Chapter 10
Conclusions and Suggestions

Several steps have been carried out in the development of product quantity and product quality models, from data collection, data conditioning, performing a Principal Component Analysis (PCA) , performing a Partial Least Squares modeling and finally, model validation.

A good production quantity model that described the relation between the conversion (1-R) and the influencing variables (seven) can be obtained from this exercise. This model is valid and can be used for any other condition and different type of production grade. In the future, one can use this model for the conversion prediction and conversion optimization by controlling the involved variables. However, it should be noticed that the developed model is valid only in the certain range of process conditions, since the developed model is linear, whereas the real relationship between the output and input variables is non-linear. As mentioned before, the non-linear model can be linear in a certain range of process conditions.

For the melt index modeling, a relatively good model can be obtained. Shifting process inputs in time can increase the prediction capability of the model by capturing more variance. However, the model only has a good fit for one condition but not for other conditions, even for the same production grade or type. The model cannot follow the changes that occur in each production run. A recursive least squares model has been applied to make a model that can adapt to the process changes. This model works extremely well. The recursive model can, however, not be applied to predict far into the future, since it is adapting all the time.

In order to improve the prediction capabilities of a model to be developed, the following steps could be undertaken:

1. Identify whether the measured variables contain sufficient information for the prediction of the melt index. At least 80 percent of the variance should be captured if the variables contain sufficient information.
2. A better procedure is required for the estimation of the required time shift (time delay correction).
3. Different procedures should be investigated for variable selection. In this study a trial and error approach was followed, however, one could, for example, apply genetic algorithms or use other approaches.
4. It is interesting to be further investigated whether it is necessary to shift means in the model. Since in the PLS modeling, it assumes that the variables involved in the model have a constant mean. If the means is changing, then the model prediction can deteriorate and deviate from the real value.
5. It is expected that some variables have a short-term impact on the melt index while other variables have a longer-term impact. This could possibly require to investigate whether hierarchical modeling leads to better models with better prediction capabilities. The main advantage of this type of model is that it can also be used for long-range prediction.

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