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On different strategies for the prediction of coating properties in a HVOF process

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Contents

1 Introduction

Modelling and controlling of a thermal spraying process is an active field of research. To measure coating properties is very time-consuming and expensive as the layer has to be destroyed. Hence it is desirable to predict coating properties on the basis of process parameters or particle properties which can be measured online. Direct statistical modeling of the coating properties by means of process parameter settings is the common way to study the relationship between parameter settings and coating properties, as in Tillmann *et al.* (2010a). Rehage *et al.* (2012) find that identical parameter settings can result in different properties of in-flight particles depending on non-controllable day effects. Therefore, it can be expected that the coating properties also differ. Several questions arise which are investigated in this contribution. How reliable is the prediction of coating properties from process parameter settings? Can the prediction be substantially improved by including particle properties? Is it maybe even better to predict the coating properties only on the basis of in-flight particles? Basically, these questions relate to different strategies towards the derivation of a statistical prediction model for coating properties from planned experiments. First of all, a common direct model between process parameters and coating properties can be built. Next, we call a prediction strategy composite which is composed of separate models between process parameters and particle properties on one hand and particle and coating properties on the other hand. Here the models for the second relationship are based on particle properties predicted by the first model. Furthermore we take also a model between observed particle properties and coating properties into account, later denoted as indirect strategy. Finally, we consider a combination of the direct and indirect strategy which we call hybrid strategy. Here, a model is built between process parameters plus selected particle properties and coating properties.

The experimental set-up for the analyzed High velocity oxygen fuel spraying (HVOF) process is described in Section 2. In Section 3 the different modeling strategies are introduced in more detail. Section 4 introduces an additional day adjustment for the composite strategy. The resulting models and corresponding diagnostics together with verification experiments are presented in Section 5. A discussion and outlook follows in Section 6. All calculations are done in R (see R

Core Development Team (2011)).

2 Experimental set-up

Experiments were conducted using a Wokajet 400 HVOF spray gun from Sulzer and an agglomerated and sintered WC-12Co powder of type WOKA 3102 from Sulzer Metco. Details on the method of in-flight analysis can be found in Rehage *et al.* (2012).

For metallographic analysis of the WC-Co layers produced in the experiments, the coated specimens were cut and polished. Porosity and layer thickness were determined using a light optical microscope type Axiophot and image processing software Axiovision 4.6 from Zeiss. The hardness was investigated by a micro hardness tester type Leco M400. The roughness was measured by a tracing stylus instrument of type Hommel T-1000 according to DIN 4760. Layer thickness, roughness, porosity and hardness were tested five times each, taking the arithmetic mean and standard deviation as results.

Based on results from previous experiments (Tillmann *et al.* (2010b)) four controllable process parameters, namely kerosene, lambda as the fuel/oxygen ratio, stand-off-distance and feeder disc velocity, are varied in the experimental design. The particle properties in-flight measured are temperature, velocity, flame intensity and flame width. Coating properties are given by porosity, hardness, thickness and deposition rate. Table 1 shows all considered variables together with short names. The analysis of this article refers to the results of an orthogonally blocked central

process parameters **X**	particles in-flight properties **Y**	coating properties **Z**
Kerosene (K)	Temperature (Te)	Porosity (Po)
Lambda (L)	Velocity (Ve)	Hardness (Ha)
Stand-off Distance (SOD)	Flame width (Wi)	Thickness (Th)
Feeder Disc Velocity (FDV)	Flame intensity (In)	Depositon rate (Dr)

Table 1: Controllable and measured variables in the spray process

composite design (**CCD**) with 30 runs in total. It was not possible to conduct the full design on one day because the coating process is very time consuming. Therefore we performed the design in two orthogonal blocks on two successive days. The first block consists of a full factorial design plus 4 central points with 20 runs in total. The remaining 10 runs (star points plus 2 central points) were conducted on the second day. The experimental design together with the values of the process parameters is given in Appendix 7.2.

3 Strategies for prediction of coating properties

In this section we introduce four different strategies for prediction of coating properties in more detail. We make use of generalized linear models (McCullagh and Nelder, 1989) which consist of a distributional assumption for the response variable Y coming from the exponential family and of a structural component

$$g(E(Y)) = f(x)^T \beta,$$

or to be more precise

$$g(E(Y|x)) = f(x)^T \beta,$$

where g is an appropriate link function, $f(x)$ a vector of regressors and β a vector of unknown coefficients, commonly estimated by the maximum likelihood method. As distributional assumption we consider either gamma or Gaussian distributions of the response variables. The gamma distribution is preferred over the default Gaussian distribution of classical linear models as the skewness and positivity of the considered measurements is better captured. We build models separately for particle and coating properties by means of four different strategies, which we call direct, indirect, composite and hybrid strategy. Figure 1 illustrates these strategies, which are next discussed in more detail. Generally, let $x_{new} = (x^1_{new}, \ldots, x^4_{new})$ be a new process parameter setting and $y_{new} = (y^1_{new}, \ldots, y^4_{new})$ the corresponding particle properties.

3.1 Direct Strategy

The direct strategy models the relationship between process parameter and coating properties directly.We use a separate generalized linear model for each coating

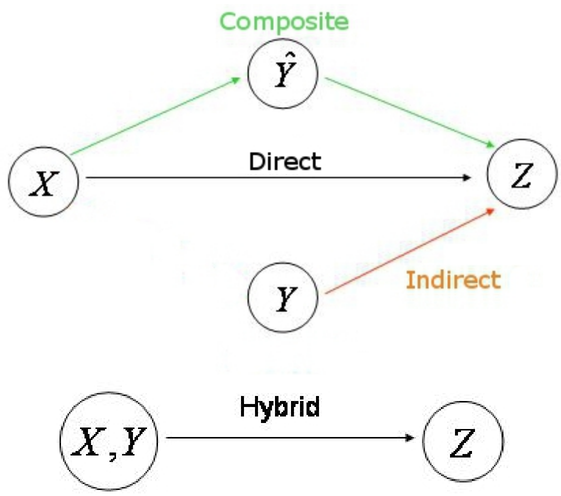

Figure 1: Prediction strategies

property with structural component

$$g(E(Z|X)) = f(X)^T\beta$$

where g is a suitable link function for the coating property Z, $f(X)$ is the vector of regressors, e.g. including main effects, two-way interactions and squared effects of the process parameters and β is the corresponding coefficient vector. Based on estimates $\hat{\beta}$ of β, the outcome of Z can be predicted as

$$\hat{Z} = g(^{-1}f(x_{new})^T\hat{\beta})$$

for any process parameter setting x_{new}.

3.2 Indirect strategy

The indirect strategy uses only the particle properties for the prediction of coating properties. Here, we build generalized linear models for the relationships between particle properties $Y = (Y_1, \ldots, Y_4)$ and coating property Z,

$$g(E(Z|Y)) = f(Y)^T\delta.$$

Prediction is based only on values of the particle properties and on estimates $\hat{\delta}$ of δ

$$\hat{Z} = g^{-1}(f(y_{new})^T\hat{\delta}).$$

3.3 Hybrid strategy

The hybrid model is a combination of the direct and indirect strategy as follows

$$g(E(Z|X,Y)) = f_1(Y)^T\delta + f_2(X)^T\delta^*.$$

Here, $f_2(X)$ is a regressor vector depending on process parameters X and $f_1(Y)$ is a regressor vector depending on particle properties Y.

The hybrid strategy leads to predictions based on both x_{new} and y_{new} and estimates $\hat{\delta}$ and $\hat{\delta}^*$,

$$\hat{Z} = g^{-1}(f_1(y_{new})^T\hat{\delta} + f_1(x_{new})^T\hat{\delta}^*).$$

3.4 Composite strategy

The composite strategy models coating properties on the basis of expected particle properties and therefore it is a composition of the models between process parameters and particle properties on the one hand and particle properties and coating properties on the other hand.

The model between particle properties and coating properties is assumed to follow

$$g(E(Z|E(Y|X))) = f(E(Y|X))^T \cdot \delta.$$

with

$$E(Y|X) = (E(Y_i|X))_{i=1,\dots,4} = (g_i^Y(f_i(X)^T\beta_i)^{-1})_{i=1,\dots,4}.$$

Denoted by $\hat{y}_{new}$ be the predicted particle properties for a process parameter setting x_{new}. Then prediction of a coating property is conducted based on $\hat{y}_{new} = (g_i^Y(f_i(x_{new})^T\hat{\beta}_i)^{-1})_{i=1,\dots,4}$ with estimates $\hat{\beta}_i$, $i = 1,\dots,4$, and an estimate $\hat{\delta}$ as follows

$$\hat{Z} = g^{-1}(f(\hat{y}_{new})^T \cdot \hat{\delta}).$$

3.5 Comments on the four strategies

The direct strategy is so far commonly used and also employed in Tillmann *et al.* (2010a) for a thermal spraying process. It predicts coating properties merely on the basis of process parameters. Therefore, non-controllable factors, which can be observed in the particle properties, are not reflected by the prediction. On different days identical coating properties are predicted for fixed parameter settings although it can be expected that the coating is affected by non-controllable effects.

In order to take also non-controllable factors into account, the hybrid strategy can be applied which includes process parameters as well as the particle properties which vary among different days. The hybrid strategy is expected to produce better predictions than the direct model and to reflect the variation due to day effects more reliable.

Additionally, it is examined in the following if predicting the coating properties only on the basis of the measured particle properties might even be good enough, refering to the indirect strategy. By predicting the coating properties through the connection of models, as in the composite strategy, it is possible to adjust the first models for particle properties on a different day with the aid of a few initial experiments which is described in the next section in more detail.

4 Composite Strategy with day effect and prediction on another day

In this section we explain the application of the composite strategy with respect to the day effect adjustment in more detail. Due to technical reason the experiments to which the introduced strategies are to be applied in Section 5, could not be run in one day. Hence, we have the problem of possible day effects within the data. We therefore go back to models derived for the relationship between process parameters and particle properties in flight in Rehage *et al.* (2012) and apply the introduced day adjustment. Let X_{day1} be the subset of the CCD X for day 1 with n_1=20 settings and X_{day2} be the subset of X for day 2 with n_2=10 settings. Furthermore, let X^i_{day1} refer to i-th setting on day 1 and X^j_{day2} correspond to the j-th setting on day 2.

Day adjustment

We denote the models from Rehage *et al.* (2012) as follows

$$h_i(E(Y_i)) = f^*(X)^T \hat{\delta}^*_i, \quad i = 1, \ldots, 4,$$

with h_i the chosen link function for the i-th particle in-flight property Y_i, $f^*(X)$ the vector of regressors and $\hat{\delta}^*_i$ the estimated vector of coefficients.

A day adjustment is achieved by estimating additional effects δ_{day1} for day 1 and δ_{day2} for day 2 in the following way.

$$\begin{aligned}
\text{day 1: } & h_i(E(Y_i)) = f^*(X)^T \hat{\delta}^*_i + \delta_{\text{day1}}, \quad i = 1, \ldots, 4 \\
\text{day 2: } & h_i(E(Y_i)) = f^*(X)^T \hat{\delta}^*_i + \delta_{\text{day2}}, \quad i = 1, \ldots, 4
\end{aligned}$$

After estimating the values δ_{day1} and δ_{day2} by the maximum likelihood method, we use the above models in order to get vectors of predicted values

$$\hat{Y}_i = \begin{pmatrix} h_i^{-1}(f^*(X^1_{\text{day1}})^T \hat{\delta}^*_i + \hat{\delta}_{\text{day1}}) \\ \vdots \\ h_i^{-1}(f^*(X^{n_1}_{\text{day1}})^T \hat{\delta}^*_i + \hat{\delta}_{\text{day1}}) \\ h_i^{-1}(f^*(X^1_{\text{day2}})^T \hat{\delta}^*_i + \hat{\delta}_{\text{day2}})) \\ \vdots \\ h_i^{-1}(f^*(X^{n_2}_{\text{day2}})^T \hat{\delta}^*_i + \hat{\delta}_{\text{day2}})) \end{pmatrix}$$

for the particle properties Y_i, $i = 1, \ldots, 4$.

Afterwards we build generalized linear models for the relationships between particle properties and coating properties based on the matrix of predicted particle properties

$$\hat{Y} = (\hat{Y}_1, \ldots, \hat{Y}_4)$$

as follows

$$g_i(E(Z_i|\hat{Y})) = f(\hat{Y})^T\hat{\delta}_i, \quad i = 1, \ldots, 4.$$

with again g_i a suitable link function for coating property Z_i and δ_i the vector of unknown coefficients.

Prediction on a new day

In order to predict coating properties for a setting x_{new} on a new day the adjustment of the models for the particle properties as described above needs to be repeated by estimating a new additional effect δ_{newday}. This additional effect is estimated on the basis of measured particle properties resulting from an initial design on the actual experimental day. Then the vector of predicted particle properties

$$\hat{Y}_{new} = (h_1^{-1}(f(x_{new})^T\hat{\delta}_1^* + \hat{\delta}_{newday}),\ \ldots\ , h_4^{-1}(f(x_{new})^T\hat{\delta}_4^* + \hat{\delta}_{newday}))$$

is again used for prediction by plugging $\hat{Y}_{new}$ as follows

$$\hat{Z}_i = g_i^{-1}(f(\hat{Y}_{new})^T\hat{\delta}_i), \quad i = 1, \ldots, 4.$$

5 Results

In this section we present the generalized linear models built from the observed data set for the different prediction strategies. Afterwards we compare the goodness-of-fit of the different models as well as their ability to predict desired coating properties on the basis of verification experiments.

5.1 Model selection

First of all, to build a generalized linear model we need to choose an appropriate link function and to make an assumption on the distribution of the response. Here, we consider the gamma and Gaussian distribution. Furthermore we choose log, inverse and identity as link candidates. In this way the usual linear model with Gaussian distribution assumption plus natural link identity is included. Furthermore

Distribution	Link	deposition rate	Porosity	Hardness	Thickness
	log	179.36	141.66	378.09	323.86
Gaussian	inverse	181.57	143.45	376.80	**319.11**
	identity	177.24	133.11	379.33	329.09
	log	179.25	132.75	378.12	322.13
Gamma	inverse	182.18	142.51	376.92	319.97
	identity	**176.52**	**130.86**	**375.59**	323.54

Table 2: Link and distribution selection based on BIC

we have strictly positive responses and therefore gamma is a reasonable alternative distribution assumption and the natural inverse link for the gamma distribution is also included. The log link ensures that the predicted response will always be positive, thus it is reasonable to take also this link into account.

We build separate generalized linear models for each coating property with particle properties as covariates for all combinations of link functions and distributions. We start with maximal models including main, interaction and quadratic effects for the composite, indirect and direct strategy. Afterwards we conduct a combination of backward and forward selection. The initial model for the hybrid strategy contains the regressor vector from the selected direct model filled up with remaining main effects and main effects together with interactions of particle properties. Subsequently, a backward and forward selection is performed on the hybrid model.

Finally, we compare the selected models by the BIC (see Schwarz (1978)) criterion. The results are listed in Table 2. Due to a larger penalty, the BIC criterion leads to models with less effects than the AIC criterion and is therefore easier interpretable. For example, the hybrid model for thickness selected by means of the AIC criterion is

$$\begin{aligned}
\mathrm{E(Dr)} = 79.2 &- 24.5 \cdot \mathrm{Ve} + 7.7 \cdot \mathrm{Te} + 15.1 \cdot \mathrm{Wi} - 4.0 \cdot \mathrm{In} + 2.4 \cdot \mathrm{K} \\
&- 2.2 \cdot \mathrm{FDV} + 1.0 \cdot \mathrm{FDV}^2 - 14.9 \cdot \mathrm{Ve} \cdot \mathrm{Wi} + 8.8 \cdot \mathrm{Ve} \cdot \mathrm{In} \\
&+ 14.1 \cdot \mathrm{Te} \cdot \mathrm{Wi} - 4.9 \cdot \mathrm{Te} \cdot \mathrm{In}.
\end{aligned}$$

The selected model based on the BIC criterion has three less effects and reduces to

$$
\begin{aligned}
\mathrm{E(Dr)} = {} & 73.5 - 17.7 \cdot \mathrm{Ve} + 1.4 \cdot \mathrm{Te} + 17.3 \cdot \mathrm{Wi} - 8.3 \cdot \mathrm{In} - 1.4 \cdot \mathrm{FDV} \\
& - 11.1 \cdot \mathrm{Ve} \cdot \mathrm{Wi} + 7.2 \cdot \mathrm{Ve} \cdot \mathrm{In} + 3.4 \cdot \mathrm{Te} \cdot \mathrm{Wi}.
\end{aligned}
$$

The model selected by AIC will lead to a only slightly better goodness-of-fit but with the drawback of worse prediction ability. Therefore we choose the link functions and distribution assumptions by the BIC criterion, resulting in the gamma distribution with identity link for porosity, deposition rate and hardness and Gaussian distribution plus identity link for and thickness.

The hybrid model takes the process parameters and particle properties into account. In order to be able to compare the effects of the covariates on the response, we transform the particle properties to the same scale as the coded process parameters. Table 3 summarizes the coded particle properties together with the process parameters. After this precalculation step we apply our modeling strategies. The

	Coded values				
	-2	-1	0	1	2
Kerosene level (K)	15	17.5	20	22.5	25
Lambda (L)	1	1.075	1.15	1.225	1.3
Stand-off distance (D)	200	225	250	275	300
Feeder disc velocity (FDV)	5	7.5	10	12.5	15
Velocity	375	487.5	600	712.5	825
Temperature	1300	1400	1500	1600	1700
Flame Width	5	8.75	12.5	16.25	20
Intensity	10	15	20	25	30

Table 3: Coded process parameters and particle properties

resulting models can be found in section 7.2 of the appendix. The direct models contain only main effects of process parameters except for thickness where also four interactions are included.

For the composite strategy the model for porosity contains all main effects plus three interactions and for hardness the main effect Te and Wi. However, the model for thickness depends on all main effects. It contains three interactions and one quadratic effect. Furthermore, the model for deposition rate contains only the main effect Te. For the indirect strategy, the model for porosity contains all main effects plus one quadratic effect and two interactions. The model for hardness depends also on Wi and Ve whereas the sign of the effect Te is the same as for composite strategy. The model for thickness depends on all main effects together with some interactions for composite strategy whereas the model from indirect strategy contains also two quadratic effects.

5.2 Comparison with respect to goodness of fit

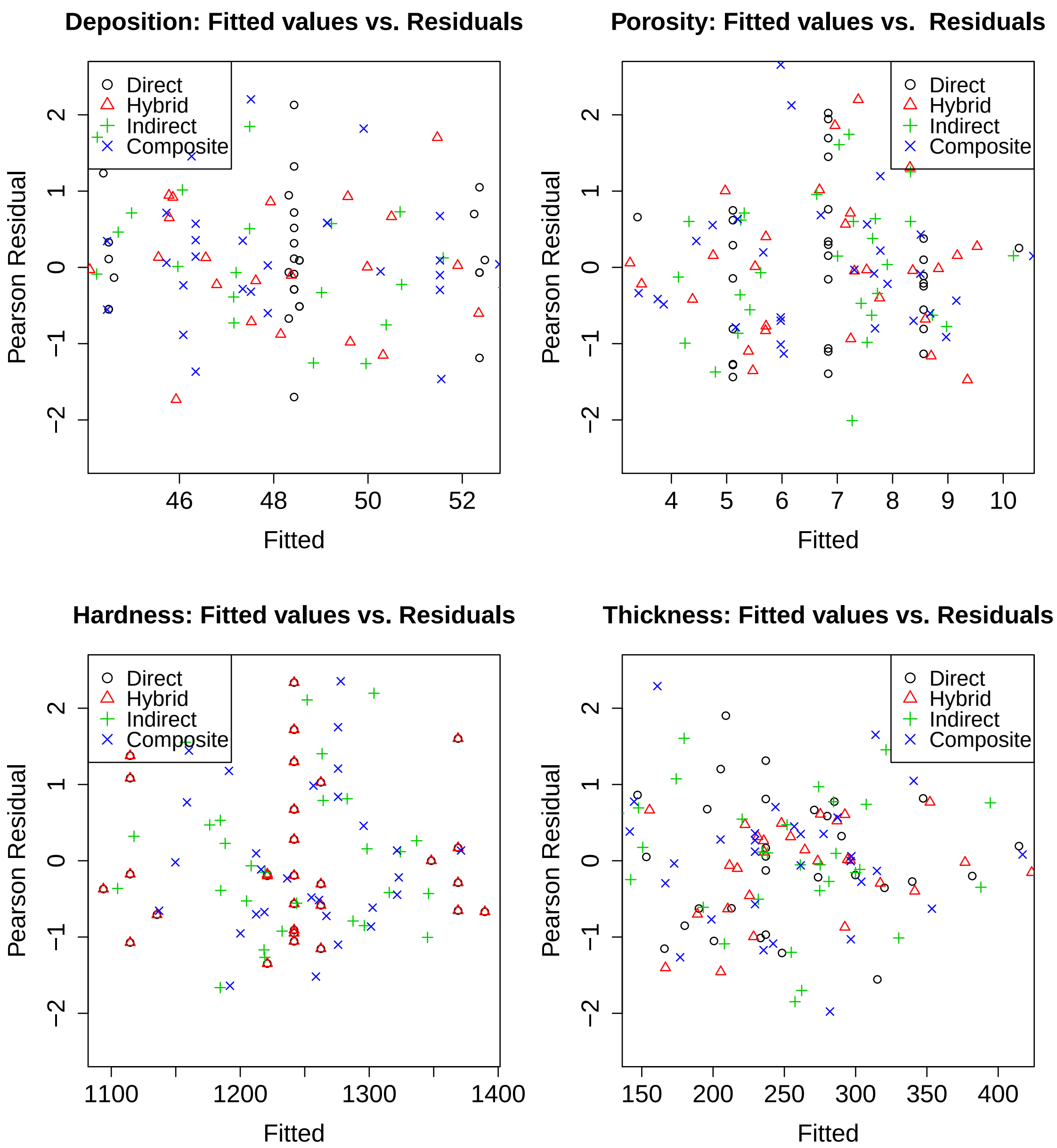

Figure 2: Residual plots for coating properties, fitted vs. residuals

In this section we investigate the goodness of fit of the selected models with respect to the four different strategies. First of all, Figure 2 shows the corresponding Pearson residuals against the fitted values. The residual plots show the desired random scattering of the residuals around zero.

Figure 3 displays the measured values against the fitted values for all model strategies. Here the red line indicates a perfect fit and the blue lines stand for $\pm 10\%$. The thickness is rather well predicted by every strategy. The hybrid strategy performs best in this case. The resulting model contains most effects thus it can be assumed that this model overfits the data and may suffer from a worse prediction ability. Nearly all points lie in or close to the $\pm 10\%$-band. Deposition rate is fitted well for all strategies, only a few points lie outside the $\pm 10\%$-band. Hardness could also be modelled quite well. Here, only a few points lie outside the $\pm 10\%$-band. Porosity is not well predicted by any of the strategies. It is known that it can't be measured very reliably. This is still an open engineering problem. Therefore it can be expected that a reliable prediction will not be possible for porosity and hardness.

So far, we investigated the fit of models w.r.t. to data they have been built from. However, prediction of new data points is more important but new data sets are not easily available because measurements of coating properties are very time consuming. Thus, we additionally compare the modeling strategies on the basis of the prediction error sum of squares (PRESS)

$$\text{PRESS} = \sum_{i=1}^{n} (y_i - \hat{y}_{i,-i})^2,$$

where y_i is the i-th observed value and $\hat{y}_{i,-i}$ is the i-th fitted value on the basis of the whole data set excluding the i-th observation. The results are summarized in table 4. The lowest PRESS value for thickness is clearly achieved by the hybrid strategy. Obviously, for hardness the lowest PRESS value is achieved by the hybrid and direct strategy. The PRESS statistic for porosity takes a minimal value for the hybrid model. The composite strategy leads to a minimal PRESS value for the deposition rate. Therefore, we have no clear favorite. In the next section we compare the performance of the four strategies on the basis of four new experiments.

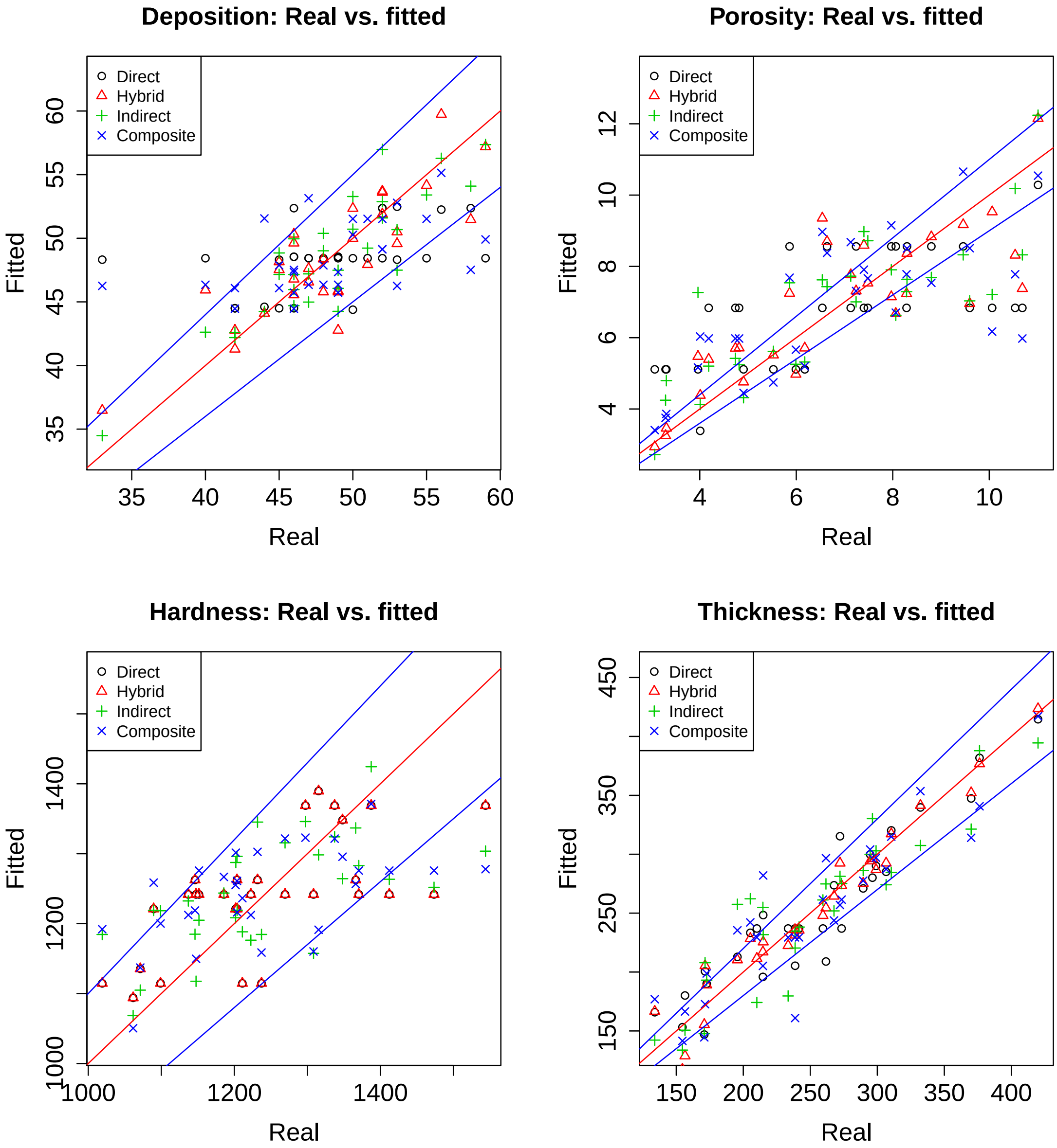

Figure 3: Experimental results against fitted values for coating properties

5.3 Performance with respect to new experiments

In this section, we compare the prediction performance of the four different strategies on a different day on the basis of two experiments with replication. Table 5 contains the corresponding parameter settings. We try to predict coating properties by means of the models based on the CCD. The composite strategy uses the model adaption for particle properties and is therefore expected to predict well. In order adapt the models for the particle properties for the composite strategy, an initial fractional factorial design with eight runs in total was conducted and particle properties were

	Hardness	Porosity	Deposition	Thickness
Direct	**313767.97**	104.32	816.15	60196.20
Indirect	347405.58	104.79	898.11	**55321.00**
Hybrid	**313767.97**	**75.45**	1135.51	139003.24
Composite	383515.10	157.67	**725.65**	96541.52

Table 4: PRESS values for each particle property and each modeling strategy

	A1	A2	A3	A4
Lambda	-1.28	-1.28	-0.23	-0.23
Kerosene	0.51	0.51	0.48	0.48
SOD	-1.15	-1.15	-1.44	-1.44
FDV	-0.64	-0.64	1.24	1.24

Table 5: Parameter combinations for verification experiments

measured. On the basis of these measured particle properties the models for the particle properties are adapted as described in section 3.

Figure 4 shows the predicted and measured values for the four coating properties. The values itself can be found in Table 7, Appendix 7.1. The composite strategy leads to very good predictions for porosity whereas the remaining strategies lead to strongly underestimated prediction values. The goodness-of-fit of the models for porosity was also poor and additionally, the porosity measurements are known to be not reliable. Thus, the composite strategy works surprisingly good.

Concerning the coating property hardness, there is a high variation in observed values within the parameter setting A1 and its replication A2. The assumption that this variation can be already observed in the in-flight particle properties does not hold. The measured particle properties, listed in table 6, do not show a noteworthy variation within the parameter setting A1 and A2. Perhaps additional particle properties like shape or size might expose a reason for this effect. Therefore all observed outcome cannot be predicted well by any of the strategies. However, the indirect strategy produces very good predictions of the hardness for A2, A3 and A4. The composite strategy leads to a slightly better prediction for A2. It can be observed that the direct strategy is beaten for all parameter settings here.

The hybrid strategy performs best for thickness for A3 whereas the direct strategy is slightly better for A1 and A2. For A4 the composite strategy is best. Finally, the

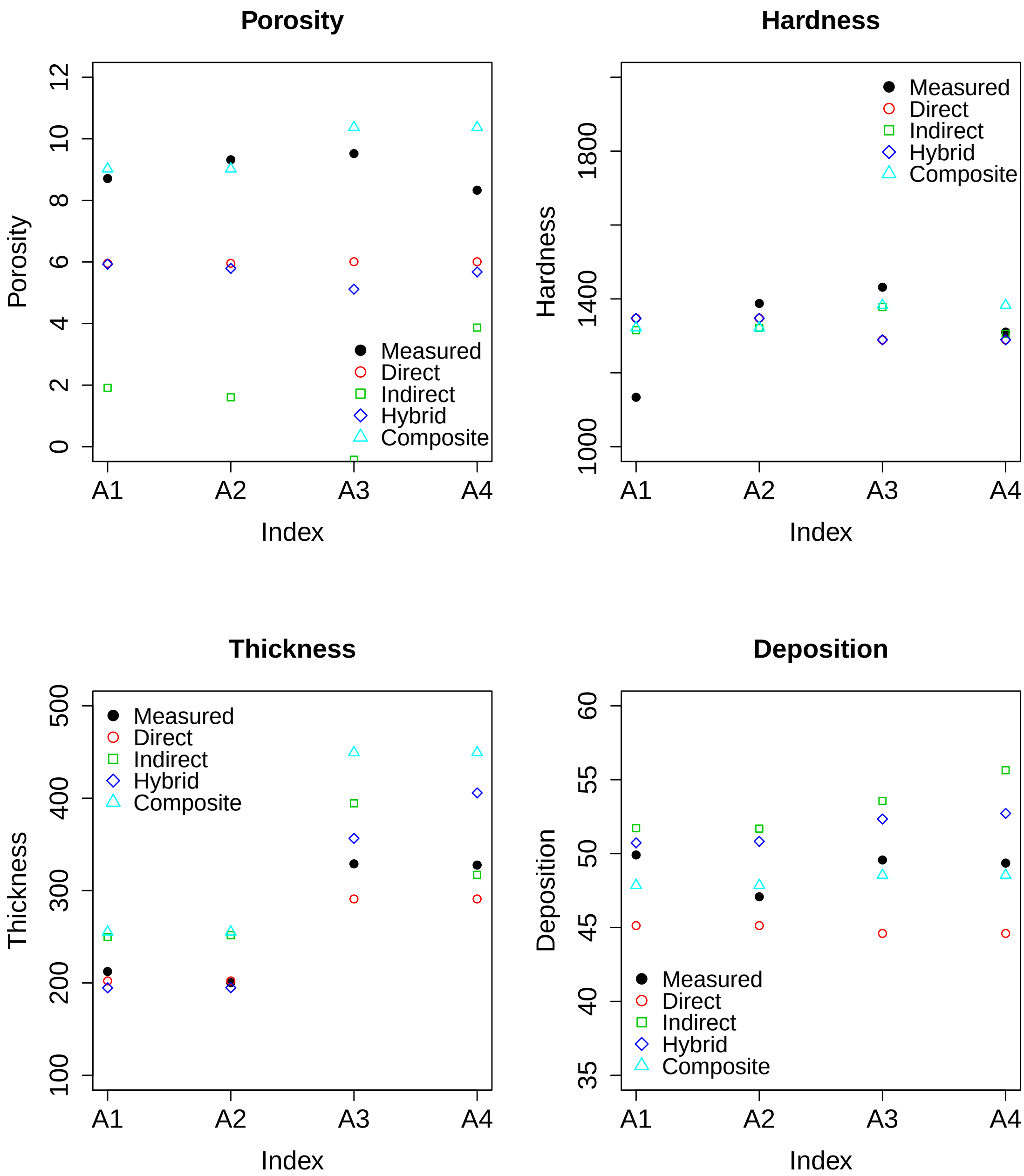

Figure 4: Comparison of new experimental results from a different day and predicted values based on BIC

deposition rate is clearly best predicted by the composite strategy. Here, the hybrid strategy is better for A1 only. The composite strategy leads to best predictions for A2, A3 and A4.

To sum up, the composite strategy, the indirect strategy and the hybrid strategy lead to better predictions than the direct strategy in almost every case. Therefore

	A1	A2	A3	A4
Te	1551.48	1556.17	1552.97	1521.02
Ve	743.19	742.81	742.60	723.82
Wi	11.24	11.27	13.95	12.67
In	19.10	19.16	22.43	20.77

Table 6: Particle properties of new experiments

it is important to include the in-flight particle properties in the models in order to predict coating properties.

6 Discussion and Outlook

The aim of this article is to investigate if coating properties can be predicted reliably from process parameters and if it can be improved by including in-flight particles. Maybe it is even enough to predict the coating properties only on the basis of the in-flight particles. These introductive questions led to four different prediction strategies. The first strategy builds a generalized linear model between the process parameters and coating properties. It has the drawback that it does not adjust for any disturbances during the process which are manifested in the particle properties. Therefore, we consider a connection of models for the particle properties and coating properties (composite strategy), a model for coating properties with particle properties only as covariates (indirect strategy) and a model that incorporates both process parameters and particle properties in order to predict coating properties (hybrid strategy).

The composite strategy goes from process parameters to coating properties through the particle properties. Here, the models for the particle properties can be adapted for a certain day and afterwards the process parameters are used for prediction. On the other hand, this strategy builds models between particle properties and coating properties. Thus, it relies only on the particle properties. Finally, the hybrid strategy uses both the process parameters and the particle properties in one model for prediction of the coating properties.

The results in this article show that the particle properties have an essential impact on the coating properties. Therefore, it is important to incorporate particle properties into models for the prediction of coating properties. There is still further research necessary to improve the indirect, composite and the hybrid strategy. The verification experiments do not yield a clear favorite among the applied strategies but the direct strategy is beaten in almost every case. It has to be pointed out that more verification experiments have to be done in order to obtain more reliable results concerning the comparisons between the different strategies. Additionally, we plan to construct a special optimal initial design in order to adapt the models for the particle properties on a certain day. This will probably lead to better predictions for the hybrid and composite strategy. Further experiments have to confirm this assumption. Lastly, we will make use of generalized functional linear models in order to include also the time dependent behaviour of the particle properties in the model.

Acknowledgements

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7 Appendix

7.1 Results from verification experiments

		a1	a2	a3	a4
Hardness	Measured	1133.80	1387.70	1431.70	1310.2
	Direct	1347.53	1347.53	1289.47	1289.47
	Indirect	1315.13	1321.16	1378.21	1305.31
	Hybrid	1347.53	1347.53	1289.47	1289.47
	Composite	1321.79	1321.79	1382.64	1382.64
Porosity	Measured	8.71	9.32	9.52	8.33
	Direct	5.96	5.96	6.01	6.01
	Indirect	1.91	1.61	-0.42	3.87
	Hybrid	5.93	5.79	5.12	5.68
	Composite	9.02	9.02	10.37	10.37
Deposition	Measured	49.91	47.08	49.57	49.36
	Direct	45.13	45.13	44.60	44.60
	Indirect	51.72	51.69	53.57	55.64
	Hybrid	50.73	50.83	52.34	52.72
	Composite	47.86	47.86	48.54	48.54
Thickness	Measured	212.37	200.36	328.94	327.59
	Direct	202.21	202.21	290.95	290.95
	Indirect	249.78	251.69	394.46	317.02
	Hybrid	194.76	194.78	356.59	405.72
	Composite	255.19	255.19	449.37	449.37

Table 7: Results from verification experiments

7.2 Models for coating properties and data sets

Direct strategy

Porosity:

$$\mathrm{E(Po)} = 6.84 - 1.72 \cdot \mathrm{K}$$

Hardness:

$$\mathrm{E(Ha)} = 1241.75 - 53.18 \cdot \mathrm{L} + 73.94 \cdot \mathrm{K}$$

Thickness:

$$
\begin{aligned}
\mathrm{E(Th)} = (&0.0042 + 0.00033 \cdot \mathrm{L} + 0.00044 \cdot \mathrm{K} \\
&- 0.00028 \cdot \mathrm{SOD} - 0.0009 \cdot \mathrm{FDV} + 0.00021 \cdot \mathrm{L} \cdot \mathrm{SOD} \\
&- 0.00037 \cdot \mathrm{L} \cdot \mathrm{FDV} + 0.00021 \cdot \mathrm{K} \cdot \mathrm{SOD} \\
&- 0.0004 \cdot \mathrm{K} \cdot \mathrm{FDV})^{-1}
\end{aligned}
$$

Deposition rate:

$$\mathrm{E(Dr)} = 48.43 - 1.91 \cdot \mathrm{K} + 2.02 \cdot \mathrm{SOD}$$

Indirect strategy

Porosity:

$$
\begin{aligned}
\mathrm{E(Po)} = &8.05 - 2.67 \cdot \mathrm{Ve} - 9.05 \cdot \mathrm{Te} - 6.58 \cdot \mathrm{Wi} \\
&+ 6.42 \cdot \mathrm{Wi}^2 - 4.31 \cdot \mathrm{Te} \cdot \mathrm{Wi} - 6.02 + 5.36 \cdot \mathrm{Wi} \cdot \mathrm{In}
\end{aligned}
$$

Hardness:

$$\mathrm{E(Ha)} = 1240.65 + 32.16 \cdot \mathrm{Ve} + 120.49 \cdot \mathrm{Te} + 85.09 \cdot \mathrm{Wi}$$

Thickness:

$$
\begin{aligned}
\mathrm{E(Th)} = (&2.14e - 03 + 1.23e - 03 \cdot \mathrm{Ve} - 1.97e - 03 \cdot \mathrm{Te} + 6.27e - 05 \cdot \mathrm{Wi} \\
&+ 5.66e - 04 \cdot \mathrm{In} + 1.24e - 03 \cdot \mathrm{Ve} \cdot \mathrm{Te} - 1.88e - 03 \cdot \mathrm{Ve} \cdot \mathrm{In} \\
&- 1.54e - 03 \cdot \mathrm{Te} \cdot \mathrm{Wi} + 8.35e - 04 \cdot \mathrm{Te} \cdot \mathrm{In})^{-1}
\end{aligned}
$$

Deposition rate:

$$\begin{aligned}\mathrm{E(Dr)} = {} & 76.63 - 19.28 \cdot \mathrm{Ve} + 3.92 \cdot \mathrm{Te} + 21.11 \cdot \mathrm{Wi} - 11.95 \cdot \mathrm{In} \\ & - 4.53 \cdot \mathrm{Te}^2 - 2.73 \cdot \mathrm{In}^2 - 13.83 \cdot \mathrm{Ve} \cdot \mathrm{Wi} + 5.9 \cdot \mathrm{Ve} \cdot \mathrm{In} \\ & + 7.78 \cdot \mathrm{Te} \cdot \mathrm{In}\end{aligned}$$

Hybrid strategy

Porosity:

$$\begin{aligned}\mathrm{E(Po)} = {} & 6.26 - 3.12 \cdot \mathrm{Te} - 1.70 \cdot \mathrm{Wi} + 2.24 \cdot \mathrm{In} - 1.20 \cdot \mathrm{L} \\ & - 1.01 \cdot \mathrm{K} + 1.51 \cdot \mathrm{Wi} \cdot \mathrm{In}\end{aligned}$$

Hardness:

$$\mathrm{E(Ha)} = 1241.75 - 53.18 \cdot \mathrm{L} + 73.94 \cdot \mathrm{K}$$

Thickness:

$$\begin{aligned}\mathrm{E(Th)} = {} & (1.25e-03 + 1.98e-03 \cdot \mathrm{Ve} - 1.56e-03 \cdot \mathrm{Te} - 1.33e-03 \cdot \mathrm{Wi} \\ & + 2.37e-03 \cdot \mathrm{In} + 3.76e-05 \cdot \mathrm{L} - 8.52e-04 \cdot \mathrm{FDV} - 2.00e-04 \cdot \mathrm{K} \\ & - 1.09e-04 \cdot \mathrm{SOD} + 1.24e-03 \cdot \mathrm{Ve} \cdot \mathrm{Te} - 7.37e-04 \cdot \mathrm{Ve} \cdot \mathrm{In} \\ & - 7.08e-04 \cdot \mathrm{Te} \cdot \mathrm{In} + 6.55e-04 \cdot \mathrm{Wi} \cdot \mathrm{In} - 5.25e-04 \cdot \mathrm{FDV} \cdot \mathrm{K} \\ & + 4.26e-04 \cdot \mathrm{L} \cdot \mathrm{SOD} - 3.15e-04 \cdot \mathrm{L} \cdot \mathrm{FDV})^{-1}\end{aligned}$$

Deposition rate:

$$\begin{aligned}\mathrm{E(Dr)} = {} & 73.49 - 17.73 \cdot \mathrm{Ve} + 1.37 \cdot \mathrm{Te} + 17.33 \cdot \mathrm{Wi} - 8.32 \cdot \mathrm{In} \\ & - 1.41 \cdot \mathrm{FDV} - 11.11 \cdot \mathrm{Ve} \cdot \mathrm{Wi} + 7.21 \cdot \mathrm{Ve} \cdot \mathrm{In} + 3.37 \cdot \mathrm{Te} \cdot \mathrm{Wi}\end{aligned}$$

Composite strategy

Porosity:

$$\begin{aligned}\mathrm{E(Po)} &= 6.96 + 1.90 \cdot \mathrm{Ve} - 3.94 \cdot \mathrm{Te} - 6.82 \cdot \mathrm{Wi} + 6.33 \cdot \mathrm{In} \\ &\quad + 4.27 \cdot \mathrm{Ve} \cdot \mathrm{Te} + 9.23 \cdot \mathrm{Ve} \cdot \mathrm{Wi} - 7.83 \cdot \mathrm{Ve} \cdot \mathrm{In}\end{aligned}$$

Hardness:

$$\mathrm{E(Ha)} = 1286.80 + 125.50 \cdot \mathrm{Te} + 99.78 \cdot \mathrm{Wi}$$

Thickness:

$$\begin{aligned}\mathrm{E(Th)} &= (0.0037 - 0.00041 \cdot \mathrm{Ve} + 0.0017 \cdot \mathrm{Wi} + 0.0022 \cdot \mathrm{In} + 0.001 \cdot \mathrm{Te}^2 \\ &\quad - 0.0019 \cdot \mathrm{Ve} \cdot \mathrm{Wi} - 0.0032 \cdot \mathrm{Ve} \cdot \mathrm{In} + 0.00078 \cdot \mathrm{Wi} \cdot \mathrm{In})^{-1}\end{aligned}$$

Deposition rate:

$$\mathrm{E(Dr)} = 50.245 - 4.558 \cdot \mathrm{Te}$$

	L	K	SOD	FDV
1	1	-1	1	-1
2	1	1	1	1
3	-1	-1	1	-1
4	-1	-1	-1	1
5	0	0	0	0
6	0	0	0	0
7	-1	1	1	-1
8	-1	1	-1	1
9	1	1	-1	1
10	1	-1	-1	-1
11	0	0	0	0
12	-1	1	-1	-1
13	1	1	-1	-1
14	-1	1	1	1
15	1	-1	1	1
16	-1	-1	1	1
17	-1	-1	-1	-1
18	1	1	1	-1
19	0	0	0	0
20	1	-1	-1	1
21	0	0	0	0
22	0	0	-2	0
23	-2	0	0	0
24	2	0	0	0
25	0	0	0	0
26	0	0	0	-2
27	0	0	2	0
28	0	2	0	0
29	0	0	0	2
30	0	-2	0	0

Table 8: Experimental design CCD

	Te	Ve	Wi	In
1	1525.50	685.20	15.00	7.60
2	1621.50	749.60	31.30	8.40
3	1562.40	658.90	17.80	7.50
4	1605.20	645.70	31.10	8.40
5	1606.70	695.00	24.10	7.50
6	1562.20	726.40	13.40	8.10
7	1618.00	712.00	19.70	7.60
8	1669.70	765.60	34.50	9.50
9	1629.20	786.30	30.60	7.90
10	1548.90	721.00	14.80	7.40
11	1563.00	715.80	17.80	8.70
12	1626.50	763.60	18.40	7.40
13	1598.60	791.50	17.00	7.30
14	1619.40	743.00	28.40	9.00
15	1498.10	673.50	17.30	9.20
16	1532.50	644.10	20.20	8.80
17	1565.20	678.30	15.30	7.10
18	1517.40	736.40	10.60	7.40
19	1550.20	715.70	11.50	6.80
20	1538.30	684.10	17.80	7.10
21	1448.70	710.20	19.30	11.00
22	1485.40	727.90	19.80	11.80
23	1493.70	701.30	21.20	12.60
24	1416.50	754.90	16.80	9.00
25	1480.20	742.10	19.60	11.40
26	1455.50	753.90	11.40	7.50
27	1449.40	728.80	18.20	9.90
28	1511.70	792.10	20.70	12.00
29	1492.10	720.60	23.60	14.70
30	1404.20	647.60	17.30	9.40

Table 9: Particle properties based on experimental design CCD

	Po	Ha	Th	Dr
1	5.86	1237.21	195.61	52.00
2	3.31	1366.22	299.07	49.00
3	6.64	1203.86	370.03	46.00
4	8.29	1202.07	214.87	33.00
5	4.18	1370.45	241.63	49.00
6	4.74	1473.47	233.47	47.00
7	5.99	1543.99	171.48	46.00
8	5.53	1387.44	289.47	46.00
9	3.07	1231.79	272.17	45.00
10	8.06	1099.01	172.70	45.00
11	4.82	1412.24	238.55	48.00
12	4.91	1337.34	156.51	42.00
13	3.29	1203.66	154.59	42.00
14	6.18	1297.41	310.42	49.00
15	7.97	1019.16	332.18	52.00
16	9.46	1201.75	376.27	58.00
17	8.80	1089.53	205.25	53.00
18	3.96	1146.19	170.91	46.00
19	10.69	1151.59	210.12	40.00
20	7.24	1211.03	306.57	48.00
21	10.54	1222.67	273.36	52.00
22	9.60	1185.71	261.69	50.00
23	6.54	1348.15	296.37	59.00
24	7.48	1071.23	238.68	47.00
25	8.29	1137.02	259.42	50.00
26	10.06	1147.62	133.96	51.00
27	7.40	1308.48	267.69	53.00
28	4.01	1315.39	214.65	44.00
29	7.13	1269.48	419.91	55.00
30	11.01	1061.46	294.67	56.00

Table 10: Coating properties based on experimental design CCD