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Prediction of power consumption from real process data of an industrial wood chip refining plant

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Abstract:
Improving the efficiency of production processes is fundamental to minimize their environmental impact and energy consumption. The pulp and paper industry is a highly energy-intensive one that urgently needs to become more efficient, especially in the refining phase. In this framework, the model identification of a wood chips refining process operating in closed loop, pertaining to the production of Medium Density Fiberboard (MDF), is presented here, aimed to provide a long-term prediction of power consumption. We perform the identification via multi-batch Simulation Error Minimization (SEM), employing real process data collected on a large-scale MDF production plant during operation, without using sophisticated models or ad-hoc experimental sessions. The derived model obtains extremely high accuracy on a validation dataset while being simple enough to be used efficiently for production planning optimization. Moreover, it allows us to derive further models to predict the wear of the refiner disc, to be accounted for in a plant optimization procedure as well.

Keywords: Identification and signal processing, Manufacturing plant, Simulation error minimization, Refining process, Energy prediction model, Tool wear, Process data, Medium density fiberboard

1. INTRODUCTION

Automation represents a key instrument to increase the efficiency of all industrial sectors, improving production processes in terms of energy and material saving, affordability, and quality improvement, Li et al. (2013). Research in this field is aimed to minimize wasted energy and resources, which is an essential step towards the Sustainable Manufacturing (SM) goal, Jayal et al. (2010). Pulp and paper production is an important representation of an energy-intensive manufacturing process that urgently needs to become more efficient. In particular, the focus is on the refining phase, which accounts for most of the energy usage, close to 80% of the total, Talebjedi et al. (2021b). This phase is common to all processes that include wood fiber extraction, such as the engineered wood panel industry. In this context, our work deals with the modeling of a wood chips refining process operating in closed loop to produce Medium Density Fiberboard (MDF). The goal of the model is to provide a long-term prediction of energy consumption for the sake of production planning optimization.

In state of the art, a study on the modeling of the electrical energy usage of the overall refining system, with embedded low-level controllers and producing MDF panels, is missing to the best of the authors' knowledge. The literature is in fact very rich in works related to the paper industry, Du and Dumont (1996), Karlström and Hill (2018), Li et al. (2021), Qian et al. (1997), Rigatos et al. (2021), while the wood panel production field is not highly considered. The main differences in the refining process for MDF production with respect to paper are: the control of the pulp consistency, additional control inputs (e.g injection of water at the inlet of the refiner), usually two-stage refining, and different desired fiber properties. Moreover, most contributions are concerned with the control problem and consider only the main element of the process (i.e the refiner or defibrator). By modeling the refiner in open loop, and adopting the disc gap as a control input, the majority of papers aim to develop the low-level control logic, like in Schwartz et al. (1996), Harinath et al. (2011), Li and Zhou (2019). However, from the standpoint of planning and plant-wide optimization, typically such control logics are already developed and implemented by the supplier to regulate the subsystem at the desired reference working condition. Differently from the literature, we obtain a model that accounts for the (unknown) feedback controller operating in the plant, i.e. in closed loop operation. Our research is driven by living data gathered from a large-scale industrial plant for MDF production, during ordinary

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production and not by ad-hoc experimental sessions, which is very rare in the literature. One of the few works with long-term process data from an MDF plant is Gao et al. (2018), which deals only with the prediction of the product quality and not the energy usage.

Finally, we propose a novel strategy to predict the disc wear as detectable on the basis of the disc gap to be used in combination with the derived closed loop model of the plant.

2. PROBLEM DESCRIPTION

Considering the control-related aspects, one can discern two complementary levels of action for the sake of energy saving. At *low-level*, process efficiency can be improved through the use of advanced control techniques, capable to increase regulation performances, for example, using economic objectives in addition to the tracking one, Di Ruscio (1997), Harinath et al. (2011), Harinath et al. (2013), Li et al. (2021). At *high-level*, it is possible to act by scheduling the plant operations while keeping the process close to the best operating point with respect to the production plan (i.e the economic real-time optimization layer), Li and Zhou (2019), Qian et al. (1997).

In the field of thermomechanical pulping, the low level part has been investigated over the years, especially from an academic point of view, apparently without implementing and testing on real-world industrial production site Harinath et al. (2013), Du and Dumont (1996), Rigatos et al. (2021), Harinath et al. (2011), Huaijing Du et al. (1995). Moreover, due to all the difficulties involved in replacing low-level control logic with more advanced controllers, and the relatively small expected advantage, companies primarily ask for high-level decision-aiding tools to support operators in setting up the process. To meet this need, our research aims at identifying a model of the process operating in closed loop, in order to predict energy usage, starting from the living signals gathered from the plant.

2.1 Wood-chips refining process for MDF production

Medium-density fiberboard (MDF) panels are very common in the furniture assembly and joinery industry, and they mainly consist of wood fibers, which are extracted from raw wood chips. Among all processing stages, the refining process is the most responsible for energy consumption and for fiber quality, which primarily affects the property of MDF panels Olejnik (2013)). The refining plant is depicted in Fig. 1 and the related process consists of the following steps. Wood chips are transported into the pre-steam bunker or preheater, where they are collected and warmed. Next, they are pressed through a transport screw, called plug screw, that squeezes out the water they have absorbed while waiting inside the preheater. The material is moved to the second container, called the digester. Wood chips remain inside the digester for several minutes, affected by high temperature and pressure due to steam injection. This treatment is intended to soften the lignin bonds that trap the fibers. Then the mixture of wood chips and steam is gradually moved from the bottom of the digester by the discharge screw and transported through the feed screw to the defibrator inlet. The defibrator consists

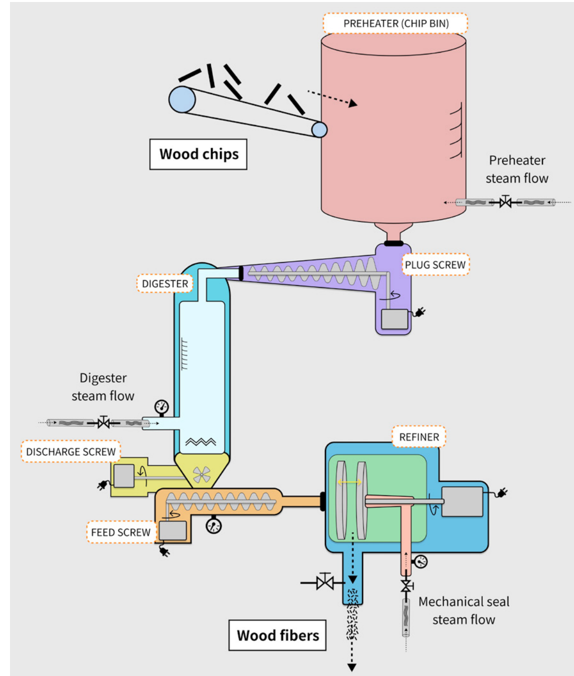

Fig. 1. Wood chips refining process, plant scheme

in a thermomechanical (TM) refiner, that separates wood fibers, freeing them from lignin bonds by the effect of heat and friction. The material is pushed through two plates provided with groves, of which usually one is fixed and the other is rotating at a constant speed (single-disc refiner).

In particular, the refiner motor and the plug screw motor are the two elements of the refining process that are more involved in electrical energy consumption. For these reasons, we aim at predicting their current usage. Indeed, we can use these quantities, coupled with the motor coefficients to compute the related electric torque.

2.2 Closed loop system

Performing a correlation analysis between the current consumption and the measure of the manipulable variables run by the operators, we have selected the following subset of input variables for the closed loop process: r_l denotes the setpoint signal of the relative level of material inside the digester (%), u_1 denotes the signal of the rotational speed of the discharge screw (rpm), u_2 denotes the mass flow of steam entering the digester (kg/s), u_3 denotes the reference signal for the Specific Energy Consumption (SEC) (MWh/t), u_4 denotes the value of the distance between the two refining discs (mm).

The plant operators act according to the following control strategy. *Production Rate:* This quantity is regulated by setting the discharge screw rotational speed (u_1). Usually, the Production Rate (PR) is assumed to be proportional to u_1, Talebjedi et al. (2021b), by considering the density of the material inside the digester as constant. *Fiber length:* The fiber length is the most challenging parameter to adjust. In industrial applications, it is controlled according to the Specific Energy Consumption (SEC). It provides a reliable measure of the refining intensity, being defined as the *"amount of refining energy received by the specific amount of refined stock during a single pass through the*

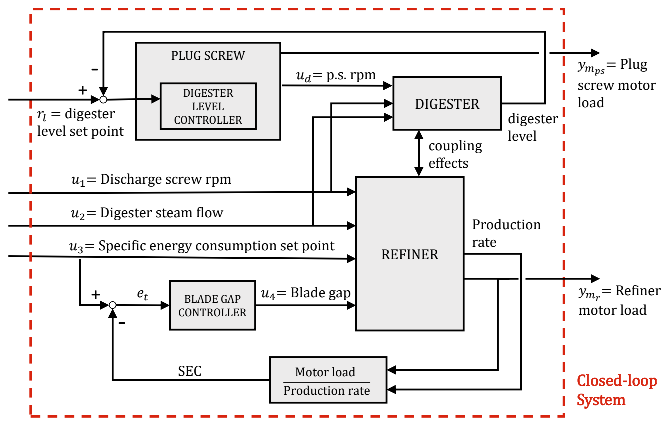

Fig. 2. Block diagram of the closed loop refining process

refining zone", Olejnik (2013), computed as the refiner motor load divided by PR. The motor load is governed by the distance between the rotating plates, which is changed automatically by the embedded low-level controller to track the SEC setpoint. Hence, u_4 is not an input variable of the closed loop system. The steam flow inside the digester is an additional parameter that the operators can use to manipulate the fiber quality, indirectly affecting the motor load. *Digester level:* The level of material inside the digester is regulated to avoid discontinuities in feeding the refiner and to handle the wood chips softening process by changing the rotational speed of the plug screw, denoted by u_d. Due to the digester level regulation, u_d is an internal variable of the closed loop system. The overall block diagram of the closed loop refining system is represented in Fig. 2, where r_l, u_1, u_2, u_3 are the input variables and where the output variables $y_{m_{ps}}$, y_{m_r}, are the plug screw motor load and the refiner motor load, respectively, expressed in terms of current consumption.

3. MODEL IDENTIFICATION

In this section, we will discuss the features of the identification process we performed, while in the next section, we will examine the validation results.

3.1 Data set

The data set used for the identification has been provided by a paramount worldwide MDF manufacturer. Signals have been gathered from the MDF line of a large-scale production plant, specifically, r_l, u_1, u_3, u_4 are obtained recording the reference signals from the control panel, while $u_2, y_{m_{ps}}$, y_{m_r} have been measured at the plant facilities.

The adopted sampling rate is 1(Hz) and it is common for all signals. The time length of the data set corresponds almost to five days of non-stop working, specifically to 116 hours and 47 min of continuous recording (i.e. $n \approx 4.2 \times 10^5$, where n indicates the number of samples for every single signal).

The data set is attached with many additional logic signals that characterize the operative status of the refiner machine, and these signals have been crucial to distinguish the section in which the plant is functioning actively (i.e during fiber production) from the section in which is working passively (i.e material rejection) or not working, such as during maintenance stops or process set up and testing operations. We removed from the data set all the intervals that belong to the second category. Therefore, we reorganized the data set into a collection of batches.

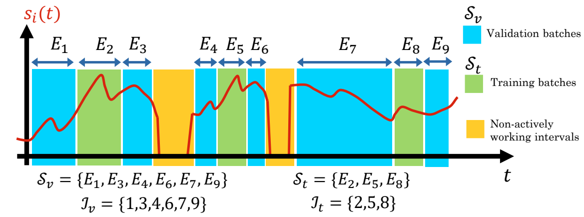

Fig. 3. Data set division into batches, in order to define the training and the validations sets, $\mathcal{S}_t$ and $\mathcal{S}_v$

We define the initial data set with $\mathcal{S}_i$, and with ${s_i}^{(k)}$ the k-th sample of the i-th signal, where $k = 1, 2, \ldots, n$ and $i = 1, \ldots, m$, denoting with m the number of signals. We recall that in our case the signals set consists in $\{s_1, \ldots, s_m\} = \{y_{m_{ps}}, y_{m_r}, r_l, u_1, u_2, u_3, u_4\}$. From this formulation, we get:

$$\mathcal{S}_i = \left\{\{{s_1}^{(1)}, \ldots, {s_1}^{(n)}\}, \ldots, \{{s_m}^{(1)}, \ldots, {s_m}^{(n)}\}\right\} \tag{1}$$

Hence, the reorganized data set $\mathcal{S}_r$ takes the following structure:

$$\mathcal{S}_r = \{E_1, \ldots, E_j, \ldots, E_{nr}\}$$
$$E_j = \left\{\{{s_1}^{(q_j)}, \ldots, {s_1}^{(p_j)}\}, \ldots, \{{s_m}^{(q_j)}, \ldots, {s_m}^{(p_j)}\}\right\} \tag{2}$$

where nr is the number of batches, E_j is the j-th batch, and q_j, p_j, are the indexes of the initial and of the final sample, respectively, associated with that batch. In particular, q_j and p_j are selected such that during each interval $[q_j, p_j]$ the refining plant is working actively without any interruption. We performed an evenly spaced interval division by choosing the number nr of batches and the related q_j and p_j values, and without intervals overlapping or leaving gaps along an active production phase.

The number of the remaining samples in $\mathcal{S}_r$ for each individual signal is $\approx 4.15 \times 10^5$ (i.e the length of the reorganized data set), and we decided to use 17% of the data set for the identification set while the remaining 83% for the validation set, to obtain a highly robust model. The structure of the training set $\mathcal{S}_t$ and validations set $\mathcal{S}_v$ is the same as the reorganized data set. The set creation is performed by assigning each batch $E_i \in \mathcal{S}_r$ only to one between $\mathcal{S}_t$ or $\mathcal{S}_v$, with nt denoting the number of elements in the training set, and nv the number of elements in the validation set. We use $\mathcal{I}_t$ and $\mathcal{I}_v$ to point at the set of batch indexes that belong to $\mathcal{S}_t$ and $\mathcal{S}_v$, respectively. The division must be consistent with the selected training-validation proportions. The data set structure is explained in Fig.3, and the two sets are described as follows:

$$\begin{aligned}
\mathcal{S}_t &= \{E_j : j \in \mathcal{I}_t\} \\
\mathcal{S}_v &= \{E_j : j \in \mathcal{I}_v\} \\
\mathcal{I}_t \cup \mathcal{I}_v &= \{1, \ldots, nr\} \\
\mathcal{S}_t \cup \mathcal{S}_v &= \mathcal{S}_r \\
\mathcal{S}_t \cap \mathcal{S}_v &= \emptyset
\end{aligned} \tag{3}$$

3.2 Model structure

The relationship between the motor load and the disc gap is strongly nonlinear, as described by the characteristic curves proposed in the literature Harinath et al. (2013). Furthermore, the system is time-variant due to the gradual wear of the disc's working surface. A solution to this problem is to develop a short-term model and then a long-term model that explicitly introduces time dependence and corrects the drift of the time-invariant model Talebjedi et al. (2021b) Lama et al. (2006). In addition, the system is subjected to high uncertainty due to the variability of the raw wood quality, (e.g. wood species, chip bulk density).

On the contrary, the identification of the closed loop system allows us to easily overcome many of the problems highlighted above. In fact, under the assumption of a properly designed SEC controller, the process is kept within an almost steady operating point, imposing to work close to the linear condition. Moreover, the wear of the discs is compensated by the integral control action, which progressively reduces the disc gap as the wear increases, in order to reestablish the reference value of refining intensity. In this way, the closed loop process can be easily assumed as a time-invariant system, without the necessity of a separation between short-term and long-term models. In addition, the closed loop system partially rejects the disturbances due to the variability in the material quality.

The previous statements have been empirically verified from the good performances obtained by adopting a linear, discrete, time-invariant, dynamical model for the identification both of the refiner motor current and the plug screw motor current. The choice of this model structure is also justified by the need of obtaining a model that can be easily employed in an optimization problem and whose parameters can be easily updated. The preference for black-box identification w.r.t. a first principle modeling is due to the unknown structure of the low-level controllers and to the high complexity in developing an accurate physics-based model for this kind of industrial process Talebjedi et al. (2021a).

Hence, we adopted two MISO ARX models featuring 3 inputs, that are collected in the following input array $\mathbf{u}(t) = [u_1(t) \quad u_2(t) \quad u_3(t)]^T$, both in refiner and plug screw cases. We discard the setpoint signal for the digester level r_l, because it consists only of a constant reference value and therefore it is irrelevant to the identification process. Furthermore, t is the discrete-time instant and $[\dots]^T$ represents the matrix transpose operation.

The general output value $\hat{y}$ of the model indicates $\hat{y}_{m_r}$ for the model of the refiner motor current and $\hat{y}_{m_{ps}}$ for the model of the plug screw motor current. The general model form is:

$$\hat{y}(t+1) = \hat{\varphi}(t,\theta)^T\theta \tag{4}$$

in which θ is the array of the model parameters to be estimated, with the form:

$$\theta = [\theta_y^1, \dots, \theta_y^{na}, \theta_{u1}^1, \theta_{u2}^1, \theta_{u3}^1, \dots, \theta_{u1}^{nb}, \theta_{u2}^{nb}, \theta_{u3}^{nb}]^T \tag{5}$$

Specifically, we have selected the order na and nb of the input and output variables featuring the two models by iterating the identification process for increasing values. We select them in terms of a trade-off between performance improvement and model complexity. For the refiner motor current, we adopt $na = 1$ and $nb = 2$, while for the plug screw motor current, we adopt $na = 2$ and $nb = 3$.

The model regressor $\hat{\varphi}(t,\theta)$ takes the form:

$$\begin{aligned}
\hat{\varphi}(t,\theta) &= \begin{bmatrix} \hat{Y}(t,\theta) \\ \hat{U}(t) \end{bmatrix} \\
\hat{Y}(t,\theta) &= [\hat{y}(t) \ \hat{y}(t-1) \ \dots \ \hat{y}(t-na+1)]^T \\
\hat{U}(t) &= \left[\mathbf{u}(t+1)^T \ \mathbf{u}(t)^T \ \dots \ \mathbf{u}(t-(nb-1)+1)^T\right]^T
\end{aligned} \tag{6}$$

Notice that we express the model regressor $\hat{\varphi}(t,\theta)$ as a function of the parameters vector in order to point out that $\hat{y}(t)$ is computed in free-run simulation. It depends on previous values estimated by the same model (i.e. φ contains the past values of the simulated output and not the measured ones).

3.3 Multi-Batch Simulation Error Minimization

We choose to perform the estimation of the model parameter in Eq. 4, adopting the Simulation Error Minimization (SEM) approach with a multi-batch strategy. The problem consists of computing the best parameter values that minimize the Mean Squared Error (MSE) between the measured output and the simulated one, for all the training batches $E_j \in \mathcal{S}_t$ concurrently. This strategy is to be preferred w.r.t. the Prediction Error Minimization (PEM) when the purpose of the model is to perform a free-run simulation (e.g. in our case we need to provide the long-term prediction of the current consumption). In any case, it shows better general performances than PEM, especially for output error models (such as in the case of measuring error), and it is largely confirmed to be more robust Aguirre et al. (2010).

As a drawback, SEM method is more computationally intensive, the optimization problem is nonconvex and the relation between the model parameters and the resulting computation of the output values along the simulation horizon is strongly nonlinear, Tobenkin et al. (2010). This problem is not heavily effective when we are dealing with few parameters, as in our case. Furthermore, it is possible to adopt global optimization algorithms to overcome this problem. We used a randomized multi-start strategy to improve the quality of the solution.

Performing the SEM identification with a multi-batch approach allows the use of a more informative training set, computing the best fitting parameters for different operating conditions, and at the same time making the identification more robust in case of localized measure or process disturbances. Furthermore, it avoids catching the residual time-depending drifts in the system behavior that are not immediately compensated by the low-level controllers. Before performing the identification, the signals have been normalized. In addition, we set $t_u = 5s$ as the time step value for the discrete-time model. Hence, according to the selected t_u, we re-sampled the initial data set $\mathcal{S}_i$, so as the resulting sets $\mathcal{S}_r$, $\mathcal{S}_t$, $\mathcal{S}_v$, and the related batch indexes (i.e. q_j, p_j), are consistent with the model.

The SEM optimization problem is a nonlinear unconstrained problem with a quadratic cost function $J(\theta)$, fea-

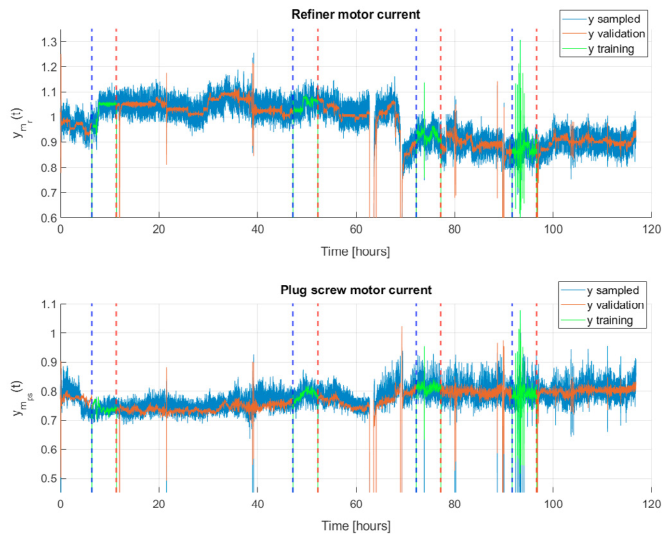

Fig. 4. Comparison between the measured signal (blue), simulation along the training (green), and validation batches (orange). (Normalized values for confidentiality reasons)

turing the function of the simulation errors $F_j(\theta)$ related to the simulation along the j-th training batch, consisting in:

$$J(\theta) = \sum_{j \in \mathcal{I}_t} F_j(\theta)^T F_j(\theta)$$
$$F_j(\theta) = \begin{bmatrix} y(q_j + ni) - \hat{y}(q_j + ni) \\ \dots \\ y(p_j) - \hat{y}(p_j) \end{bmatrix} \tag{7}$$

where $y(t)$ is the measured value of the output, while $\hat{y}(t)$ is the simulated one from the model described by Eq.4. Moreover, the model regressor $\hat{\varphi}(q_j + n_{in}, \theta)$ is initialized at the beginning of each training batch with the measured values, and n_{in} is the number of steps needed for the initialization, computed as $n_{in} = max\{na, nb - 1\}$. In conclusion, the quadratic unconstrained optimization problem is formulated as:

$$\min_{\theta} J(\theta) \tag{8}$$

We used a Sequential Quadratic Programming (SQP) algorithm to compute θ, due to the nonlinear nature of the problem. In particular, we adopt an unconstrained Gauss-Newton approach, which is efficient in solving Nonlinear Programming in a quadratic form, like the SEM problem described above, Messerer et al. (2021). The results obtained in the training phase will be discussed together with the validation performances in the next section.

4. VALIDATION PERFORMANCES

The comparison between the measure and the simulation of the refiner and plug screw motor current has been reported in Fig. 4. For the identification, we use $nt = 4$ training intervals, each one 5 hours long. The batches related to the training phase are colored in green, while the ones related to the validation phase are colored in orange. The blue line indicates the measured signal. Table 1 provides model performances, where MSE is the Mean Squared Error, while MPE is the Mean Percentage Error, computed as $\sqrt{MPE}/\bar{y}$.

Table 1. Model performance

Output	Training		Validation	
	MSE	MPE	MSE	MPE
y_{m_r}	6.51×10^{-4}	2.62%	$7,94 \times 10^{-4}$	2.89%
$y_{m_{ps}}$	13.34×10^{-4}	4.69%	$7,97 \times 10^{-4}$	3.63%

The two models proved to perform well for the long-term prediction of current consumption, without a significant difference between the validation set and the training set, (e.g plug screw model performs even better in validation, due to a proportionally larger presence of unexpected phenomena in the training set w.r.t the validation set, such as sudden occlusions or errors in digester level measuring). Furthermore, from the residual analysis, we point out that in both cases they are close to a Gaussian distribution with almost zero mean.This result entails that when the models are used to compute the total current usage, by integrating the simulated current values, the model error is negligible. The obtained validation residuals could be explained as the stochastic component of the process, due to the uncertainty in the raw material quality, which is not perfectly rejected by the low-level controllers.

5. DISC WEAR PREDICTION

As mentioned in section 2.2, the disc wear is compensated by the control action of the SEC regulator, which reduces the distances between the two discs in order to overcome the slow decrease of the refining intensity. In previous works, dealing with open loop models, the long-term behavior of the torque has been modeled by making explicit the time dependence, otherwise the disc wear effect is simply ignored. Considering the case of a closed-loop system, we suggest modeling the disc wear in terms of the disc gap, which is set by the regulator to keep the process at the desired operating point. The time drift depends on the operating conditions, such as the PR and the SEC reference. Furthermore, instead of representing the disc wear as a function of the elapsed working time, we propose to estimate it w.r.t the total power consumed. Thus, we are able to adopt the model we have already identified for predicting the refiner motor current in order to feed the blade gap predictive model.

In Fig.5 we present the results of a preliminary test on the identification of the position of the discs. We use almost 30% of the data set for the training set and a first-order, LTI, dynamic model structure. The inputs selected for the identification are the SEC reference signal, the discharge screw rotational speed, and the refiner's total current consumption. In the figure, we distinguish the case in which we are estimating the disc gap using the measured current to compute the energy consumption (red line) and using the model estimated current (yellow line). As can be noticed in the figure, this method can be successfully used to predict when the disc position will reach the limit.

6. CONCLUSION AND FUTURE WORKS

The refiner and plug screw motor current models have been identified and validated with excellent results, sufficiently accurate to provide a long-term prediction of electrical power consumption (motor currents MPE ≈ 3%). Furthermore, the combined use of the refiner motor current

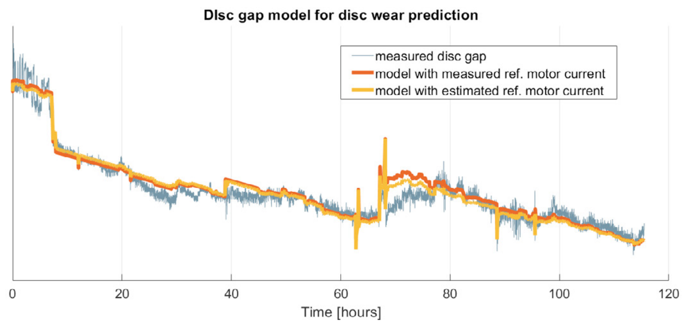

Fig. 5. Model for predicting the disc gap drift in order to measure the tool wear. Dimensionless for confidentiality reasons

model and the blade gap model has revealed promising results in predicting disc wear and needs further investigation.

In the next steps, we aim at providing a real-time multi-objective economic optimization of the process, that will deal with the trade-off between reducing energy consumption, increasing fiber quality, production rate, and extending the life of the refiner discs. That process will compute the best setpoint values for the low-level controllers, feeding the closed loop model of the refining process, which we aim at completing by adding the prediction of the fiber quality.

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