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Procedia Technology 00 (2016) 000–000
Procedia Technology
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3rd International Conference on System-integrated Intelligence: New Challenges for Product and Production Engineering, SysInt 2016

Design and Implementation of Intelligent Control Software for a Dough Kneader

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Abstract

In traditional dough kneading machines the ingredients, e.g. flour, water, salt and yeast are filled into a cylindrical vessel and mixed by means of a rotating spiral. In order to assure consistent dough quality while environmental conditions and flour characteristics vary, an experienced baker needs to 1) manually set the rotational speed as well as the time for kneading and 2) continuously monitor the kneading process. The overall goal of this work is to develop an intelligent kneading machine that autonomously decides how to set the speed and when to stop kneading. This machine assists the bakers work and allows for more efficient use of kneaders as part of autonomous production systems. We describe the design of intelligent information processing algorithms that were implemented in a technology demonstrator and validated with the expertise of professional bakers. While focusing on the control software, the underlying concepts are explained and relevant results are shown. In particular, reliable detection of phase-shifts and model-based prediction of dough properties was achieved.

Keywords: autonomous dough kneading process; dough model; detection of kneading phases

1. Introduction and motivation

In industrial bakeries, dough is kneaded in batches when relatively small amounts of dough with varying recipes are needed. Therefore, so-called batch mixers are typically found in craftsman's businesses. Nevertheless, because of their flexibility, they also come to use in the context of automated production plants with high performances. Spiral kneaders in particular can produce either wheat-flour, rye or rye-wheat dough [1]. For this purpose, the ingredients are filled in a bowl, in which the spiral kneading tool is located. Then, usually both the bowl and the spiral are rotated to initially produce a nearly homogeneous mixture (mixing phase). This is a prerequisite for good baking results and is done using lower rotational speeds. After approximately 2–3 minutes, speed is increased and the 6–8 minute kneading phase begins, during which proteins form the gluten network. To obtain optimal dough, which can be characterized

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2212-0173

e.g. by fermentation stability, a certain amount of mechanical energy is necessary. While under-kneading results in insufficient gas retention capacity of the dough, the gluten network is destroyed when kneading is considerably too long (over-kneading). The latter leads to reduced water absorption capacity and impairs the dough's ability to rise. Dough becomes dry and inelastic with a rough structure [1].

The two phases and the corresponding speeds of bowl and spiral are usually controlled using a time-based approach. This relies on fixed time intervals, which are set in advance. However, dough is a natural product and the essential ingredient, flour, is often subject to high variations in quality. The mixing ratio of wheat and the quality and amount of the contained gluten significantly influence the necessary kneading time and the resulting baked volume for example. Furthermore, depending on the number of mechanically damaged starch granules and the gluten content, water absorption of the flour can vary between 35 and 75 % of the dry weight [2]. Additionally, environmental conditions (e. g. room temperature) as well as the quality of the remaining ingredients are far from constant. These issues currently make the expertise of experienced bakers indispensable. They continuously monitor and control the kneading process with the objective of achieving constant dough quality, which is a prerequisite for steady industrial processes and excellent baked goods. However, the fact that baker's judgment is based on subjective optical and haptic impressions can also impede reproducibility. Today, clinical measurements can only be performed after stopping the process (c. f. [3]). While in practice, this situation still results in varying properties of the dough, the principle feasibility of drawing rheologic conclusions from online-measurements of e. g. the spiral-torque has been suggested [4]. However, a control software, which determines these information in industrial kneaders and which is capable of dealing with high disturbance ratio appearing in the signals, is yet to be found. The goal of this work is therefore to design intelligent information processing that continuously determines the actual dough characteristics and autonomously controls the kneading process. Focusing on wheat-flour dough, a number of measurements were performed to this end. They constitute the basis of a model-based design process. In its course, expert bakers evaluated the outcomes and helped towards identifying characteristic points and signals.

2. Measurements

Designing the test bench, we paid a great deal of attention to ensure transferability of our findings to series-production kneaders. Thus, it was derived from the ECO 50 mixer of WP Kemper and noninvasive measuring facilities were chosen. This spiral kneader has a bowl with a capacity of up to 50 kg of flour and is equipped with a "guide bar". The latter is responsible for a frequent change between oxygen and energy input (3-zone-mixing concept) and integrates a platinum resistance sensor (PT 100) that measures the dough temperature. Contrary to the ECO 50 mixer, servo-drives were used and belt drives were replaced with a bevel helical gearbox. This allows reproducible control of the revolution speeds as well as the determination of drive torque and angular position. Furthermore, a measuring flange measures the torque of the spiral at the output end. All measurements and the subsequent studies were performed using constant proportions of the dough ingredients. Exemplary, the following recipe for conventional rolls was chosen: 25 kg wheat flour (German flour type No. 550), 14.5 l water, 0.5 kg salt, 0.75 kg bakery improver ("Malzperle") and 0.5 kg yeast. To ensure a homogeneous mass before starting to knead (parts of) the dough, as well as to reduce flour dust and the risk of explosions, the spiral is rotated counter-clockwise at a lower speed of 110 rpm. As a guide value one can assume a mixing time of 3 minutes followed by approximately 7 minutes of kneading at a rotational speed of 220 rpm. However, in order to be able to exactly determine the varying point of optimal dough after the measurements, kneading time was considerably longer and dough was heavily over-kneaded. Meanwhile, the bowl rotates in the same direction at a constant speed of 12 rpm throughout the entire kneading process.

3. Modeling of dough in the kneader

Informative simulation models constitute the basis for many modern, intelligent information processing algorithms. They facilitate efficient, fast and reproducible tests and help to increase system knowledge. Furthermore, values that are not directly measurable can be inferred/observed by means of physical models. Regarding the complex interactions between the kneader and the dough, one particularly has to find a sufficient level of detail that fits the underlying tasks or questions. To describe the (rheologic) behavior of fully formed dough, a variety of different modeling approaches exist (c. f.[5–8]). These are compared with measurements, which are performed by means of rheometric instruments.

However, little is known on how to describe the change of rheological properties during kneading. Also, the influence of yeast is often neglected. Therefore, it remains questionable whether results are directly applicable to the geometry of an actual kneader. On this account, Shehzad et al. perform measurements with a small spiral kneader [9]. Here, the energy input with reference to the dough mass (specific energy input) is varied and the resulting temperature rise is analyzed. Furthermore, a relatively simple energy balance to calculate the dough temperature at the end of the kneading process is derived. The presented results therein suggest that the specific energy input E_S is a suitable reference, which is independent of the operating speeds and the dough mass.

3.1. Torque-energy-curve

It was found that the mechanical resistance of the dough contains important information and can be used to characterize the current state of the kneading process. Dough resistance, however, is mainly visible in the torque signal of the kneading tool M_t. On the contrary, the rotation of the bowl is primarily responsible for achieving uniform transportation of the dough into the kneading zone. Consequently, the torque M_b to be applied for this purpose oscillates around a roughly constant value. This was therefore neglected to describe the mechanical properties of the dough in the following. For the same reason, the introduced dough strain is related to the differential speed of kneading tool and bowl. In order to be able to compare and evaluate the various measurements carried out, we determine the effective dough resistance M_d and then the relation to the specific energy E_S is investigated (c. f. Figure 1). For this purpose, the signal is smoothed offline using a zero-phase low-pass filter in a first step. Secondly, we subtract losses of the drive train (M_{loss}). To describe this frictional torque an idealized model is assumed and parameters are identified by conducting measurements with an empty bowl. Thus, we obtain:

$$M_d = M_t - M_{loss} = M_t - (d_{fric} + M_0)$$

Multiplying M_d with the relative angular velocity and integration over time yields the specific energy E_S. Figure 1 exemplarily shows the dough torque M_d in relation to the specific energy for 6 different measurements. It can be seen that the initial temperature of the water has a decisive influence on the torque curve. While the plots of measurements with similar initial water temperatures T_{w0} are approximately congruent, a shift towards lower energy and torque levels can be observed at higher initial temperatures. Regardless of the temperatures, we observe qualitatively similar curves with a clear maximum. This marks the point of optimal dough, where gluten network is completely formed and thus the dough offers the greatest mechanical resistance. To describe the relationship between the specific energy and the dough torque M_d an averaged torque-energy-curve was created (see Figure 1). Here, we included all the measurements with an initial water temperature within the defined tolerance range of 3–7 °C. The characteristic specific energy at which the maximum is reached can then be specified with approximately $\overline{E}_S = 22.5\,\mathrm{kJ/kg}$.

3.2. Idealized dough model

In the face of constantly changing dough properties, environmental conditions, and complicated chemical relationships that are heavily dependent on the natural ingredients, their composition and quality, it seems almost impossible to describe the dough in its entirety and for all its states. A dynamic model that can be used in the system context, therefore, can not be formulated entirely independent of the prevailing conditions in the special kneader at hand. Thus, a combination of physical and empirical description of the dough is selected. The starting point is the average characteristic curve (c. f. Figure 1), which gives the nonlinear relation $f(E_S)$ and forms the basis of an idealized continuous model (Equation 1). Here, the introduced mechanical power $P_{d,mech}$ is determined by the product of current speed ω and low frequency dough torque $M_{d\varphi}$. This is divided by the dough mass m_d and is integrated to obtain the specific energy. The engine torque can then approximately be determined by summing the friction losses and taking the gear ratio i into account. Figure 2 (a) shows a comparison of simulation and measurement.

$$\begin{aligned} M_{d\varphi} &= m_d \cdot f(E_S) \\ E_S &= \frac{1}{m_d} \cdot \int P_{d,mech}\,\mathrm{dt} \approx \frac{1}{m_d} \cdot \int M_{d\varphi} \cdot \omega\,\mathrm{dt} \end{aligned} \tag{1}$$

In order to display the dough temperature, the model was expanded based on the energy balance of Shehzad et al. [9]. Herein, the warming of the dough through mechanical power is described. Additionally, a monitored time lag in

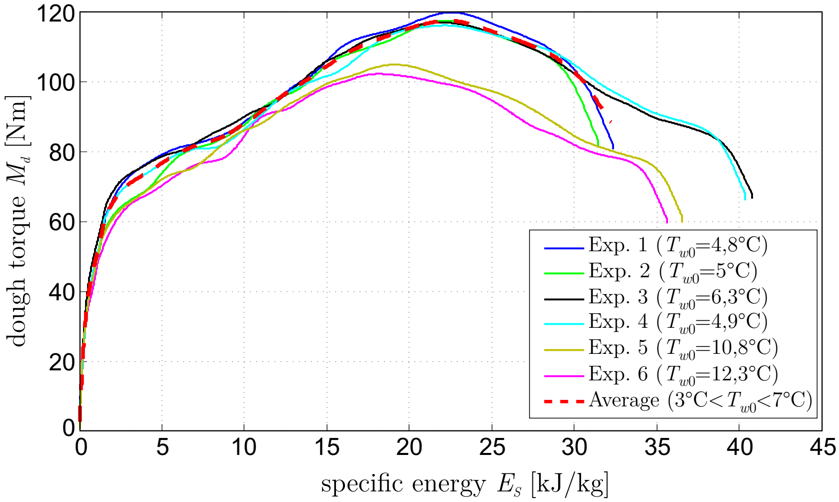

Fig. 1. Average characteristic curve shown for six exemplary kneading trials.

the heating was reflected by inserting a first order delay element, which has a time constant that varies depending on the specific energy input. The parameter variance may be explained by different temperature fields over time. While in the mixing phase the average warming is relatively slow because of an inhomogeneous temperature distribution, the more uniform temperature distribution towards the end of the kneading process causes a faster temperature rise. Consequently, we formulate the following equations for thermal power $P_{d,therm}$ and the dough temperature T_d in the Laplace domain:

$$\begin{aligned} P_{d,therm} &= P_{d,mech}\,\frac{1}{T(E_S)\cdot s+1} - P_{d,loss} \\ \Leftrightarrow T_d &= \frac{1}{m_d\,C_p\cdot s}\left(M_{d\varphi}\cdot\omega\frac{1}{T(E_S)\cdot s+1} - h_d\,S_d\cdot(T_d - T_{env})\right) \end{aligned} \tag{2}$$

Here, C_p is the specific heat capacity, h_d depicts the heat transfer coefficient for the heat exchange between the dough and the surrounding area and S_d represents the dough surface that results from the filling height and the bowl diameter. The unknown parameters were identified by parameter optimization algorithms (see Figure2 (b), red curve). The green plot corresponds to a parameterization of the model with the literature parameters from [9]. It is a prerequisite for the accuracy of the temperature model that the approximations, namely a homogeneous mass and uniform temperature distribution, are valid. This is only given after the mixing phase, which therefore delimits the scope of this part of the idealized dough model. During the kneading phase there is a very good agreement between simulation and measurement.

4. Information processing

The control software has to process the recorded sensor signals and calculate appropriate reference values for the servo-drives of bowl and spiral in order to operate the kneading process. It consists of three parts: "Detection", "Control" and "Prediction". In this paper, we focus on the detection part that identifies the phases during kneading. On this basis, reference signals for the rotational speeds are derived. Additionally, to predict the expected end of the kneading phase and the final dough temperature, the aforementioned idealized model is used (c. f. Section 3). For this purpose, the differential equations are initialized with the current input values and integrated numerically using an explicit Euler algorithm until the point of optimal dough is reached. The resulting predicted values are updated every 5 seconds.

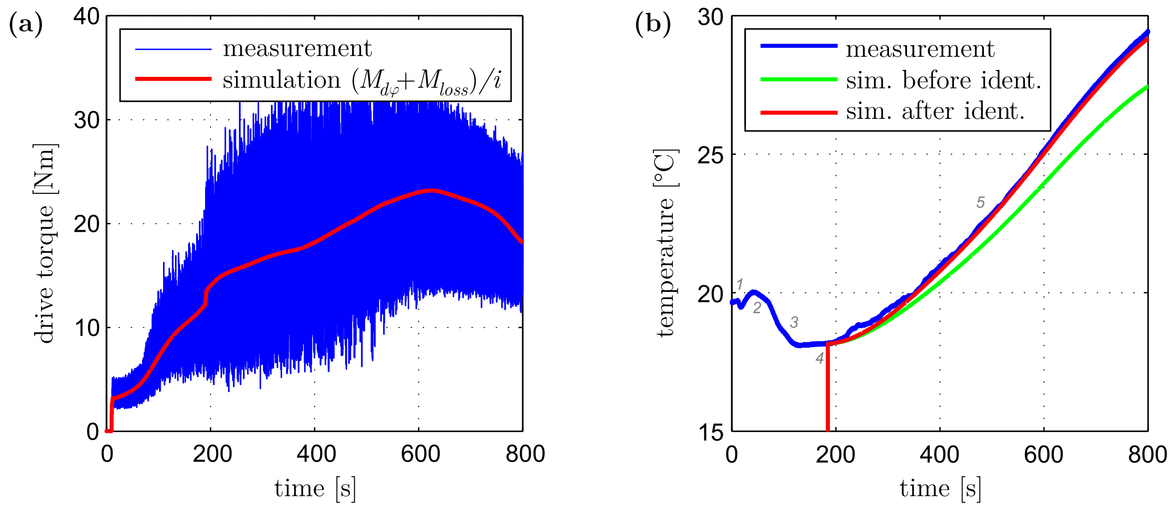

Fig. 2. Comparison of measurement and simulation results for (a) drive torque and (b) dough temperature before and after parameter identification.

To identify the separate kneading phases, different methods have been developed which either refer to individual sensor signals (signal-based approach) or base on the recognition of a learned relationship between various signals (data-driven approach).

4.1. Signal-based detection

The information processing receives the measured signals of the torque, speed and temperature as input variables. Based on these time series, the current state of the dough shall be evaluated. Therefore, criteria for the completion of both the mixing and the kneading phase have to be derived.

4.1.1. Mixing phase

While on the one hand the mixing phase should be as short as possible to save time, it should not be ended too soon on the other hand in order to ensure a good homogenization and to avoid flour dust. For the completion of the mixing phase, the dough temperature signal was found revealing. In most cases, a very characteristic signal curve becomes apparent (c. f. Figure 2 (b)). This can be explained as follows: At the beginning of the measurement the temperature sensors is surrounded with warm flour (1). After more or less random temperature fluctuations (2) resulting from inhomogeneity, one can see a cooling phase (3) because of the different initial temperatures of flour and water. However, the theoretical mixing temperature is not reached because frictional heat is introduced and a saturation effects occur. Thus, a distinct temperature minimum (4) results, which we used as a criterion for good mixing. Once it is detected mixing may be terminated, speed of the spiral is doubled and the kneading phase begins. While kneading, further heating of the dough can be observed, because of the continuous energy input (5).

4.1.2. Kneading phase

During the kneading phase, gluten structures are formed in the dough, so that the kneading resistance rises slowly and results in a maximum, which simultaneously represents a maximum dough viscosity. Exceeding this point will destroy the structure and deteriorate the final product. The maximum of dough resistance can therefore be used as a criterion for stopping the kneading process. Retrospectively, this point in time can easily be determined using the offline-filtered torque profile seen (see Figure 2 (a)). However, the information processing should already be able to intervene in the course of the kneading process and thus offline filtering is not applicable. Online detection of this phenomenon in real-time is highly complex though, because the dough characteristics are still inhomogeneous and constantly varying. In addition, the asymmetric spiral and inconstant contact between the spiral and the dough lead to high disturbance ratio. Consequently, the measured variables are too noisy to identify the criteria in a simple way. Filtering with time constants that would sufficiently smooth curves for safe detection would certainly result in unacceptable delays. Therefore, four different combinations of filtering techniques and model-based observers were applied to get smoothed curves with the lowest possible phase. The four signal-based methods (M1-M4) rely on different approaches and provide criteria in the form of Boolean signals b_i. But still, false detections remain possible. To increase the reliability, each of them is multiplied with a sigmoid function that reflects the probability of optimal dough using the characteristic specific energy amount $\overline{E}_S$ (see Equation 3). The combined criterion

$$\kappa = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{1 + e^{-(E_S - \overline{E}_S)}} \cdot b_i \tag{3}$$

superimposes the resulting n criteria by averaging them. The end of the kneading phase is detected when κ reaches a threshold $\overline{\kappa}$, i.e. $\kappa \geq \overline{\kappa}$.

Method 1. Different filters were constructed and tested in order to get a reasonable compromise between acceptable reliability of maximum detection and a tolerable time delay. As a result of that, a discrete moving average filter (MA), which calculates the mean value of all samples in a moving window of 10 s, was chosen. It constitutes the first and easiest way to partially eliminate some of the noise in the torque signal.

Method 2 and 3. The second and third extraction method use a linear model-based observer, which calculates counteracting torques from the dough based on the measurement of the engine torque. It can be assumed that the dynamic dough torque M_d consists of a viscosity-dependent, low-frequency damping part $M_{d\varphi}$ and high-frequency parts $M_{d\omega}$. The latter result from the elasticity of the dough, which is subjected to cyclic squeezing through the small gap between kneading tool and bowl wall. The dough torque however can be considered as a disturbance when attempting to control the driving speed. Consequently, disturbance observers are formulated for each of its components. For the low-frequency torque a piecewise constant form is adopted. During kneading, both the elastic force and the lever arm oscillate with respect to the drive axis. Furthermore, the rotation of the spiral is kept approximately constant during kneading with $\omega_t(t) \approx \omega_k = 3.67\,\text{Hz}$. The result is that two dominant frequencies appear in the signal at $\omega_1 = \omega_k$ and $\omega_2 = 2\omega_k$. The observer formulation summarizes the individual dynamics and feeds back the estimation error between the observed and the measured engine torque. Friction and the spiral inertia J is incorporated by a direct feedthrough:

$$\underline{\dot{\hat{x}}} = \begin{bmatrix} \dot{M}_{d\varphi} \\ \dot{M}_{d\omega,1} \\ \ddot{M}_{d\omega,1} \\ \dot{M}_{d\omega,2} \\ \ddot{M}_{d\omega,2} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & -\omega_k{}^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & -(2\omega_k)^2 & 0 \end{bmatrix} \cdot \begin{bmatrix} M_{d\varphi} \\ M_{d\omega,1} \\ \dot{M}_{d\omega,1} \\ M_{d\omega,2} \\ \dot{M}_{d\omega,2} \end{bmatrix} + \underline{L} \cdot (M_t - \hat{M}_t)$$

$$\hat{y} = \hat{M}_t = [\,1\;\;1\;\;0\;\;1\;\;0\,] \begin{bmatrix} M_{d\varphi} \\ M_{d\omega,1} \\ \dot{M}_{d\omega,1} \\ M_{d\omega,2} \\ \dot{M}_{d\omega,2} \end{bmatrix} + [\,J\;\; d_{fric}\;\; 1\,] \begin{bmatrix} \dot{\omega}_t \\ \omega_t \\ M_0 \end{bmatrix} = \underline{C}\,\underline{\hat{x}} + \underline{D}\,\underline{u}$$

The observer dynamics can be designed by choosing the matrix L. Methods 2 and 3 only differ with respect to the design criteria of the observer matrix. While the eigenvalues were placed according to Luenberger in method 2, a continuous Kalman filter was chosen as method 3. In both cases detection of optimal dough takes place by means of the low-frequency torque $M_{d\varphi}$. In order for it to be smooth, the corresponding eigenvalue or weighting factors were kept small.

Method 4. In analogy to the model above (c. f. Equation 2), an observer can be formulated, which uses the measured dough temperature to reconcile with reality. Herein, the low-frequency torque of the dough $M_{d\varphi}$ is also represented by a piecewise constant disturbance model (Equation 4). In this case, the high frequency components need not be modeled, as these frequencies are not reflected in the measured temperature signal anyway. Due to the limited validity of the chosen approach (see above) for inhomogeneous dough, the estimated torque is only significant in the kneading phase and accuracy of the estimation increases with time (see Figure 4).

$$\underline{\dot{\hat{x}}} = \begin{bmatrix} \dot{M}_{d\varphi} \\ \dot{T}_d \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ \frac{\omega_S}{m_d C_p} & -\frac{h_d S_d}{m_d C_p} \end{bmatrix} \cdot \begin{bmatrix} M_{d\varphi} \\ T_d \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{h_d S_d}{m_d C_p} \end{bmatrix} T_{env} + \underline{L} \cdot (T_d - \hat{T}_d)$$
$$\hat{y} = \hat{T}_d = [0\ 1] \begin{bmatrix} M_{d\varphi} \\ T_d \end{bmatrix} \tag{4}$$

4.2. Detecting kneading phase transitions with a data-driven model

Complementary to the physical modeling, we also follow a data-driven modeling approach to detect the end of the mixing and kneading phase based on sensor readings. Data-driven modeling based on machine learning techniques is agnostic to the actual physical process and solely relies on regularities of the kneading process reflected in the data. Detection of kneading phases is formulated as supervised classification problem, where sensor readings $\mathbf{x}(k)$ at time step k are assigned to one of three classes $c(k) \in \{C_1$ (mixing phase), C_2 (kneading phase), C_3 (kneading finished)$\}$.

The following sections focus on two important questions for the development of a data-driven kneading phase detector: Firstly, which sensor channels are relevant predictors to detect phase transitions of the kneading process? Secondly, how well do learned kneading phase detectors generalize to novel kneading data that was not used for training?

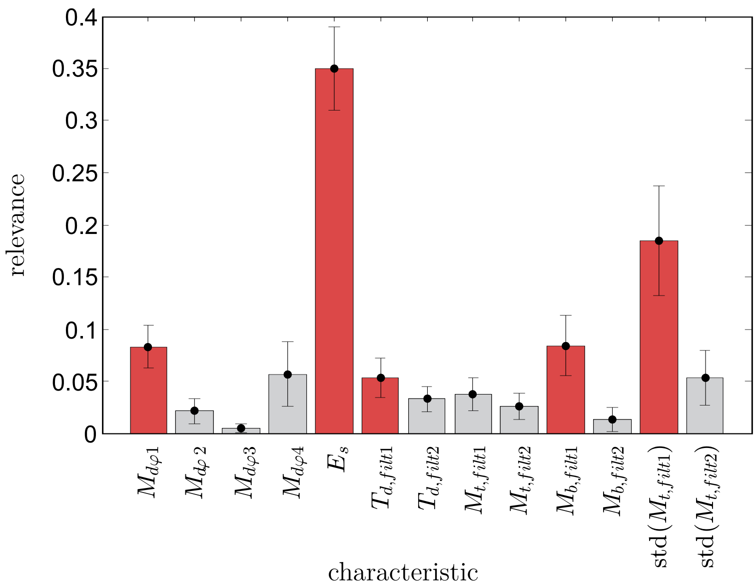

Fig. 3. Relevances of the features for classification of kneading phases computed by GRLVQ (subscripts $filt1$ and $filt2$ indicate different filtering techniques).

4.2.1. Feature selection by Relevance Learning

The selection of features is important for successful implementation of a data-driven kneading phase detector. Fewer features can reduce the need for training data in order to achieve sufficient sampling for learning. Also, it is apriori unclear which filtering of the sensor readings is best suited for classification of kneading phases.

While there are different approaches available for feature selection, we apply Generalized Relevance Learning Vector Quantization (GRLVQ, [10]) to identify relevant features. GRLVQ is a supervised clustering technique with adaptive Mahalanobis metric used to measure dissimilarity of input samples. The parameters of the adapted metric can be interpreted as relevance of the respective input components for pattern discrimination. GRLVQ was applied to classify the dough kneading phases. Figure 3 shows the relevances of the input channels computed by GRLVQ. The results in Figure 3 indicate that the five channels marked by red bars are the most relevant predictors for the kneading phases. These features are selected for training and evaluation of kneading phase detectors in the following.

4.2.2. Generalization of learned kneading phase detectors

We train classifiers $\hat{c}(k) = f(\mathbf{x}(k))$ that receive the relevant features

$$\mathbf{x}(k) = (M_{d\varphi 1}(k), E_s(k), T_{d,filt1}(k), M_{b,filt1}(k), \mathrm{std}(M_{t,filt1})(k))^T$$

as input, where $\mathrm{std}(M_{t,filt1})$ is the standard deviation of the tool motor torques in a time window of 5 s. Outputs of the classifier are the estimated kneading phase labels $\hat{c}(k)$ for each time step k. Training is accomplished with labeled sequences $\{(\mathbf{x}_s(k), c_s(k))\}_{k=1,\ldots,K_s}$, where K_s is the length of sequence s. Labels $c_s(k)$ were computed by the offline method to determine the time of optimal dough described in Section 3.1. We use a feed-forward neural network with a single hidden layer to implement the classifier $f(\mathbf{x}(k))$ and apply an efficient training scheme [11]. Phase transitions of the kneading process are determined online by postprocessing the estimated kneading phase label sequences $\hat{c}(k)$.

To evaluate the generalization of the learned classifiers to novel kneading trials, which were not part of the training data, we conduct a crossvalidation scheme by training classifiers for permuted splits of the available data into training and test sets. In each crossvalidation fold, a kneading trial is left out for training and used as test set. This procedure is iterated for each kneading trial. The learned kneading phase detection estimates the end of the kneading phase accurately with average absolute deviation of *12.6 s* also for novel kneading trials not part of the training data. Hence, the learned kneading phase detection is a valuable complement to the physical modeling discussed previously. The physical and data-driven model are combined according to Equation 3 in order to increase the robustness of kneading phase detection.

5. Results of automated kneading

The individual components of information processing were designed and adjusted in simulations (Model-in-the-Loop). Also, testing was carried out by means of the recorded measurement data for heavily over-kneaded dough. For these measurements the maximum resistance was identified manually and by hindsight using the zero-phase filtered torque signal. Table 1 shows a comparison of these points in time with those of a simulation of automatic online-recognition based on the actual measured values for 8 representative measurements. The recognition method 4 (M4) was thereby turned off, because it led to no advances of reliability, however, in some cases, caused delays. It turns out that a reliable detection of phase-shift is possible with a satisfactory delay of about 20 seconds or less when superimposing all criteria (c. f. Equation 3). Experiment 7 and 8 illustrate the robustness of algorithms. For these trials, water was added so that a dough yield of 162 and 166 was achieved. Nevertheless, the deviation remains in the aforementioned boundaries. Also, flour from another batch was used in the comparative measurements 9 and 10, which

Table 1. Results of detection compared to optimal finishing time (visually derived from zero-phase filtered torque signal and/or approved by baker).

Measurement No.	**Optimal finishing time** ($\pm 1 s$)	signal-based ($\bar{\kappa} = 0.35$)	**Detected finish *(deviation)*** data-driven (ELM)	combined ($\bar{\kappa} = 0.35$)
1	623 s	642.7 s *(19.7 s)*	607 s *(-16 s)*	642.5 s *(19.5 s)*
2	632 s	643.2 s *(11.2 s)*	624 s *(-8 s)*	637.2 s *(5.2 s)*
3	606 s	604.1 s *(-1.9 s)*	606 s *(0 s)*	606.0 s *(0 s)*
4	624 s	648.0 s *(24.0 s)*	617 s *(-7 s)*	644.7 s *(20.7 s)*
5	661 s	680.4 s *(19.4 s)*	681 s *(20 s)*	681.0 s *(20.0 s)*
6	674 s	685.6 s *(11.6 s)*	675 s *(1 s)*	685.6 s *(11.6 s)*
7 (d. y. 162)	695 s	672.0 s *(-23.0 s)*	667 s *(-28 s)*	672.0 s *(-23.0 s)*
8 (d. y. 166)	772 s	788.4 s *(16.4 s)*	762 s *(-10 s)*	788.4 s *(16.4 s)*
9 *	535 s	556.0 s *(21.0 s)*	567 s *(32 s)*	564.5 s *(29.5 s)*
10 *	610 s	644.2 s *(34.2 s)*	643 s *(33 s)*	644.2 s *(34.2 s)*
mean deviation	-	18.2 s	15.5 s	18.0 s

* *in the comparative measurements 9 and 10 flour from a different batch was used*

were not used in the course of the design process. These were conducted to illustrate the performance of the criteria (especially the combined criterion) in future kneading machines. It becomes apparent though that detection quality is slightly deteriorated in these cases. Thus, it can be concluded that the software needs to automatically adapt to other recipes and new flour batches when it is applied to series-production machinery. For the data-driven approach, it should also check whether the apparent conditions are similar to those of the data used for training.

After the successful test of the complete information processing model, it was transferred to the demonstration machine (rapid control prototyping). With the help of experienced master bakers it was proven that automatic production of optimal or slightly over-kneaded dough succeeds reproducibly with the combined criterion. Therefore, the baking experts assessed the dough after the end of the process. While under-kneaded dough (negative deviation) always leads to lower quality of baked goods, reasonable over-kneading of wheat doughs (positive deviation) can be considered less critical and is sometimes even intentionally in the case of strong adhesive doughs. Negative effects can largely be compensated by a prolonged period of rest when needed. Figure 4 shows the measured and extracted torques during automatic kneading. Provided that the current kneading conditions approximately correspond to the prediction-model, it is possible to inform the operator about the expected finishing time and final temperature. The accuracy of the model-based prediction increases with time and is in the range of 10 s or 1°C at the beginning of the kneading phase.

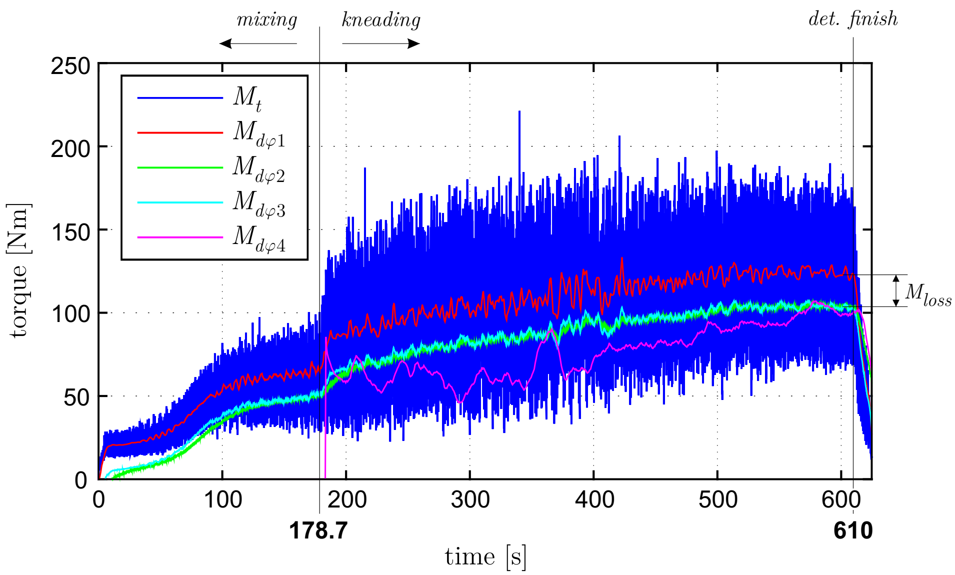

Fig. 4. Torque signals during intelligent control of kneading process ($\bar{\kappa} = 0.4$).

6. Conclusion and outlook

In this paper, we described the design of intelligent information processing algorithms for a spiral kneader that were implemented in a demonstrator and validated with the expertise of professional bakers. The intelligent control software of the presented demonstrator was newly designed, whereas its basic mechanical system largely complies with a conventional spiral kneader. In a model-based design process, idealized simulation models were build up, which rely on representative measurements of the conventional, time-controlled kneading process. Herein, the specific energy contribution was chosen as a suitable reference value. By analyzing the measurements and simulation results, it was confirmed that wheat flour dough shows maximum resistance when its kneading process is finished. This can be identified by the torque signal of the spiral-motor, which rises while the internal structure of the dough is build up and falls when kneading is too long and the dough-structure degenerates. However, online detection of this phenomenon in real-time is highly complex, because the dough characteristics are still inhomogeneous and constantly varying. In addition, the asymmetric spiral and inconstant contact between the spiral and the dough lead to high noise ratio. Therefore, an intelligent sensor evaluation was designed to extract relevant information from sensor signals.

Here, model-based observers, filters and learning algorithms were applied. On this basis, the kneading process is monitored and suitable reference values for the drives are chosen. Furthermore, the intelligent control calculates a model-based prediction of the required time and the expected dough temperature at the end of the process. To achieve series-production readiness, algorithms need to be tested and adjusted for other types of dough and recipes in future. Therefore, further series of measurements have to be conducted. Besides temperature sensors, kneading machines need to be equipped with servo-drives to achieve constant velocities and allow torque measuring. The new information gained by the kneading machine can then also be communicated to subsequent machines of a production line. Thus, e. g. intelligent dividing and molding machines could adapt to the actual flour and dough at hand.

Acknowledgments

This research and development project is funded by the German Federal Ministry of Education and Research (BMBF) within the Leading-Edge Cluster "Intelligent Technical Systems Ost-WestfalenLippe" (it's OWL) and managed by the Project Management Agency Karlsruhe (PTKA). The authors are responsible for the contents of this publication. Also, the authors want to thank our colleagues from Bielefeld University of Applied Sciences for taking numerous measurements in the course of the project.

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