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Improving the Prediction of the Roll Separating Force in a Hot Steel Finishing Mill

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Abstract

This paper focuses on the development of a hybrid phenomenological/inductive model to improve the current physical setup force model on a five stand industrial hot strip finishing mill. We approached the problem from two directions. In the first approach, the starting point was the output of the current setup force model. A feedforward multilayer perceptron (MLP) model was then used to estimate the true roll separating force using some other available variables as additional inputs to the model.

It was found that it is possible to significantly improve the estimation of a roll separating force from 5.3% error on average with the current setup model to 2.5% error on average with the hybrid model. The corresponding improvements for the first coils are from 7.5% with the current model to 3.8% with the hybrid model. This was achieved by inclusion, in addition to each stand's force from the current model, the contributions from setup forces from the other stands, as well as the contributions from a limited set of additional variables such as: a) aim width; b) setup thickness; c) setup temperature; and d) measured force from the previous coil.

In the second approach, we investigated the correlation between the large errors in the current model and input parameters of the model. The data set was split into two subsets, one representing the "normal" level of error between the current model and the measured force value, while the other set contained the coils with a "large" level of error. Additional set of data with changes in each coil's inputs from the previous coil's inputs was created to investigate the dependency on the previous coil.

The data sets were then analyzed using a C4.5 decision tree. The main findings were that the level of the speed vernier variable is highly correlated with the large errors in the current setup model. Specifically, a high positive speed vernier value often correlated to a large error. Secondly, it has been found that large changes to the model flow stress values between coils are correlated frequently with larger errors in the current setup force model.

Introduction

Maintaining product consistency and quality in the manufacturing process has become a widespread concern as a result of increasing competition in the world markets. Increasing demands on the quality of rolling mill products have led to great efforts to improve the control and automation systems of the rolling process [1-3]. Hot steel rolling is one of the most important steel manufacturing processes. Hot rolling is the first metal shaping process after the slab has been cast, in flat products such as plate, strip and sheet. The final shaping stage of hot rolling steel strip is normally performed on a tandem mill known as a finishing mill consisting typically of two to six stands. Here the final thickness, flatness and profile of the work-piece are determined. It is important to have a sound understanding of the behavior of the roll gaps in the finishing mill for design, scheduling and control purposes [2]. In particular, accurate predictions of the roll separating force are necessary to meet the current and the future quality standards of final product dimensions and flatness.

This paper focuses on the development of a hybrid phenomenological/inductive model to improve the current physical setup force model on a five stand industrial hot strip finishing mill. The motivation for the application of inductive learning-based methodologies lies in the fact that they do not require the expert development of phenomenological models [4-7]. This technology could provide a powerful tool for accurate prediction of the roll separating force, thereby ensuring that the products manufactured conform to target specifications and thus contribute to enhanced business benefits.

The mill settings are determined from the physical models based on expert metallurgical and mechanical knowledge. The set-up of these models is crucial since it determines, to a large extent, the thickness of the final product. In practice, it is sometimes observed that the roll-gap settings produced by set-up models are not as accurate as those required by increasing consumer product-quality demands. Although small errors can usually be compensated for by the mill controllers, larger errors lead to quality degradation and potentially out-of-specification product. This is particularly prominent in the case of first coils in a rolling campaign whenever there has been a change in width or thickness or steel grade [3].

The mill set-up errors arise since the set-up model only uses factors whose exact physical relationships are understood. Unfortunately, the rolling process involves many additional factors that affect the elastic/plastic material deformation in the roll gap, particularly due to the stochastic nature of the rolling process. In this sense, the physical model is far from perfect.

Experimental Results

We are interested in improving a current setup force model on five stand hot strip industrial finishing mill using the input, intermediate and output values of various setup models and the measured values of the force at each stand. We approached the problem from two directions. Firstly, we analyzed which variables may add more information to the estimation of the true force for each stand. Secondly, we investigated which variables were correlated to large errors in the current setup force model.

Improving the estimation of the stand forces

A feedforward multilayer perceptron (MLP) model [8] was used to investigate possible improvements to the setup force model for each stand. The starting point was the output of the current setup force model for the available 10,000 records of production coils. An MLP model was then used to estimate the true force at each stand using some other available variables as additional inputs to the model.

The MLP model enables us to measure whether inclusion of certain variables, or groups of variables, in the current setup force model can:

a) provide additional information about the rolling stands that has not been included in the current model;
b) achieve a better estimation of the true roll separating force.

The sensitivity of each of the MLP's input variables gives an indication of how much information each variable can add to the current model. The input parameters to the MLP model were chosen based on a sensitivity analysis where only the most important variables were retained. The final selection of the input variables can be found in the Table 1.

Table 1. The final input parameters to the MLP model

Variable Name
Aim width (current and the previous coil)
F4 roll balance reference (current and the previous coil)
F5 roll balance reference (current and the previous coil)
Setup Force (F1-F5) (current and the previous coil)
Delayed Measured Force (F1-F5) (previous coil only)
Setup Forward Slip (F1-F5) (current and the previous coil)
Setup Speed (Entry and F1-F5) (current and the previous coil)
Setup Temp (Entry and F1-F5) (current and the previous coil)
Setup Thickness (Tbar and F1-F5) (current and the previous coil)
Arc of Contact (F1-F5) (current and the previous coil)
Strain Rate (F1-F5) (current and the previous coil)
Carbon (current and the previous coil)
Molybdenum (current and the previous coil)
Niobium (current and the previous coil)
Phosphorus (current and the previous coil)
Sulphur (current and the previous coil)
Speed Vernier (current and the previous coil)
Thickness Vernier (current and the previous coil)

The obtained results for both the current setup and the hybrid models are in Table 2.

Table 2. The results of the estimation of the roll separating force by the current setup and the hybrid model for test data set (3000 coils). First Bar results are for first bars only for the test data set (752 coils). Here, F1-F5 are the roll separating forces for the respective stands, and Relative Error = Abs(Predicted Force - Measured Force)/Measured Force.

		Relative Error (Current Setup Model)					**Relative Error (Hybrid Model)**				
		F1	**F2**	**F3**	**F4**	**F5**	**F1**	**F2**	**F3**	**F4**	**F5**
Overall	**Avg**	0.036	0.049	0.061	0.044	0.073	0.018	0.020	0.025	0.024	0.043
	Stdev	0.034	0.045	0.045	0.040	0.063	0.018	0.021	0.025	0.026	0.043
First Bars	**Avg**	0.054	0.073	0.078	0.066	0.104	0.027	0.032	0.038	0.037	0.064
	Stdev	0.043	0.057	0.058	0.051	0.083	0.025	0.028	0.034	0.034	0.053

As can be seen from the Table 2, it is possible to significantly improve the estimation of a roll separating force from 5.3% error on average with the current setup model to 2.5% error on average with the hybrid model by adding some additional variables to the MLP model. The corresponding improvements for the first coils are from 7.5% with the current model to 3.8% with the hybrid model. This was achieved by inclusion, in addition to each stand's force from the current model, the contributions from setup forces from the other stands, as well as the contributions from a limited set of additional variables in Table 1.

The scatter plots of the estimated forces versus measured forces for each stand with the hybrid model are in Figs 1-10.

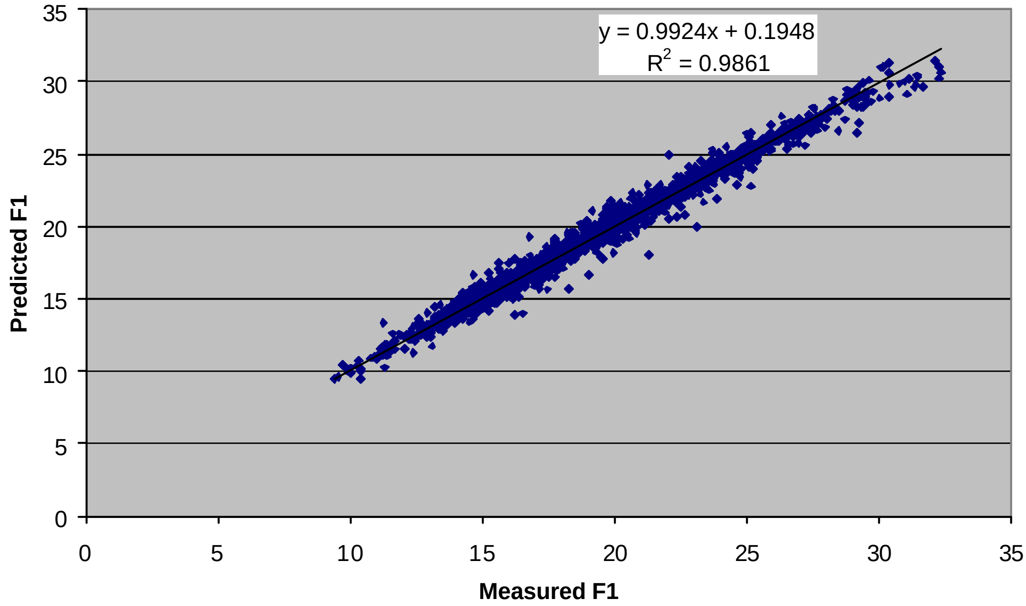

Fig 1. Predicted rolling force F1 [t] versus measured rolling force F1 [t] with a hybrid model (overall)

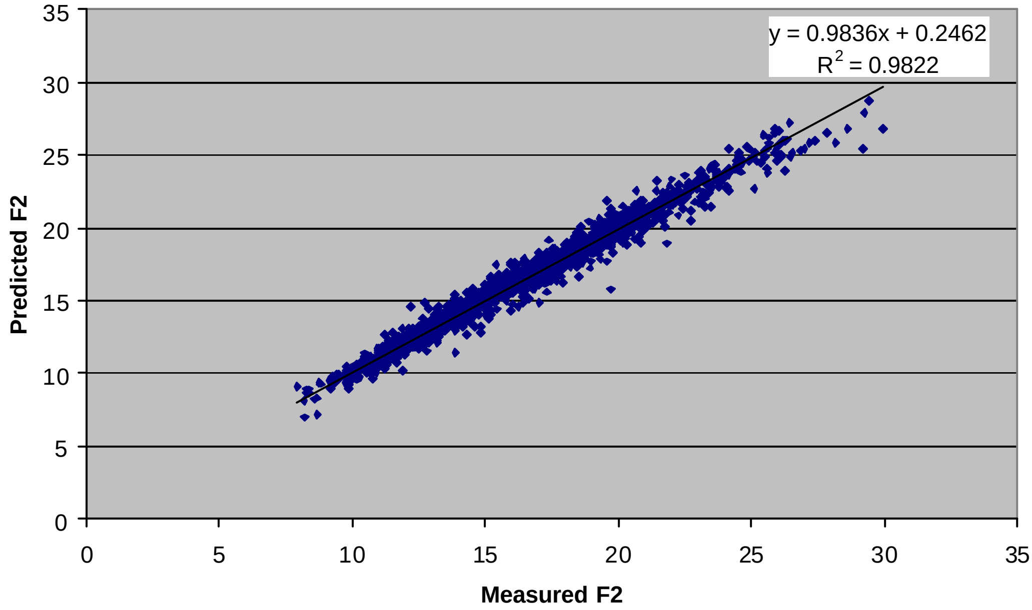

Fig 2. Predicted rolling force F2 [t] versus measured rolling force F2 [t] with a hybrid model (overall)

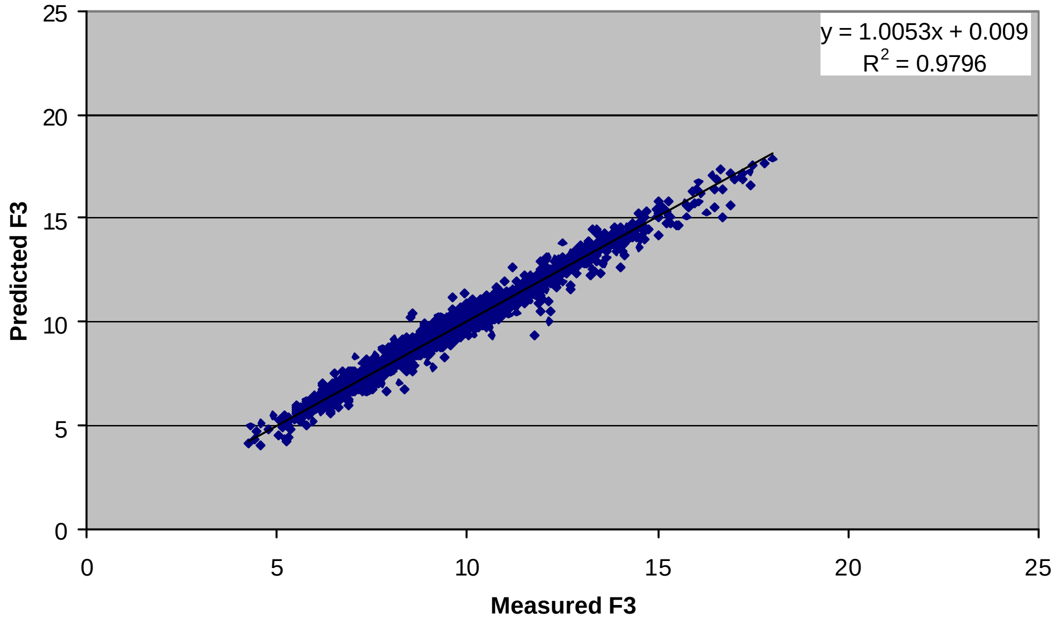

Fig 3. Predicted rolling force F3 [t] versus measured rolling force F3 [t] with a hybrid model (overall)

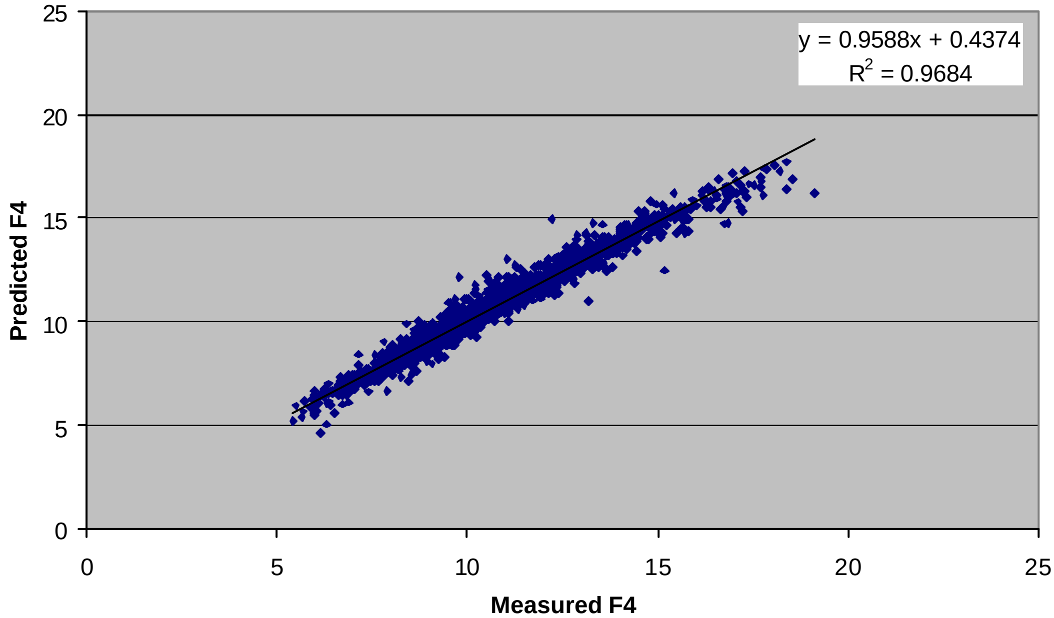

Fig 4. Predicted rolling force F4 [t] versus measured rolling force F4 [t] with a hybrid model (overall)

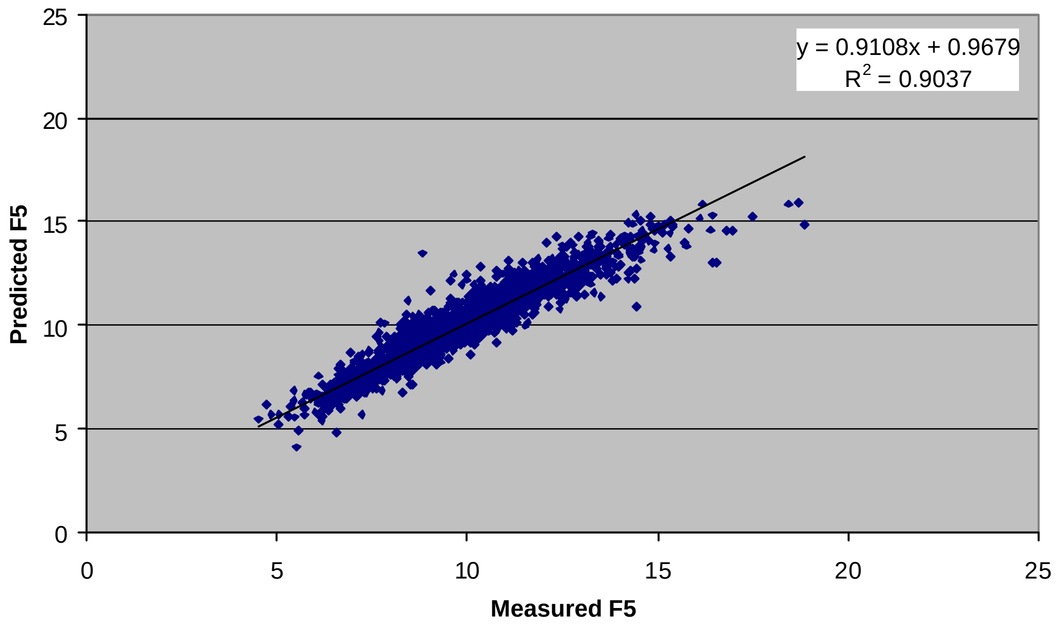

Fig 5. Predicted rolling force F5 [t] versus measured rolling force F5 [t] with a hybrid model (overall)

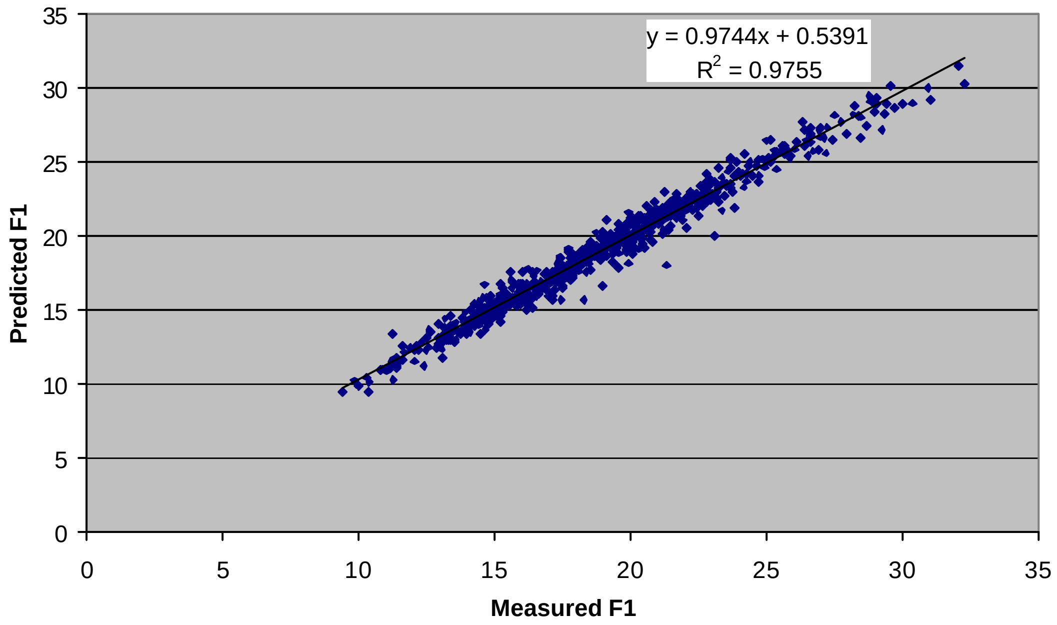

Fig 6. Predicted rolling force F1 [t] versus measured rolling force F1 [t] with a hybrid model (first bars)

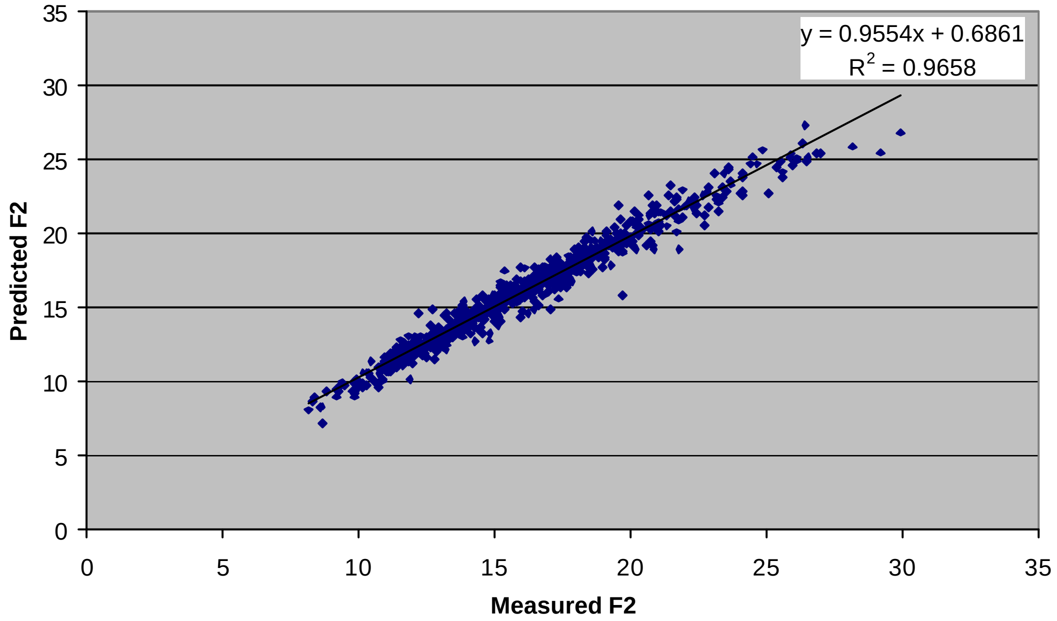

Fig 7. Predicted rolling force F2 [t] versus measured rolling force F2 [t] with a hybrid model (first bars)

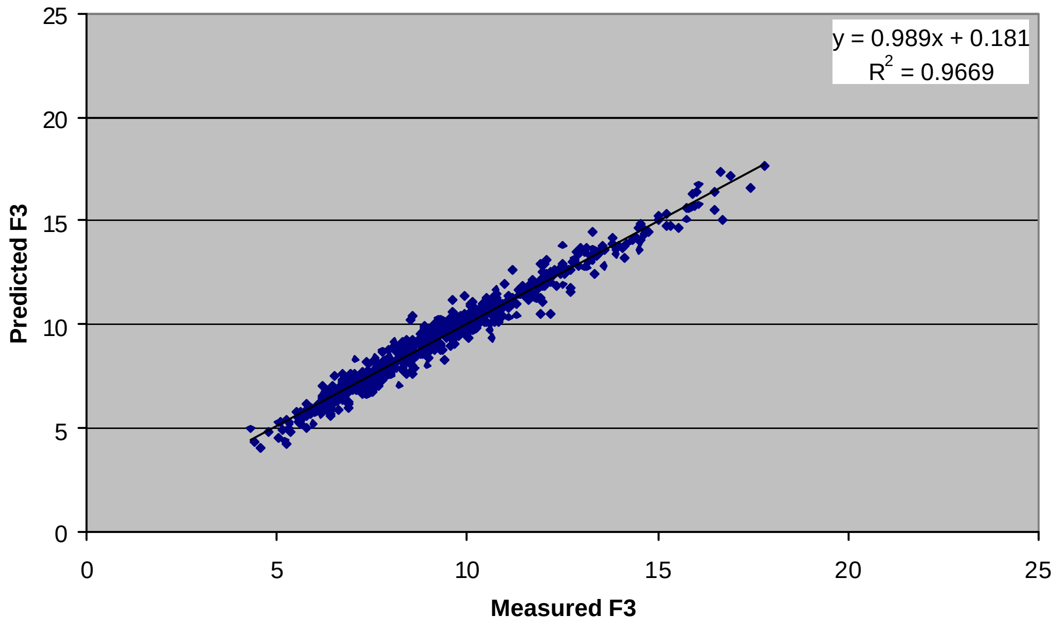

Fig 8. Predicted rolling force F3 [t] versus measured rolling force F3 [t] with a hybrid model (first bars)

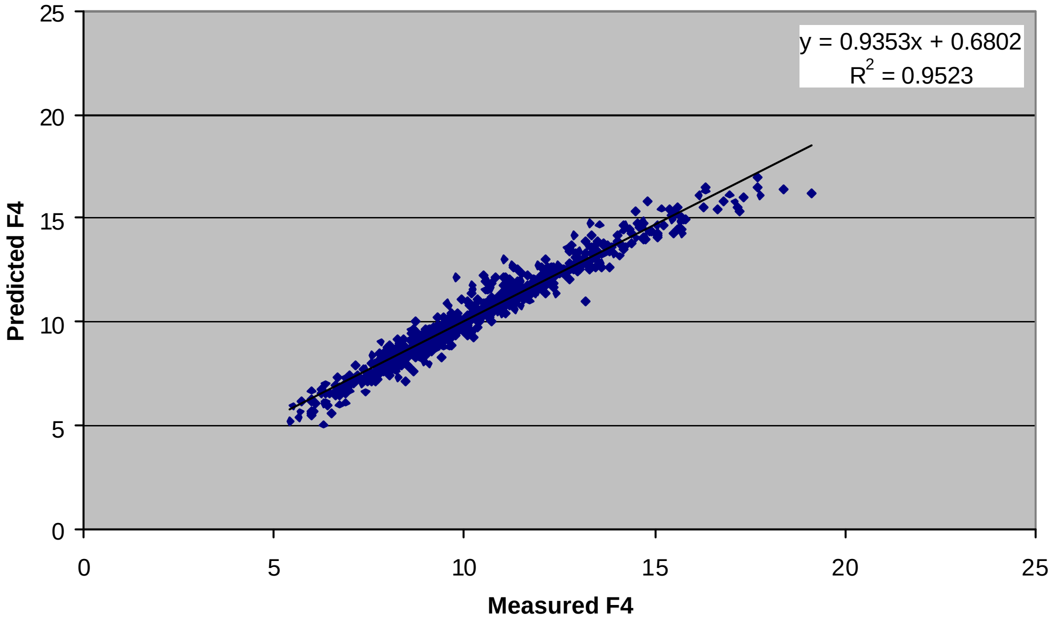

Fig 9. Predicted rolling force F4 [t] versus measured rolling force F4 [t] with a hybrid model (first bars)

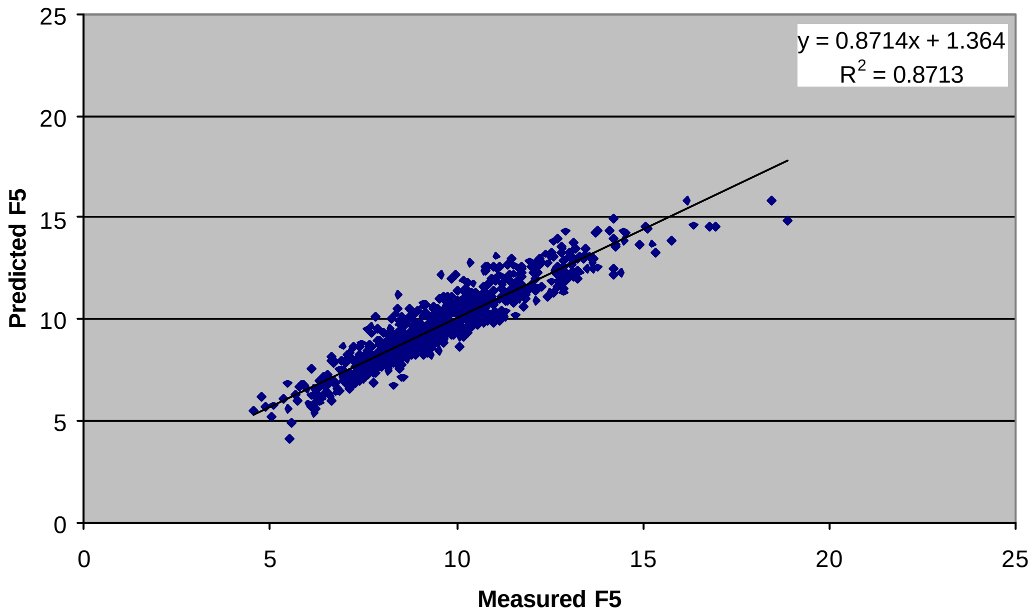

Fig 10. Predicted rolling force F5 [t] versus measured rolling force F5 [t] with a hybrid model (first bars)

The ranking of the input variables to the hybrid model in order of their importance are in the Table 3.

Table 3. The ranking of variables in order of their correlation with F1-F5 overall.

Variable Name	Relative importance
Aim Width	0.208
Setup Thickness	0.178
Arc of Contact	0.149
Setup Strip Temp	0.129
Strain Rate	0.120
Setup Force	0.114
Delayed Measured Force	0.113
Setup Roll Speed	0.071
Carbon	0.061
Setup Predicted Forward Slip	0.059
Niobium	0.045
Molybdenum	0.039
F5 Roll Balance Ref	0.027
Phosphorus	0.020
F4 Roll Balance Ref	0.015
Sulphur	0.011
Thickness Vernier	0.011
Speed Vernier	0.010

Correlating current setup force model errors

The second approach to improving the current setup force model was to investigate the correlation between the large errors of the model and a restricted set of input parameters (or initial conditions) of the current setup force model. The intermediate variables, such as Arc of Contact, were not considered. The setup force, which is an output of the current model, was also chosen as a (input) variable of interest. The list of variables used in this analysis can be found in Table 4.

Table 4. The input parameters of the current setup force model for correlation analysis.

Variable Name
F4 Roll Balance Ref
F5 Roll Balance Ref
Model Flow Stress F1-F5
Base Temp Entry F1-F5
Lower thread speed limit
Upper thread speed limit
Hardness code
Aim Width
Aim Thickness
Aim Exit Temp
Aim Coil Temp
Chemical composition
Work Roll Diameter F1-F5
Setup Draft
Tension ref looper 1-4
Angle ref looper 1-4
Thickness Vernier
Speed Vernier
Gauge Meter Error F1-F5

The data set of production coils was split into two subsets (for each stand), one representing the "normal" level of error between the current model and the measured force value, while the other set contained the coils with a "large" level of error. A second set of data was created to see if there was any dependency on the previous coil. A change in each coil's inputs from the previous coil's inputs was recorded (the inputs of the very first coil in the data set were set to zero).

The data sets of the input parameters and the output variable for each stand were then combined and analyzed using a C4.5 decision tree. The decision tree is useful in finding a model that can classify data into two or more discrete classes. The decision tree can also be converted into rule sets for each class; these rules are often easier to interpret than the tree diagram.

The data distribution of the "normal" sets and the corresponding "large error" sets is highly skewed as each "normal" set contained on average 95% of the data. To alleviate this problem, the decision trees were grown using an over-sampled "large error" set and then tested on the unmodified sample distribution. This provides a bias for the model to the "large error" data to extract any significant, but small in frequency, relationships. A cross validation was used to prevent the model from over-fitting. Next, a rule set was extracted for each condition.

The main findings from the analysis of the errors between the output of the current model and the measured force for each stand are that the level of the Speed Vernier variable is highly correlated with the large errors in the current setup force model. Specifically, it was discovered that a high positive Speed Vernier value often correlated to a large error. Secondly, it has been found that large changes to the Model Flow Stress values between coils are correlated frequently with larger errors in the current setup force model.

The minor findings are that the large errors in the first four stands are not influenced by a coil's chemical composition. The last stand was slightly influenced by the Carbon content and the coil to coil change in the Chromium levels. There were also minor consistent influences across most stands by the Lower Thread Speed Limit and the Aim Exit Thickness variables. The found rules are below. Only the first two most accurate rules for Stands 4 and 5 are shown for space reasons, this can lead to anomalies (or interesting results) because often the most accurate rules are not the most frequently used rules. A rule (in the IF-THEN format) is made up of ANDed expressions. A second or third coil is a proceeding coil following a first coil (without any changes in the input conditions). The rules for the current condition variables use the following labels:

- Low for values that are one standard deviation or more below the average value for that variable;
- Medium for values that are within one standard deviation from the average value of the variable;
- High for values that are above one standard deviation from the average value of the variable.

The first order difference variables are treated differently due to them being mainly zero average, so the low, medium and high labels do not apply in the same manner. The first order difference variable ranges from large negative changes to large positive changes. Slight positive or negative changes are those that are much smaller than one standard deviation.

Stand 4

Combined Current Condition and First Order Difference data sets

Rule set error = 18.9%

18 rules (6 for normal condition, 12 for large errors)

Normal Condition:

Rule 1:

- IF Set-up Force F3 is at low or medium levels
- AND Δ F4 Roll Balance Ref is slightly negative or is positive
- AND Δ Model Flow Stress F2 is contained within less than one standard deviation around zero
- AND Δ Set-up Force 1 is slightly negative or is positive

- AND Coil is not a First Bar
- THEN Not a Large Error

Rule 2:

- IF Set-up Force F3 is at a high level
- AND Set-up Force F4 is at a high level
- AND Δ Model Flow Stress F2 is contained within less than one standard deviation around zero
- AND Coil is not a First Bar
- THEN Not a Large Error

Large Error Rules:

Rule 1:

- IF Set-up Force F3 is at low or medium levels
- AND Set-up Force F4 is at a high level
- AND Gauge Meter Error is at a high level
- AND Coil is not a First Bar
- THEN Error is Large

Rule 2:

- IF Aim Exit Temperature is at a medium temperature and above
- AND Carbon is at a medium to high carbon steel level
- AND Δ Set-up Force 5 is very negative
- THEN Error is Large

Primary variable	**Secondary variables**	**Tertiary variables**
Coil Counter (reset at each First Bar)	Δ Model Flow Stress F2 Aim Exit Temperature	Δ Model Flow Stress F2 Speed Vernier

Stand 5

Combined Current Condition and First Order Difference data sets

Rule set error = 15.1%

16 rules (3 for normal condition, 13 for large errors)

Rule 1:

- IF F5 Roll Balance Ref is at a low or medium levels
- AND Lower Thread Speed Limit is at a low or medium levels
- AND Set-up Force F5 is at a medium level and above
- AND Δ Set-up Force F1 is slightly negative or is positive
- AND Coil is not a First Bar
- THEN Not a Large Error

Rule 2:

- IF Lower Thread Speed Limit is at a low or medium levels
- AND Set-up Force F1 is at a medium level or above
- AND Set-up Force F5 is at a medium level or above
- AND Δ Set-up Force F1 is slightly negative or is positive
- AND Coil is not a First Bar
- THEN Not a Large Error

Large Error Rules:

Rule 1:

- IF Aim Exit Thickness is at a medium level and above
- AND Carbon is at a high carbon steel level

- AND Δ Set-up Force F5 is slightly negative or positive
- THEN Error is Large

Rule 2:

- IF Aim Exit Thickness is at a medium level or above
- AND Carbon is at a high carbon steel level
- AND Δ Model Flow Stress F4 is very negative
- AND Δ Set-up Force F1 is very positive
- THEN Error is Large

Primary variable	Secondary variables	Tertiary variables
Coil Counter (reset at each First Bar)	Set-up Force F5	
		Lower Thread Speed Limit
	Base Temp Entry F1	
		Δ Chromium

Conclusion

We were interested in improving a current setup force model on five stand hot strip industrial finishing mill. We approached the problem from two directions. Firstly, we analyzed which variables may add more information to the estimation of the true force for each stand. Secondly, we investigated which variables were correlated to large errors in the current setup force model.

The most promising direction found for improvement of the current setup model is to include in addition to each stand's force from the current setup model a weighted contributions of setup forces from the other stands; as well as contributions from a limited set of additional variables. It was also found that the improvements made to force estimation on First Bars were similar to the overall improvements made to the current setup model with the exception of the Stand 5. Stand 5 required additional minor variables to improve its force estimation on First Bars.

The second direction of this investigation has revealed that the Speed Vernier variable is highly correlated to the large errors in the current setup model. Moreover, large changes to the Model Flow Stress values between coils are correlated with large errors in the current setup model.

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