of Fit” test with a statistical summary value of F equal to 19.61, after eliminating the interactions among the factors deemed as not-significant. It can be noted that the pure error is maintained at acceptable values even if these are greater than in 4^2 designs of magnitude, thus going from 10^{-3} to 10^{-1}. This occurs as a result of the replications carried out in survey points other than those used in 4^2design. It should also be noted that the fifth- and sixth-order models are “aliased” for Design Expert, as in the case of 4^2, i.e., there is no adequate number of survey points to calculate the regression factors, while the fourth order is under-performing compared to the cubic model chosen.

An analysis of the response surface (Fig. 11) gives a performance similar to that of 4^2. There is the same tendency of the plane to curve at higher levels of A.

ANOVA for Response Surface Reduced Cubic Model

Analysis of variance table [Partial sum of squares]

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Model	24271.83	7	3467.40	2114.49	< 0.0001	significant
A	*3523.25*	*1*	*3523.25*	*2148.54*	*< 0.0001*	
B	*7.63*	*1*	*7.63*	*4.65*	*0.0368*	
A²	*692.90*	*1*	*692.90*	*422.54*	*< 0.0001*	
B²	*14.45*	*1*	*14.45*	*8.81*	*0.0049*	
AB	*597.71*	*1*	*597.71*	*364.49*	*< 0.0001*	
A³	*106.02*	*1*	*106.02*	*64.65*	*< 0.0001*	
A²B	*185.28*	*1*	*185.28*	*112.98*	*< 0.0001*	
Residual	68.87	42	1.64			
Lack of Fit	*64.07*	*17*	*3.77*	*19.61*	*< 0.0001*	*significant*
Pure Error	*4.80*	*25*	*0.19*			
Cor Total	24340.70	49				

Fig.10

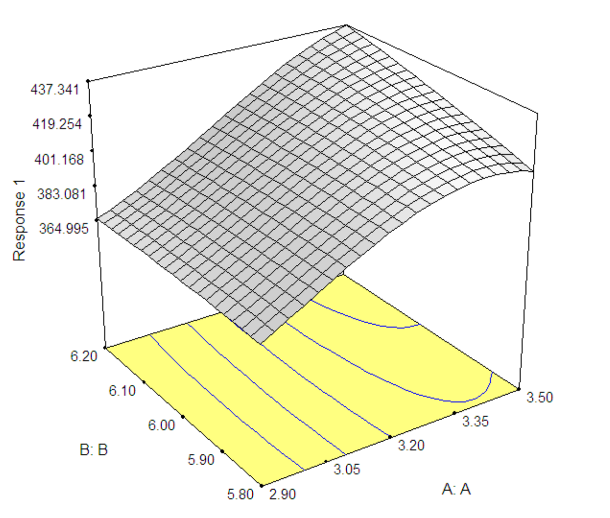


Fig.11

$$\hat{y} = +404.44 + 35.67A + 0.86\,B - 8.90A2 - 1.29B2 + 6.91AB - 6.86A3 + 6.51A2\,B \quad (3)$$

IV. SEVEN-LEVELS FACTORIAL DESIGN

This design can be considered as a refined 4^2 design, as three intermediate levels were added for each factor (Fig.6). By doing so, a tighter grid made of 49 survey points was created. In this case as well, two replications for each survey point were used in order to allow the software to run the "Lack of Fit" test.

The software suggests adapting a sixth-order model (Fig. 12).

The adapted model does not pass though the "Lack of Fit" test (Fig. 13): even though the non-significant interactions among the factors were removed from the model, the F value for the test is still very high (142.05).

Response: Response 1

Sequential Model Sum of Squares

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Mean	1.564E+007	1	1.564E+007			
Linear	41917.68	2	20958.84	607.05	< 0.0001	
2FI	874.94	1	874.94	34.20	< 0.0001	
Quadratic	1144.96	2	572.48	41.80	< 0.0001	
Cubic	760.23	4	190.06	33.46	< 0.0001	
Quartic	26.66	5	5.33	0.94	0.4626	
Fifth	172.26	6	28.71	7.35	< 0.0001	
Sixth	92.70	7	13.24	4.45	0.0004	Suggested
Residual	208.18	70	2.97			
Total	1.569E+007	98	1.601E+005			

Fig.12

Analysis of variance table [Partial sum of squares]

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Model	44964.80	19	2366.57	792.93	< 0.0001	significant
A	2171.13	1	2171.13	727.45	< 0.0001	
B	64.92	1	64.92	21.75	< 0.0001	
A^2	14.41	1	14.41	4.83	0.0310	
B^2	47.97	1	47.97	16.07	0.0001	
AB	89.84	1	89.84	30.10	< 0.0001	
A^3	35.75	1	35.75	11.98	0.0009	
A^2B	237.24	1	237.24	79.49	< 0.0001	
A^4	16.70	1	16.70	5.59	0.0205	
B^4	30.14	1	30.14	10.10	0.0021	
A^3B	19.52	1	19.52	6.54	0.0125	
AB^3	39.69	1	39.69	13.30	0.0005	
A^5	10.00	1	10.00	3.35	0.0710	
B^5	35.51	1	35.51	11.90	0.0009	
A^4B	131.67	1	131.67	44.12	< 0.0001	
A^2B^3	12.53	1	12.53	4.20	0.0438	
A^5B	9.14	1	9.14	3.06	0.0841	
A^4B^2	45.24	1	45.24	15.16	0.0002	
A^2B^4	36.00	1	36.00	12.06	0.0008	
A^3B^3	25.47	1	25.47	8.54	0.0046	
Residual	232.80	78	2.98			
Lack of Fit	230.06	29	7.93	142.05	< 0.0001	significant
Pure Error	2.74	49	0.056			
Cor Total	45197.60	97				

Fig.13

Moving on to the analysis of the residuals, the first and foremost thing that can be noted is that the model has two outliers: the two replications of the point (3.1 – 6.13). It was easy to anticipate this result simply by looking at the large distance from other points in Fig. 14.

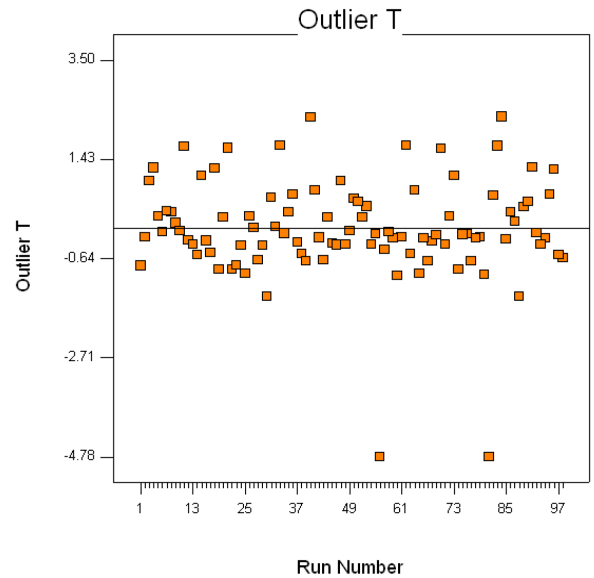


Fig.14

The presence of this disturbance challenges the model, which, in the effort to follow the survey point, ends up worsening the fit in the other survey points. The surface shows depressions that do not match the actual behavior of the physical system (Fig. 15).

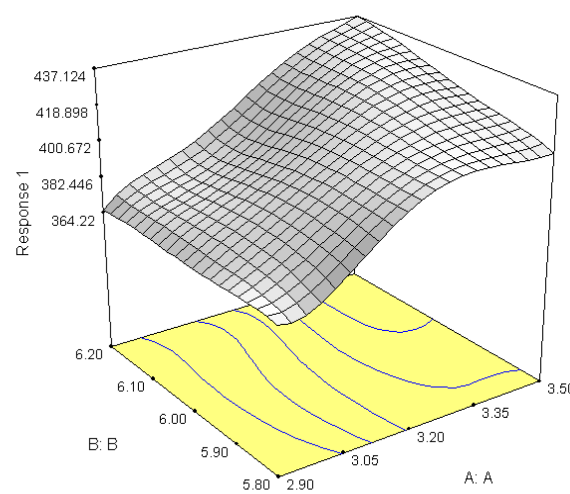


Fig.15

The meta-model equation is:

$$\hat{y} = +403.90 + 38.82A - 1.70B - 0.63A^2 - 3.09B^2 + 15.66\,AB - 10.16A^3 - 8.45B^3 + 29.14A^2B - 1.80AB^2 - 7.94A^4 + 2.52B^4 - 8.35A^3B - 12.49AB^3 - 18.33\,A^2B^2 + 9.54B^5 - 17.30A^4B + 1.97A^3B^2 - 3.97\,A^2B^3 + 18.28\,A^4B^2 + 11.95A^3B^3 \quad (4)$$

V. NINE-LEVELS FACTORIAL DESIGN

The fourth and last factorial experiment obtained can be seen as a refined version of 5^2 above. Four levels were added for each factor, thus providing an experimental grid made of

81 survey points. The experiment was replicated for the same reasons expounded for the previous designs.

As for design 7^2, the software suggests, once again, a sixth order as a better adaptation of the response surface.

As in the case of the previous model though, the "Lack of Fit" test is not passed even though the statistical summary value F has dropped to 12.31 (Fig. 16), which is the lowest value among all those obtained in all the previous designs.

The examination of the residuals shows 3 outliers: one replication of the point (3.2 – 6.2) and both of the point (3.27 – 5.85). The values of the residuals are 4.799 and 3.615 – 3.623 respectively as it can also be noted in Fig.17

ansform | Fit Summary | Model | ANOVA | Diagnostics | Model Graphs

ANOVA for Response Surface Reduced Sixth Model

Analysis of variance table [Partial sum of squares]

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Model	68545.60	14	4896.11	12793.76	< 0.0001	significant
A	3172.00	1	3172.00	8288.57	< 0.0001	
A^2	11.02	1	11.02	28.79	< 0.0001	
AB	5.40	1	5.40	14.10	0.0002	
A^3	54.45	1	54.45	142.29	< 0.0001	
A^2B	340.18	1	340.18	888.91	< 0.0001	
AB^2	45.13	1	45.13	117.93	< 0.0001	
A^4	29.59	1	29.59	77.31	< 0.0001	
A^3B	31.46	1	31.46	82.22	< 0.0001	
A^2B^2	47.84	1	47.84	125.01	< 0.0001	
A^5	9.64	1	9.64	25.19	< 0.0001	
A^4B	81.25	1	81.25	212.31	< 0.0001	
A^3B^2	29.95	1	29.95	78.26	< 0.0001	
A^5B	30.16	1	30.16	78.81	< 0.0001	
A^4B^2	38.71	1	38.71	101.14	< 0.0001	
Residual	56.26	147	0.38			
Lack of Fit	51.15	66	0.78	12.31	< 0.0001	significant
Pure Error	5.10	81	0.063			
Cor Total	68601.86	161				

Fig.16

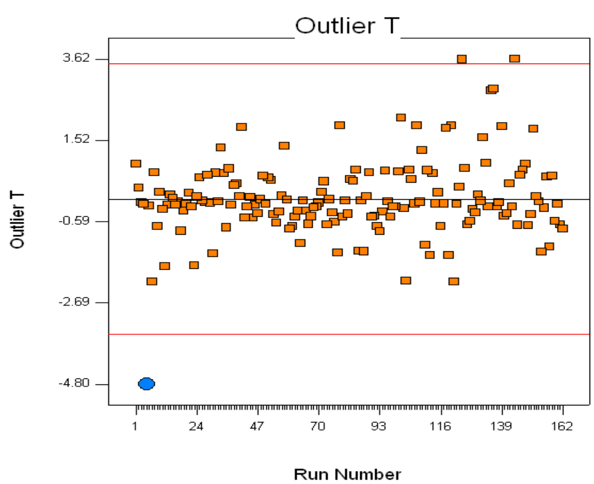


Fig.17

Therefore, it is a model that lacks in robustness. The region comprised between levels 3.2 – 3.27 of A and all levels of B is marked by a great sensitivity to the variation in the response of the regressor.

The response surface obtained (Fig. 18) shows a trend like that of 5^2, i.e., it is almost planar for the lower levels of A, while the higher ones have at least three warps. The fit difficulty in this domain region is hence confirmed.

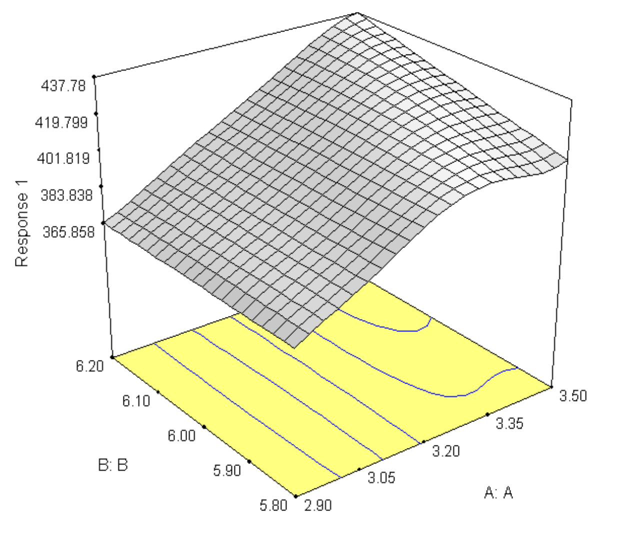


Fig.18

$$\hat{y} = +404.90 + 40.02A - 3.47A^2 + 2.20\,AB - 16.53A^3 + 15.74A^2B - 5.86AB^2 - 5.74A^4 + 19.05A^3B - 10.42\,A^2B^2 + 5.21A^5 - 8.60A^4B + 5.98A^3B^2 - 14.29\,A^5B + 10.48\,A^4B^2 \quad (5)$$

VI. Lesson learnt: limits of regression meta-models applied to high order designs

A progressively increasing density of the survey points in the domain under analysis shows that regression, when deprived of its essence of identifier of trends within a cloud of experimental responses, shows clear signs of a lack of robustness and hence of excessive sensitivity to the position of the survey points within the domain.

This is in full agreement with the approach to Response Surface Methodology of Montgomery and Myers [21] who consider factorial designs with at most three levels.

In this case study, in fact, the only way to fit a regression meta-model, keeping a low MS_{PE} amount, would be to increase the equation order. Moreover, it should be noted that acting in such a way means to chase the background noise that is typical of the real system and always present in the discrete and stochastic simulation models. The meta-model ends up not achieving a fit, as it fails the "Lack of Fit" test and shows internal warps that have little or nothing to do with the actual behavior of the real system.

VII. Fitting with neural networks

Considering these limits of regression, the problem was addressed, despite the small number of experimental points, using neural networks in order to achieve an understanding of which was the shape of the actual response surface for the problem under consideration. Authors, in particular, want to investigate the potentials of neural networks versus regression meta-model when it should be necessary to work on experiments with a high number of levels and, at the same time, a limited amount of information compared to what is normally required working with neural networks.

The neural networks are one of the main forms of “soft-computing”, which defines all those data processing methods that are based on algorithms that do not simply process the information received, but create other algorithms and procedures fit for this task. In practice, these are “meta-algorithms” capable of creating the algorithms needed to process the data that they receive.

In the study under consideration, the main focus was their operational use without dwelling in detail on their structure. Therefore, the neural network was considered as a kind of “black-box”, which, once trained, can provide an output for each input; feed-forward backpropagation networks with supervised training was used.

The two dataset that have been considered as input of the neural net are related to the four-levels factorial designs, which have motivated this study. Fig. 19 and 20 show the surfaces obtained by the network.

In both cases the neural network wrongly fits the experimental responses with two linear models: the network's behavior depends on the especially low number of survey points used (16 replicated points). In order to provide adequate response surfaces, as known, the networks need to work with a definitely larger number of points.

So authors, after testing some types of networks (back propagation, whirpool and Levenberg-Marquardt methods) on the 5^2, 7^2, and 9^2 DoE designs, gather that significant results could be achieved with a Levenberg-Marquardt net applied on a 9^2 design replicated twice. Using a variable number of hidden neurons between 2 and 100 it was possible to point out that using 30 neurons the net error get to a stable value of about 10^{-2} spending only a few minutes of computer time [15]. To confirm the effectiveness of the author’s choice it could be noted that in all 81 domain points there’s no sign of outliers.

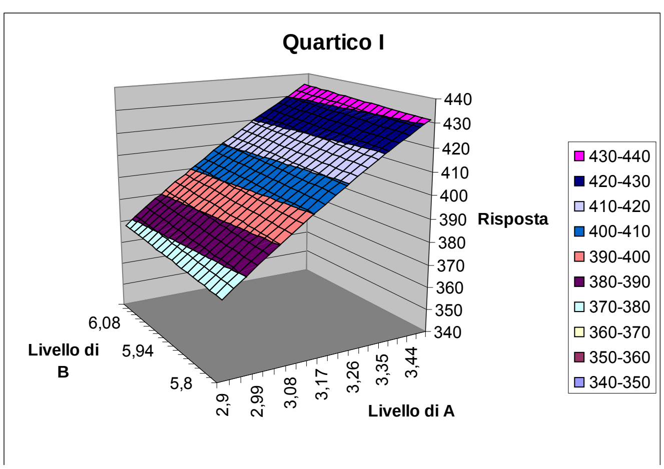


Fig.19

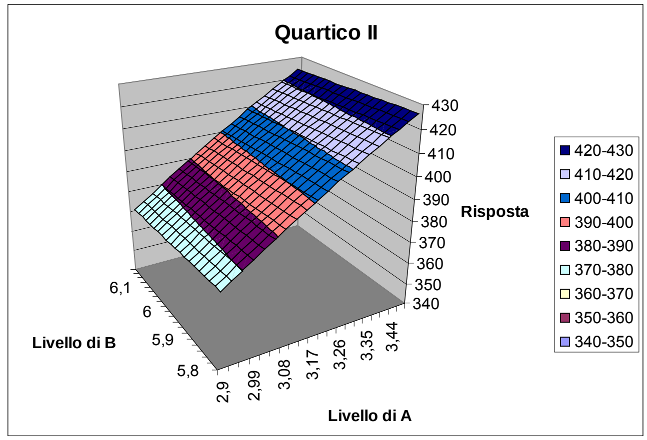


Fig.20

The surfaces obtained using 30 neurons is shown in Fig 21. It should be noted that the surface, though continuous, cannot be described by means of any form of conventional equation and this explains why the problem could not be addressed with regression meta-models.

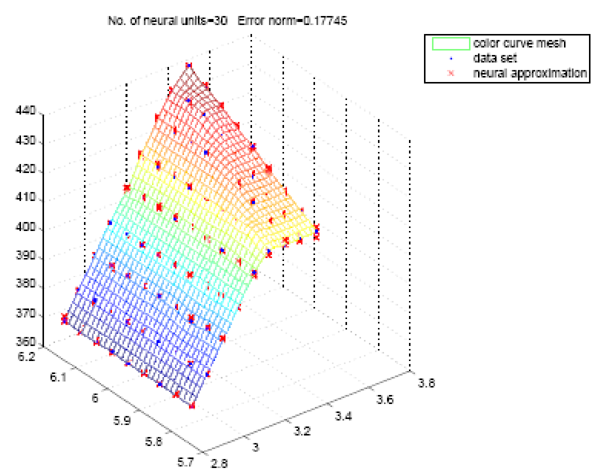


Fig.21

In view of this last consideration, the authors decided to conduct a further study on the true nature of the response surface and the ability of neural networks to describe adequately the behavior of the objective function. For this reason they have implemented a screening of the factors through a direct interface between the simulator and the software Matlab. In this way it was built the matrix of values of the objective function by varying the two factors (multi-step grinding machines and dimensional check machines) within their range of variability.

To obtain the 256 values of the objective function, referring to the same number of combinations of the two factors, it was necessary to pay a computational cost equal to 25 hours of processing (machine time). From the matrix was, then, possible to derive the shape of the true response surface. The "edgy" form in Figure 22 allows to confirm the considerations previously deduced on the difficulty of adaptability of the regression meta-models and the greater flexibility of Neural Networks.

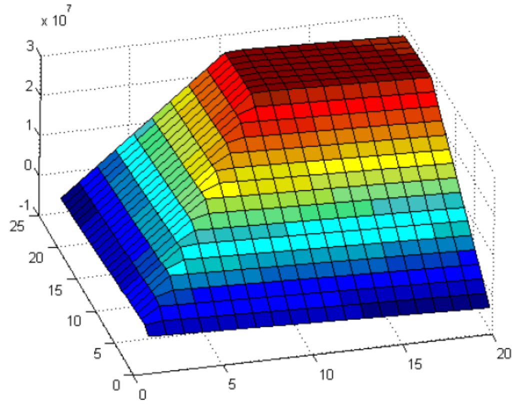


Fig.22

Knowing now the trend of the response surface of the objective function, and using the 256 information derived from the screening matrix, the authors wanted to test, further, the descriptive ability of neural networks using the Matlab CGM Neural Network Application.

In about 10 minutes the application has provided, after a series of 370K iterations, the surface of Figure 23.

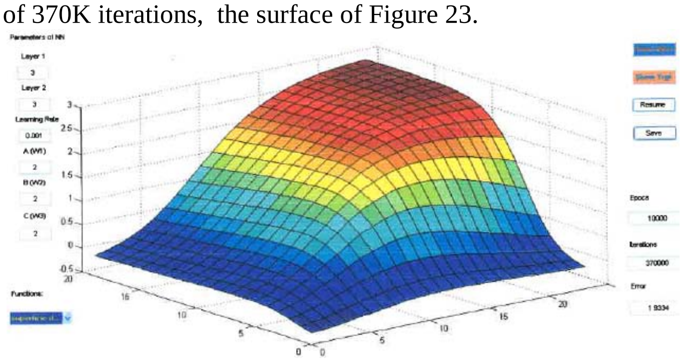


Fig.23

Interesting to observe the results of Figure 24 which illustrate the progress in the descriptive ability of the network at growing the number of iterations of the application.

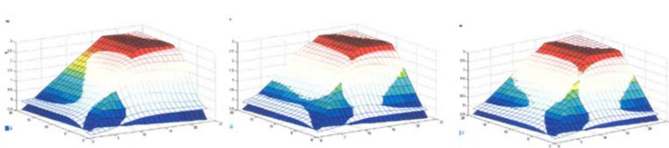


Fig.24

VIII. Conclusions

The Response Surface Methodology provides various opportunities to analyze the relationship between independent variables and the dependent variable in a same experimental domain, in case of simulation systems with time-varying experimental error. Depending on the need for accuracy of the response, it is up to the researcher to determine, starting from the MS_{PE} curve and hence from a preset level of variance of the experimental error, a regression model having an adequate level of fit. However it is necessary to bear strongly in mind that, in order to pass the Lack of Fit Fisher's Test, the smaller the MS_{PE} is, the smaller MS_{LOF} must also become[23].

However, this can lead to use high-order polynomial meta-models, which do not follow the conventional RSM assumption, that consists into finding a fit with models having the lowest possible order (usually first and second order).

This study concerning the use of DoE designs with a high number of experimental levels has put in evidence that the effort to improve the quality of the response surface, by increasing the number of survey points in the experimental domain, can lead to always less flexible regression meta-model in terms of fitting capability. Therefore, in order to achieve a fit in certain particularly interesting survey points, the surface undergoes such distortions that lead it to, heavily, prejudice other points of the response surface and, hence, to produce too high residuals.

The recourse to the neural network as a "smart" regressor, that is capable of behaving like a flexible shell, becomes the possible path that a researcher can take. It is significant that, in the case under consideration, the resulting surface cannot be described using a conventional polynomial due to the presence of linear elements mixed with higher-order terms. In consideration of an especially low fitting error, the surface traced out by the network manages to generate residuals that are aligned with the others also in those points where the regression, due to its nature of hard shell, would generate a local lack of fit. As a result of this study, the initial attitude of absolute trust in regression meta-models has been questioned [2], [3], [4], [6], [7], [10], [13], [17], [18]. Therefore, for the sake of precaution, decision-makers should limit the role of the response surface, under the form of a regression meta-model, to that of a simple identifier of the tendency in behavior between the dependent variable and the independent variables. In order to determine the actual response value of the system, in the areas of experimental interest, identified thanks to the response surface obtained, the Authors suggest to conduct punctual experiments using a simulation time such as to minimize the MS_{PE} and, consequently, the error which affects the accuracy of the results.

Eventually, it could be of some speculative interest noting that, referring to this specific case study, it is possible to gather a relationship between the type of design chosen (so the number of experimental points) and the type of usable methodology, in order to identify the connection between dependent and independent variables.

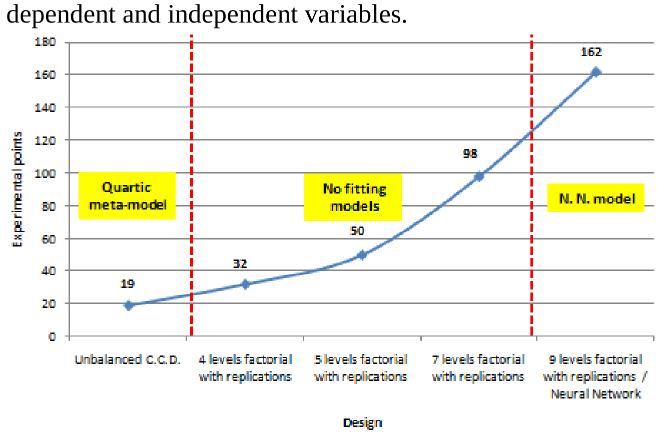


Fig.25

Figure 25 shows how a two level design (Central Composite Design-CCD), adapted to a 4th order meta-model as strictly needed, could bring to an acceptable regression surface with just 19 simulation runs.

On the contrary when the number of level grows up to 9, with 162 simulation runs, a neural network, if conveniently chosen, become an essential tool in order to find the response surface trend with an acceptable error rate.

In between these two boundary run values, considering 32, 50 and 90 simulation runs, there is a kind of "no-men-land" , in which, wishing to act with small MSPE amounts, the regression has too many information to be able to fit them with a surface, and, on the other hand, Neural Networks have too few input data.

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Prof. Roberto Mosca : Industrial Plants Management Full Professor and DIME (Department of Mechanical Engineering) Director, he fulfilled every academic career steps since '72. Logistic and Production Eng. CCDU President and Management Eng. CCL President until '97, courses started up in University of Genova Polo of Savona; he planned and cooperated to realise this Polo where he directs the Discrete Simulation and the Automated Industry laboratories. Author of more than 240 works, published on International Congress Acts or Papers with referee. He works on industrial plants design and management modelling. Particular attention has been given to the discrete and stochastic simulators development for complex systems and to the application of original and innovative techniques for simulation experiment design and optimization (from new methodologies creation for run duration determination and the experimental error evolution control until the independent variables effects analysis on dependent variables). Particularly interesting is the design of on line simulators for the real time production management, with incorporated automated decision rules, technique later used by many other researchers. Since '90 he works on combined utilization of simulation and AI techniques and on the applicability conditions and statistical reliability of special DOE techniques to simulation problems involving an elevated number of independent variables. He is member of important papers Scientific Committee (Int. Journal of Modelling & Simulation, Impiantistica Italiana, Production Planning and Control) and National and International Congresses (ANIMP-IASTED-ESS-etc). Member of ANIMP-SCS-AIROPM- AIIG. He increased the industrial research contract amount as department Director from 250,000 USD/year in 1998 to over 5 million dollar/year in 2011 working with major international/national companies and agencies (Marconi, Elsag, COOP, NATO, Italian Navy, Fincantieri, PSTL etc.).

Lucia Cassettari Ph.D : is a researcher in University of Genoa- Department of Production Engineering, and Mathematical Modelling (DIPTEM). Her research field is focused on simulator-based applications for industrial plants with particular attention on the application of DOE and Optimization techniques to industrial plant problems using Simulation. Her main experience is in research projects involving BPR (Business Process Reengineering), Activity Based Management, Cost Control, Logistics, and Decision Support Systems. Her current teaching activity is in the Industrial Plant Management and Business Strategy degree courses.

Marco Mosca Ph.D: His professional background is in Strategic Consultancy (Andersen Consulting, then Accenture), in Bombardier, Multinational Company in the Railways, in Services Division, where he was appointed as Head of Documentation and Training Italy and then in Zurich as leader of D&T in Europe.
In 2007 he was offered the Position of Head of Business Development Europe and Rest of World.
Business Development, Strategy, Marketing, Pricing and Restructuring, are his top strengths.
In 2009 he accepted the lead a 54 People Company, in HVAC Sector, as Director and General Manager.
Since 2012 he is Managing Director of a Company which scope is to manage a Network of Dental Clinics distributed on the Mediterranean Area.
In the same year he founded (and was appointed as C.E.O.) a European Consortium, which develops in France, Italy and Slovenia, with the goals of facilitating transnational business and of attending European founding programs.
He also supports some local companies on strategies, decision making and international business development as an External, occupying the Position of Outside Director.

Fabio Rolando: is attending a PhD course in Mathematical Engineering and Simulation on Genoa University. He earned his degree in Management Engineering on Genoa University in 2010, currently is involved as Assistant in several researches in Savona Campus focused on applied modelling and simulation and Healthcare systems optimization.