Bayesian Soft Sensing in Cold Sheet Rolling

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We are concerned with the theory of soft sensing in industrial applications, namely the cold sheet rolling. In comparison to the classical sensing, the generally cheaper soft sensors provide the ability to process large amounts of measured data, used for building predictive models [1]. To achieve robustness of these sensors, their main purpose – prediction of variables which are not directly measurable – is often accompanied by other important tasks, e.g., the fault detection and diagnosis, control, graceful degradation mechanisms etc. [2].

There are three main approaches to soft sensors: physical modelling, multivariate statistics and artificial intelligence modelling [1]. Some selected approaches comprise the methods using the Kalman filter [3], neural networks [4, 5], statistical methods [6, 7] and many others. We present a Bayesian approach to the statistical soft sensing in the data-driven paradigm. Our goal is to predict a physical variable, which is crucial for the rolling process, but which can be measured only with a high traffic delay. Fortunately there exists a set of other variables measured during the process, which are more or less correlated with the quality of interest. Using a class of several different Bayesian regressive models, determining the predicted value with a reliability generally unknown at the particular time instant, the high predictive performance of the sensor is achieved by their combination in a way inspired by Bayesian model averaging [8]. The approach allows fast adaptivity of the sensor and its graceful degradation if measurements dropouts or hardware failures occur.

References

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