Towards Automatic Calibration of In-Line Machine Processes

Authors : David F. Nettleton, Elodie Bugnicourt, Christian Wasiak, Alejandro Rosales

Abstract : In this presentation, preliminary results are given for the modeling and calibration of two different industrial winding MIMO (Multiple Input Multiple Output) processes using machine learning techniques. In contrast to previous approaches which have typically used 'black-box' linear statistical methods together with a definition of the mechanical behavior of the process, we use non-linear machine learning algorithms together with a 'white-box' rule induction technique to create a supervised model of the fitting error between the expected and real force measures. The final objective is to build a precise model of the winding process in order to control de-tension of the material being wound in the first case, and the friction of the material passing through the die, in the second case. Case 1, Tension Control of a Winding Process. A plastic web is unwound from a first reel, goes over a traction reel and is rewound on a third reel. The objectives are: (i) to train a model to predict the web tension and (ii) calibration to find the input values which result in a given tension. Case 2, Friction Force Control of a Micro-Pullwinding Process. A core+resin passes through a first die, then two winding units wind an outer layer around the core, and a final pass through a second die. The objectives are: (i) to train a model to predict the friction on die2; (ii) calibration to find the input values which result in a given friction on die2. Different machine learning approaches are tested to build models, Kernel Ridge Regression, Support Vector Regression (with a Radial Basis Function Kernel) and MPART (Rule Induction with continuous value as output). As a previous step, the MPART rule induction algorithm was used to build an explicative model of the error (the difference between expected and real friction on die2). The modeling of the error behavior using explicative rules is used to help improve the overall process model. Once the models are built, the inputs are calibrated by generating Gaussian random numbers for each input (taking into account its mean and standard deviation) and comparing the output to a target (desired) output until a closest fit is found. The results of empirical testing show that a high precision is obtained for the trained models and for the calibration process. The learning step is the slowest part of the process (max. 5 minutes for this data), but this can be done offline just once. The calibration step is much faster and in under one minute obtained a precision error of less than 1x10-3 for both outputs. To summarize, in the present work two processes have been modeled and calibrated. A fast processing time and high precision has been achieved, which can be further improved by using heuristics to guide the Gaussian calibration. Error behavior has been modeled to help improve the overall process understanding. This has relevance for the quick optimal set up of many different industrial processes which use a pull-winding type process to manufacture fibre reinforced plastic parts. Acknowledgements to the Openmind project which is funded by Horizon 2020 European Union funding for Research & Innovation, Grant Agreement number 680820

Keywords : data model, machine learning, industrial winding, calibration
Conference Title : ICIEMPM 2016 : International Conference on Industrial Engineering and Manufacturing Process Modeling
Conference Location : London, United Kingdom
Conference Dates : July 28-29, 2016