Indirect Mass Flow Estimation based on Power Measurement of Conveyor Belts in Mineral Processing Applications

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***Abstract*—This study presents our most recent advances in the design of a data-driven method for mass flow rate estimation of conveyor belts. Our proposal is focused on obtaining an indirect method that uses power measurement from the conveyor belt. The aim is to replace traditional expensive measurement hardware, which results in benefits such as lowering overall costs as well as the possibility of working in hostile environments such those with adverse weather conditions and the presence of dust and vibration. The mass estimation is based on data-driven estimations of idle power and net energy consumption. We discuss different models describing the relationship between energy input and transported mass: a constant proportionality factor, a time-dependent factor and a regression model depending on the idle power. We illustrate our approach on a case study where the state-dependent model yields the most promising results across multiple working periods.**

***Index Terms*—Belt Weight Estimation, Mining Industry, Regression Model**

I. Introduction

In the context of industrial machinery, a belt scale (also known as belt weigher or conveyor scale) is an artefact to measure the flow rate and overall amount of material that has been transported using a conveyor belt. Since weight is defined as the gravitational attraction on a mass, the weight of the material transported can be calculated by just weighing the belt load and measuring the belt speed. This makes necessary a scale or other form of weighing device as well as a speed measuring instrument to determine the mass flow.

However, these kinds of artefacts are usually expensive since they require highly-specialized equipment including at least a scale, a scale integrating system, a calibration system, and a speed sensor. Otherwise, the equipment would be considered to be a source of certain error measurement. For example, while it is common that general instrumentation systems can generally tolerate an error up to 3%, belt scales demand error margins up to 0.1%. Therefore, one of the most significant issues acting as a bottleneck for the development of advanced automated industrial systems is the lack of accurate, yet inexpensive methods, to measure mass flow rates [14].

In our specific case, in addition to the traditional issues associated with belt scales, the fact that our field of study is the mining industry is also a important. This means that belt scales are often located in outdoor sites with bad weather and environmental conditions: rain, snow, wind but also large amounts of dust, vibrations, etc. which are common in most of mining settings. So the whole problem associated with the accurate calculation of the flow rate is even more difficult.

In the context of this study, we report the design and development of a virtual belt scale for the mining industry that has been specifically designed to overcome some of the drawbacks associated with the current approaches. Our research proposition is a data-driven method being able to accurately estimate the flow rate and overall amount of transported material based on the use of inexpensive equipment for power demand measurement of the conveyor belt. The rationale behind this idea is that these measurements can be specifically reused so that the final method might result in lower costs.

Therefore, the major contribution of this work is the design and implementation of a data-driven development of the virtual belt scale to estimate features such as how much material has travelled in one given time unit or to monitor material outputs of any time unit (e.g. tonnes per hour, etc.). Besides, our virtual belt scale represents a significant improvement for any further kind of analysis over the gathered data. For example, it can be exploited to perform data understanding, visualization, evaluation for customers, and so on.

The rest of this work is structured as follows: Section II presents the state of the art concerning automatic mass flow estimation in machinery. Section III then briefly introduces the case study and relevant data. Section IV outlines our technical approach based on a data-driven method to indirectly estimate the belt weight based on power measurement, followed by going into detail regarding estimating the idle power in Section V. Section VI then presents some results of the case study where our approach has been successfully applied, followed by a discussion in Section VII. Finally, we remark on the conclusions and outline future research lines in the context of this work.

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II. Related Work

A wide range of application domains requires developing and implementing automated monitoring, control, and optimization systems for material processing applications. In those cases, it is usually required to have accurate mass-flow measurements from the processes. The truth is that belt scales of small to medium cost are usually accurate when the conveyor belt is fully loaded and well-maintained. However, it is assumed that the accuracy of the belt scale decreases if the conveyor belt is not fully loaded, due to physical imperfections and its non-linear behaviour.

The use of belt scales in the industry is not new. Belt scales have been traditionally used in many production and logistic scenarios. For example, belt scales have been used for measuring throughput and consumption in production plants, internal balancing of supply and discharge, load limit signalling, and so on. Besides, it is necessary to remark that belt scales are the most common mass flow equipment used in most of the material-processing factories nowadays.

In the specific case of the mining industry, the development of monitoring and control systems for mineral processing applications is of vital importance. The reason is that it is often required to have accurate mass flow measurements. In this context, a belt scale is one of the most common artefacts to bulk material mass flow. The hard operational conditions of the mining processes cause significant challenges and restrictions (wind, dust, vibrations, etc.) for the proper usage of belt scales.

For these reasons, there is already literature that deals with aspects related to the design and optimization of these kinds of equipment. State-of-the-art solutions for the belt scale can calculate an accurate mass flow measurement from the process if calibrated properly. However, the high price of the equipment prevents the installation of multiple belt scales in most industrial premises or machinery [7]. Therefore, it makes sense to do research oriented to find innovative ways to alleviate the cost of this equipment. Some of the existing works can be categorized according to the following classification:

- Machine vision [8, 6, 2],
- Laser profilometers [4, 10],
- Ultrasonic sensors [1],
- Radiation based sensors [5],
- Power transducers [3],
- Other signal processing techniques [13],
- Kalman filtering for tachometer response correction and thus accurate flow-rate measurement [9, 11].

However, aspects such as the conveyor design, belt scale location, and installation on the conveyor determine the effectiveness with which the scale can interpret material loading on the belt. Any change in location, direction, or external conditions increases the consumption of resources in the form of time and money for most solutions that need a re-calibration according to the environment. This is the main reason why we think that power demand measurement of the belt conveyor is possibly a promising method available for mass flow measurements at a reasonable cost. This opinion is shared by several authors, including [12] where it is mentioned that the use of indirect measures such as power consumption could be an approach to be taken into account mainly due to its low cost.

The contribution of this paper is the proposal of a method that uses the motor power data for indirectly estimating the mass flow on the conveyor belt while dynamically estimating the idle power and taking into account environmental factors that influence the power consumption. This has two main benefits over other approaches: It reduces investment costs for measurement hardware and it is able to operate under adverse weather and environmental conditions without major accuracy penalties. In the remainder of this work, we present the technical details as well as an use case of this approach.

III. System under Study

A. Overview

The goal is to develop a virtual belt scale for continuous weight measurement of bulk mineral material during transport on a belt conveyor. The system is illustrated in Fig. 1. The belt conveyor moves at a constant speed and has to overcome a fixed height h. The belt is driven by an electric motor whose electrical power consumption is measured and serves as the basis for estimating the mass flow. This power consumption is divided into an idle power P_0 for driving the belt without any load and the net power P_N necessary for moving the load itself. While P_N is directly proportional to the transported mass flow, the idle power is assumed to be independent of the load itself.

In addition to the power measurement, reference measurement systems are also installed on the test setup, in the form of a belt scale and a camera system, which provide direct measurements of mass flow and volume flow, respectively, as training data for the regression model as well as for validation.

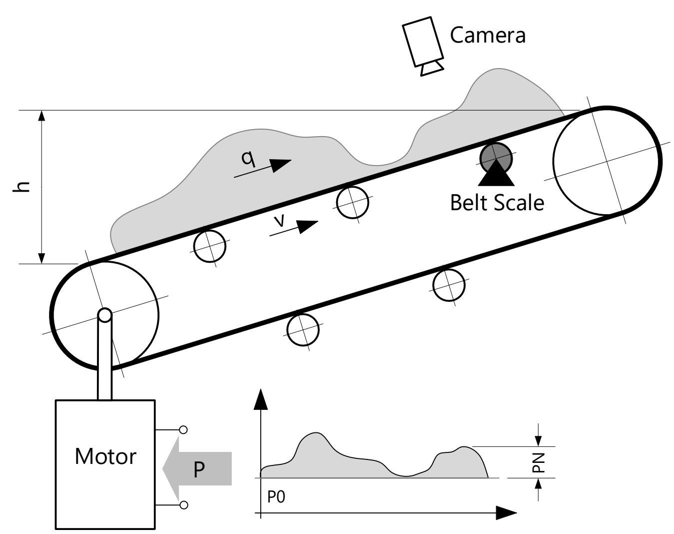

Fig. 1. System under study consisting of conveyor belt with electric drive motor and reference measurement system with Belt Scale and camera system for volume measurement.

B. Data Acquisition and Management

We work with an architecture for data collection and management based on the protocol MQTT that is widely used in the context of industrial machinery. The operation mode is based on the connection of several data buses to the module that acts as a broker of the MQTT messages and the different parts of the architecture consume only the data messages that are relevant to it. This way of working makes it possible to work with a loose coupling architecture that is usually very convenient in the development of modular solutions like this.

In the context of this work, two different buses are used for data acquisition in the field: CAN Bus and Modbus. Data from the CAN Bus are mainly related to the optical volume measurement as well as the belt scale, while Modbus provides electric power measurements. The major difference between the two buses is that, while obtaining CAN Bus data messages requires a passive read or push operation, obtaining Modbus data messages requires cyclically pooling the respective data logger in a freely configurable interval in a pull operation. Once that we can capture all these data, we consolidate them in a database so that can be the source for further analyses including the automatic assessment of the mass flow.

IV. Approach

The basic method for determining material mass flow and total mass builds on the physically motivated idea to measure the power consumption of the belt drive motor for estimating the current belt load. The total mass moved by the belt then follows by integrating the mass flow over time.

In particular, the mass

$$M(\Delta) = \int_{t_0}^{t_0+\Delta} q(t)\,dt \tag{1}$$

transported during the time interval Δ and determined by the mass flow $q(t)$ is assumed to correlate with the net energy input $E_N(\Delta)$ according to

$$E_N(\Delta) = k \cdot M(\Delta) \tag{2}$$

with the coefficient

$$k = k(\rho, \vartheta, \ldots) \tag{3}$$

depending on the friction ρ, temperature ϑ and possibly other external factors as well.

Thereby, the net energy

$$E_N(\Delta) = E_{\text{total}}(\Delta) - E_0(\Delta) = \int_{t_0}^{t_0+\Delta} P_{\text{total}}(t) - P_0(t)\,dt \tag{4}$$

is determined from the total effective power consumption P_{total} minus the idle power P_0 that is necessary for moving the belt itself without the material.

One challenge in this approach is how to model the k factor. Apart from using a constant value for k, time dependency, i.e. $k(t)$, enables the possibility to also take into account dynamic effects over time. A state-dependent model, like in Equation 3, on the other hand is able to react to changing environmental factors, but is more difficult to model in practice. Based on the assumption that friction, temperature etc. affect the total power consumption in the same manner as the idle power P_0, a suitable alternative parametrisation could be

$$k = k(P_0) \tag{5}$$

where k is modelled as a function of the idle power P_0. As a first attempt, we investigate the following model,

$$k(P_0) = \alpha_0 + \alpha_1 P_0 + \alpha_2 P_0^2, \tag{6}$$

to describe the relationship between idle power and k factor.

Given measurement data for E_{total} and the mass M, the model parameters α_i, can easily be estimated using linear regression over E_N:

$$E_N = E_{\text{total}} - E_0 \sim (\alpha_0 + \alpha_1 P_0 + \alpha_2 P_0^2) \cdot M_{\text{meas}}. \tag{7}$$

For an accurate mass estimation, it is crucial to have reliable data for the idle power P_0, due to the fact that E_N as well as the k factor depend on P_0, which in turn might be volatile due to environmental factors like temperature φ and friction ρ. For practical applications, this makes it necessary to dynamically adapt the estimations of P_0, a method for which is described in the following section.

V. Estimating Idle Power

The idle power P_0 is defined as the electric power demand for moving the belt drive without material, and the corresponding energy input during the time interval Δ is,

$$E_0(\Delta) = \int_{t_0}^{t_0+\Delta} P_0(t)\,dt. \tag{8}$$

The idle power is subject to environmental influences, such as temperature, friction, rain etc. It can therefore not be assumed constant but has to be estimated dynamically over the course of the working period.

Two steps are necessary for estimating the idle power P_0:

1) *Identification of idle phases:* In those operating phases in which the belt is empty, the measured total active power represents the current idle power.
2) *Regression model:* Use a regression model to interpolate between the identified idle points as an estimation for P_0 on the entire range.

A. Identification of Idle Phases

In our test setup, reference measurements from belt scale and volume sensor can be used to deliver accurate information about the idle phases during operation. As soon as both reference measurements show no load, i.e. values close to zero, an idle phase can be assumed. The intentional redundancy between belt scale and reference measurement provides additional robustness to mediate calibration and outlier issues. In practice, it has shown that sensor calibration issues may easily occur, which make reliable identification of idle phases more difficult. It may happen that one sensor indicates idle state, while the other one does not. This is mitigated by only using measurements where *both* sensors show values close to zero.

In addition, we check whether the power measurements from potential idle points lie within a defined, plausible range of values, e.g. in the interval $[2000, 3500]$ W. If the measurements fall outside this range, they are considered an outlier and removed from consideration.

The result is a time series of measurement points that are considered to be measurements of the belt drive power without load.

B. Regression Model

A regression model based on the idle points determined in the previous step provides an estimation of the actual idle power P_0 in phases when there is actually load on the belt.

In order to find a suitable means of approximation that best fits the requirements imposed on the model, different methods have been compared and evaluated, in particular (piecewise) linear interpolation, linear regression and convex hull.

The most satisfying results in terms of accuracy and stability were obtained by using a piecewise robust regression with bisquare weights. Thereby, the overall time period is divided into windows of fixed width, e.g. 5 minutes., in each of which a local linear regression model is fitted, provided idle points are present within this window. The obtained local models, however, are only valid within their respective support intervals within which support points are present. Outside these support intervals, the individual local regression models are connected to one another by means of linear interpolation. This is also used across time windows where not support points are available. Combined with extrapolation in the outer areas, this method provides a continuous, piecewise linear function describing the progression of the idle power over the entire working period.

C. Results

Fig. 2 shows an example with power measurement and idle power estimation on a section of a working period. The red points shows measurements where idle state is assumed, i.e. these are used for the regression. Compared to simple linear regression (see figure), the piecewise robust regression is much more dynamic, but better fits the measured progression of the idle power.

The identified idle points in the plot show that the measured idle power is not constant, but rather volatile, even with continuous idling. This is why a sophisticated and robust regression model is crucial for estimating the idle power.

VI. Case Study Results

A well-founded estimation for the idle power P_0 is a necessary prerequisite for calculating the net energy E_N for transporting the material as well as developing a regression model for the k factor, which describes the relationship between net energy E_N and mass flow M. As training data for the model, measurement values of the mass flow, M_meas, are available from the reference measurement system for several working periods. Fig. 3 depicts one working period of the training dataset with a comparison of different models for k: Constant value k_{const}, time-dependent model with hourly values k_{hourly}, and state-dependent model $k(P_0)$ according to Equation 6.

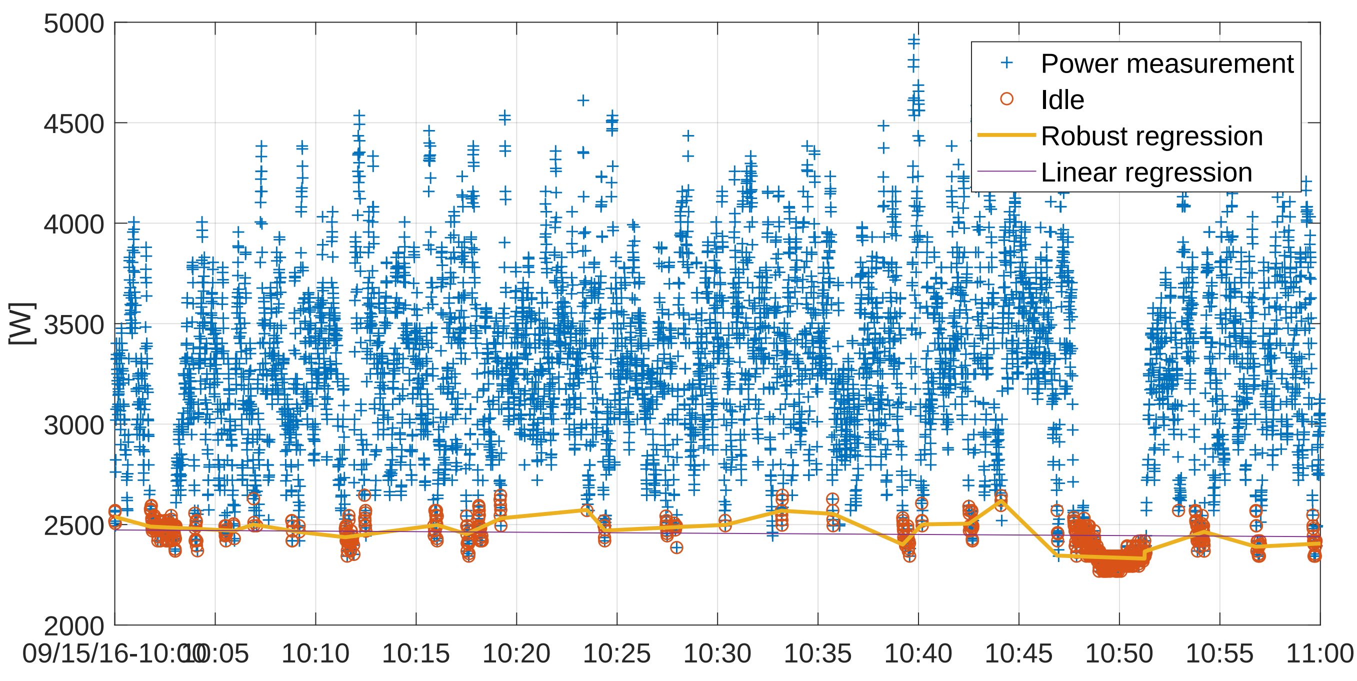

Fig. 2. Example power measurement with idle power estimation via linear regression and robust piecewise regression

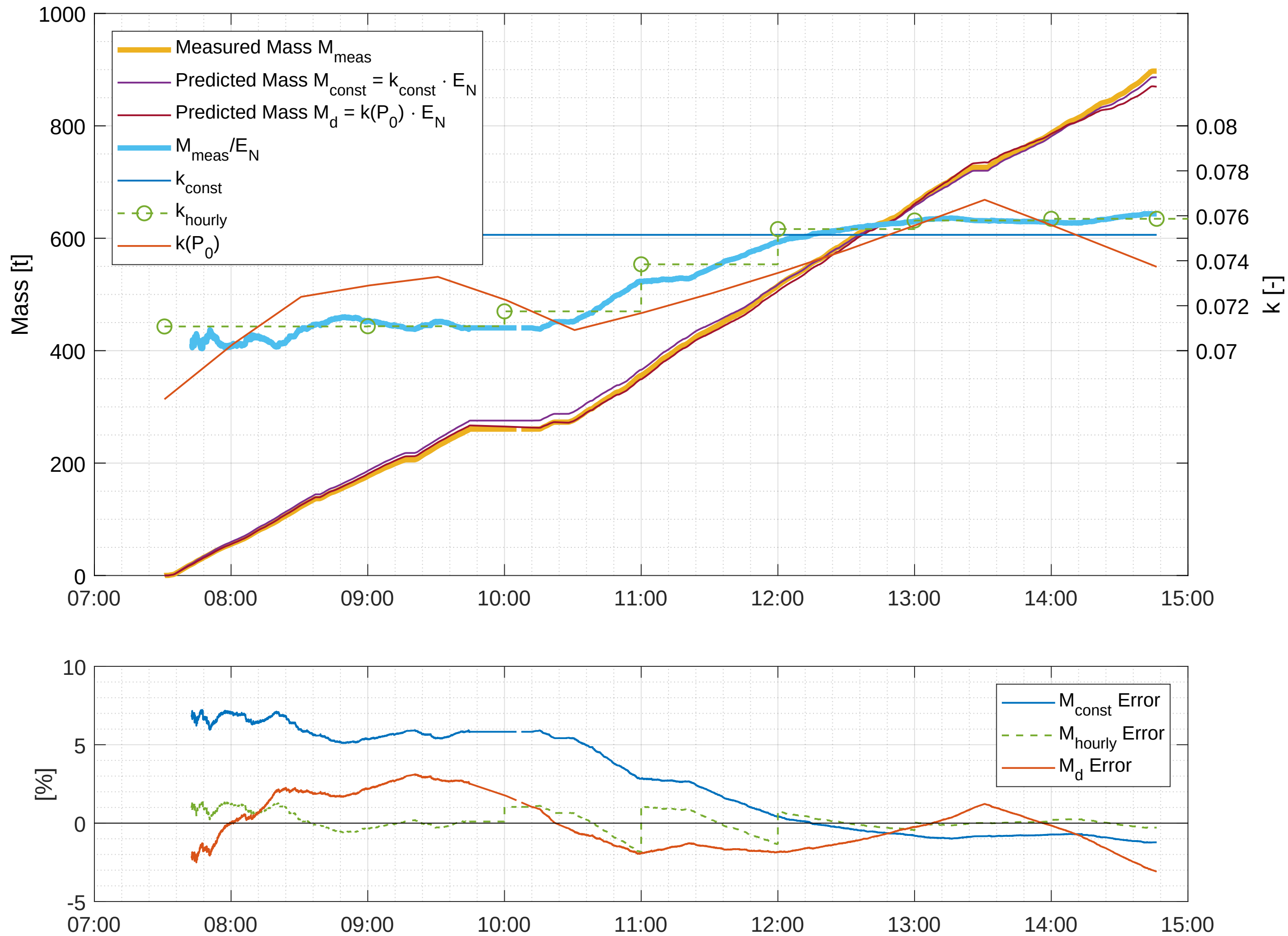

Fig. 3. Working period for training the regression model with comparison of different k models: constant value k_{const}, hourly values k_{hourly} and state-dependent model $k(P_0)$. The bottom plot depicts the resulting relative error between predicted and measured mass flows.

The plots show that, compared to the other models, the constant k value k_{const} only is a moderately good approximation of the "real" k ratio M_{meas}/E_N (shown in blue). However, the relative error in the total mass at the end of the working period is about 1.2%, which is lower than the error of the state-dependent model $k(P_0)$ with 3.1%.

The hourly approximation k_{hourly} is an even better fit on the training dataset (final error 0.3%). However, it performs worse on the validation dataset. This is shown in Fig. 4, which depicts a different working period, which is not part of the training set, to validate the k model. On the other hand, the state-dependent model $k(P_0)$ is able to provide the most accurate results on the validation dataset, with a final error at the end of the working period of about 0.1%, compared the the constant model k_{const} with a final error of 3.4%.

VII. Discussion

The simple model with k_{const} works well for individual working periods, but its accuracy is not sufficient across multiple different working periods. The time-dependent model $k(t)$ with hourly piecewise constant k values has also turned out to be insufficient because the working periods are too different in time. Validation of the state-dependent model $k(P_0)$ shows satisfying accuracy on selected working periods outside the training set. Other working periods, however, especially ones with significantly different environmental conditions, experience larger errors – in some cases beyond 10%. This variance cannot yet be adequately explained with the current model. Additional influencing factors need to be examined more closely, especially ambient temperature, transport height and varying belt speed.

For calculating the net energy E_N, it is important to have accurate estimations for the idle power P_0, especially when working under rough conditions. It shows that, unlike in other related works [12], a one-time calibration of a constant P_0 value is not sufficient in real-world applications and instead a dynamic estimation must be carried out based on measured energy data. This enables to take into account transient environmental effects, like decreasing frictional resistance or

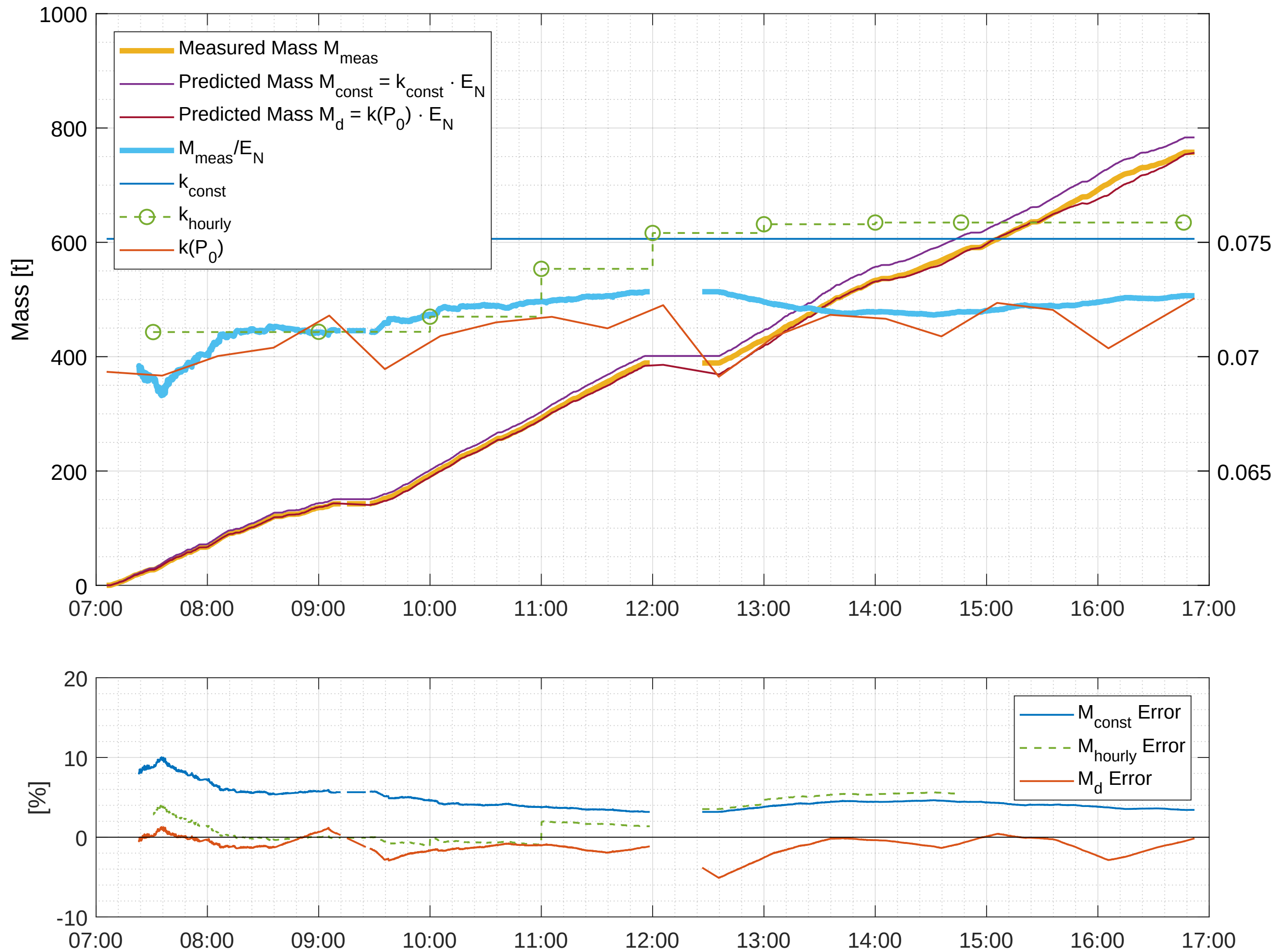

Fig. 4. Validation working period, again comparing k_{const}, k_{hourly} and $k(P_0)$.

weather conditions, which cause strong fluctuations in the power consumption.

When deploying the system in the field, where no reference measurements in the form of a belt scale or camera system are available, different methods can be employed to obtain reliable feedback about idle phases. For example, it might be possible to introduce periodic automated zeroing routines as part of the operational control system, e.g. having 30 sec. of idle time at the beginning of each working period. The denser these idle points are, the more reliably the actual P_0 can be determined.

Likewise, without a reference measuring system, no recalibration of the k model can take place. Here, ideally, a robust model can be trained on multiple machines that are equipped with a reference system, taking into account relevant external factors, after which the model may be transferred to other machines in the field.

VIII. Conclusion

In this work, we have presented our proposal for the design and implementation of a data-driven method for the indirect belt weight estimation based on power measurement of conveyor belts in mineral processing applications. In practice, the most notable advantages of this approach for measuring mass flow indirectly are twofold: The low cost of implementation compared to sensor-based solutions that require periodic recalibration and the ability to work under rough conditions including wind, rain, dust, vibration, or in general, any of the adverse situations one might expect to encounter in a mining environment and that could endanger the proper operation of the equipment.

We have compared different variants of modelling the k factor that describes the ratio between energy consumption and transported mass. The results show that it can be feasible to use a linear model with constant k factor, however, the achieved accuracy of often too low for practical applications, due to influencing environmental factors, such as ambient temperature or varying friction. Under such conditions, a model $k(P_0)$ depending on the idle power P_0 has shown to be more promising in selected working periods. Other working periods with significantly different environmental conditions, however, show significantly higher deviations, which is why accuracy and robustness of the model still need to be improved.

As future work, we intend to collect more measurement data in order to perform a more comprehensive statistical analysis on additional features. It is to be expected that a greater quantity and quality of collected data could provide us with an improvement on accuracy. The ultimate goal is to increase accuracy without incurring additional costs in terms of money, time or additional operator effort.

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