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Optimization of an Inductive Sensor for Real-time Geometry Detection of Rotating Components in Agricultural Machinery

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Introduction

This paper presents a procedure for the optimization of a real-time capable inductive sensor (Fig. 1) for monitoring the geometry of a rotating component during operation in agricultural machinery. Monitoring the geometry of rotating components during operation is of great importance especially for the wear-loaded forage harvesters. The transmission of force at the points of engagement, the transport of the material and environmental influences result in wear of the components in the process and thus in a change in the geometry of these parts. In general, this wear leads to a reduction in the efficiency of the system or even to a standstill. For this reason, the plant components are maintained at regular intervals and replaced if necessary.

In most of the applications mentioned above, rotors made of magnetically conductive, ferromagnetic material are used which rotate at a high speed. An application-dependent number of teeth or blades are usually fitted over the circumference of the rotors to transmit power or transport the material. The efficiency of the plant is strongly influenced - among other things - by the distance between the tip and the root of the tooth. This distance should be as uniform as possible over the gear wheel width. The abrasion depends on many influencing factors such as the properties of the material or the distribution across the width of the system. In the applications investigated the material or coolant usually have a significantly lower permeability than the rotor under investigation. For this reason, inductive measurement offers the possibility of measuring geometric changes in the teeth almost independently of the flow velocity or the type of bulk material [3]. Even minimal changes in the tooth tip can significantly impair the effectiveness of the system. Therefore, the sensor should be as sensitive as possible to changes in the air gap. The previous sensor system can detect coarse geometric changes in the rotating components, but the signal changes are small, making the system susceptible to external interference and noise [4].

The geometric properties of the sensor system are to be optimized through simulation studies in a magnetic field calculation program based on the FEM method. For this optimization a large number of parameters have to be considered and the given space restrictions must be observed.

Optimization Procedure and Results

A. Problem Description and Procedure

The inductive sensor to be optimized for geometry detection consists of an odd number of permanent magnets that are installed across the width of the system. The number of measuring points is adjusted depending on the width of the system to be monitored. The polarity of the permanent magnets is chosen alternately so that the magnetic circuits form particularly between the neighbouring poles. In order to reduce the magnetic flux losses and to be able to optimally introduce the field into the teeth, electrical steel sheets are used as flux conductors. The rotation of the teeth along the sensor unit changes the magnetic flux depending on the shape of the air gap. As a result of the change in the magnetic flux a voltage is induced in the measuring coils which are mounted on the permanent magnets. A signal evaluation of the induced voltage signals allows conclusions to be drawn about changes in the tooth geometry and thus enables monitoring during operation. Fig. 1 shows the basic schematic structure of the inductive sensor and clarifies the terms used below for the individual components.

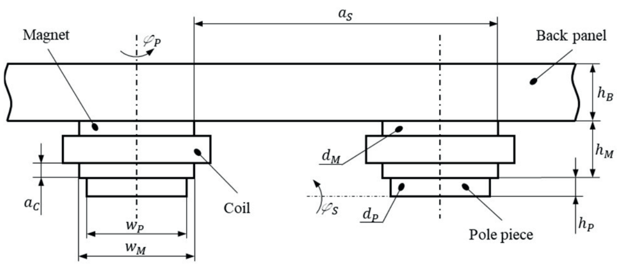

Fig. 1: Schematic representation of the inductive sensor with the component names and main dimensions used

Magnetic field simulations are used to optimize the sensor. Some of the basic conditions of the sensor system should be observed, such as the compliance with the given space restrictions for the application or the maintenance of the basic sensor concept. Therefore, the used materials and the measurement unit should not be changed. The geometric properties of the sensor components are used as optimization parameters. The procedure in this study can be divided into the following main steps: In the first step the target of the optimization study is defined and the changing influencing factors are selected. The limit values of the parameters are also defined on the basis of the installation space restrictions. In the second step the problem is modeled and parameterized in the magnetic field calculation program. Then - based on this model - a factor screening is carried out on the basis of a two-stage Plackett-Burman test plan [5][6]. In this step the number of influencing factors to be considered should be reduced to the most significant ones. Then the most closely linked parameters with the greatest effect are set in the main optimization. For this purpose, a test plan is generated from the Latin Hypercube Sampling [7] and a regression model is created from the results. After having determined the most important influencing factors, the other influencing variables are selected on the basis of individual parameter optimizations. Finally, the results of the optimized sensor are compared with the original system.

B. Target and Optimization Parameters

For the optimization, a target function or a target value has to be defined which should be improved. Since the goal is to enhance the sensor with regard to the sensitivity to record the geometric changes of the teeth and thus the change in the air gap, the study simulates and evaluates two geometric conditions for each factor setting. The first simulated geometry is a non-worn tooth in an ideal condition after the adjustment of the conveyor edge. In the second case a slightly worn edge is used which should be reliably detected by the sensor. Depending on the type and extent of the geometric changes, the air gap between sensor and teeth varies and with it the induced voltage in the measuring coils. The average rectified value of the differential voltage of the two gear wheel states is used to evaluate the sensitivity of the sensor for the investigated geometric changes. This procedure allows all signal changes to be considered with the same weighting and filters out high-frequency noise components that can be expected due to the discretization in the FEM. The following target function is used for the optimization study:

$$|\overline{u}| = \frac{1}{n} \sum_{i=1}^{n} \left| u_{\text{ind, sharp}}(\vec{x}, i) - u_{\text{ind, worn}}(\vec{x}, i) \right| \quad (1)$$

The target variable $|\overline{u}|$ thus depends on the induced voltage signals u_{ind} of the two configurations. An increase in the target value indicates an improvement in the sensitivity of the sensor. n corresponds to a period of the tooth pass and $\vec{x}$ describes the factor setting of the sensor selected in the pass. The optimization should be limited to the geometric properties of the sensor unit. The permanent magnet geometry significantly influences the magnetic energy available to the system. This is determined via the operating point of the system and depends - among other things - on the magnet width, depth and height of the square magnet used. The geometry of the so-called pole piece has been identified as another significant influencing variable. This mainly affects the flow conduction in the teeth of the gear wheel. Both the width and depth as well as the rotation of the component around the central axis of the permanent magnet are examined. The height of the back panel is also considered in the optimization. Other investigated influencing variables are the distance between the measuring points, referred to as the pole distance, the tilt of the overall sensor with the fixation on the surface line and the distance between the pole piece and the coil body in relation to the magnet height. This results in ten considered optimization parameters that have been examined.

C. Factor Screening

In this step the effects of the individual factors on the target value will be examined in order to find the important factors for the main optimization. This is necessary because a fully fledged, multi-stage test plan cannot be implemented with the large number of parameters and this would exceed the simulation capacities significantly. The interactions between the factors are also considered in the selection since some of these can be classified as significant due to the effects on the operating point of the magnet system. In this step, a two-stage Plackett-Burman design with 12 runs is used. The defined minimum and maximum factor settings are selected as levels. This partial factor plan enables a resolution level of III, which can be converted into a resolution of IV by a convolution of the test plan [8]. This results in 24 test runs for both gear wheel configurations to be examined. This procedure enables a statistically reliable evaluation of the main effects of the individual factors. Table 1 shows the results of the main effects of the target for the investigated influencing parameters. The step width of the individual factors are also listed in the table. The step width is the difference between the upper and the lower limit of a factor. A positive main effect thus indicates a system improvement in the direction of the upper limit.

Tab. 1: Main effects of examined factors and step width

Factor	Main Effect	Step Width
Magnet height h_M	-72.6 mV	20 mm
Magnet width w_M	185.4 mV	15 mm
Magnet depth d_M	172.6 mV	15 mm
Pole piece width w_P	-55.9 mV	30 mm
Pole piece depth d_P	44.7 mV	10 mm
Pole piece rotation f_P	-26.7 mV	15 °
Back panel height h_B	61.7 mV	15 mm
Pole distance a_S	45.5 mV	25 mm
Sensor tilt f_S	-6.9 mV	20 °
Coil position b_C [a]	-92.5	100 %

[a] $b_C = a_C*(h_M - h_C)^{-1} *100\%$ with h_C: coil height and a_C: distance between coil and pole piece

The main effects are calculated for factor i as follows:

$$E_{\text{Factor } i} = \frac{\sum_{k=1}^{12} |\overline{u}|_{\text{Factor } i \text{ upper limit}} - \sum_{k=1}^{12} |\overline{u}|_{\text{Factor } i \text{ lower limit}}}{24} \quad (2)$$

It can be concluded from the results that the magnet geometry parameters significantly influence the target value. High interactions are also expected among these factors, so that these should be analyzed in more detail in a multi-stage investigation. The factor of the coil position also shows a clear effect. This can be justified by stray fields on the back panel and this parameter can be set independently of the other influencing variables on the lower limit. Both the sensor tilt and the rotation of the pole pieces show a slightly negative main effect. In combination with the significantly higher manufacturing effort, these influencing factors are rejected in further investigation. Saturation is expected for the back panel height from which no significant improvements are supposed to occur. The interactions with other factors can therefore be assessed as low and a one-factor optimization is classified as sufficient. Due to the higher main effect of the pole piece width, this parameter is examined in the main optimization and its depth is only determined on the basis of a single parameter study.

D. Main Optimization

In the main optimization the factors for the application should be set in best possible way. The findings from the factor screening are used to get the optimal setting with the least possible simulation effort. The goal of the multi-factor investigation in this step is to determine the magnet geometry and the pole piece width. A test plan is created using the Latin Hypercube Sampling with 100 runs. This method is based on the Monte Carlo Simulation and enables the evaluation of the parameters across the entire examination area [6]. This also considers the interactions between the parameters that are assessed as significant. All test runs are simulated with both gear wheel configurations and the target value is calculated. The other factors are set constantly. To find the optimal factor setting the Response Surface Method [9] is used and the optimization problem is modeled as follows:

$$y = \beta_0 + \beta_A x_A + \beta_B x_B + \beta_C x_C + \beta_D x_D + \beta_{AA} x_{AA}^2 + \beta_{BB} x_{BB}^2 + \beta_{CC} x_{CC}^2 + \beta_{DD} x_{DD}^2 + \beta_{AB} x_A x_B + \beta_{AC} x_A x_C + \beta_{AD} x_A x_D + \beta_{BC} x_B x_C + \beta_{BD} x_B x_D + \beta_{CD} x_C x_D + e \quad (3)$$

The target value y corresponds to the rectification value and the variables x_i correspond to the four influencing factors examined. The magnet width is described by index A, its height by B, its depth by C and the pole piece width by D. The variable e describes the error term of the regression analysis. The model of the problem is determined by means of a regression calculation. An adjusted coefficient of determination of $\overline{R}^2$ = 0.996 can be calculated for this modeling. This results in a good adaptation of the model function to the support points from the simulation results. The model used is therefore suitable for further optimization of the sensor. The calculated regression parameters are shown in Table 2. In addition, a constant coefficient of the regression of β_0 = 216.04 mV was determined.

The optimal sensor configuration is determined with the help of an extreme point search with inequality constraints. These space restrictions due to constraints are necessary because the modeling is only valid for the problem up to the edges of the test plan. Using this method, the four examined parameters can be optimally defined for the application. An optimal factor setting is shown with an increase in the magnetic area and a decrease in the magnet height. The pole piece width has a significantly smaller influence on the target size and primarily shows a clear dependence on the magnet width. Possible installation space adaptations can be quickly incorporated in the sensor design by the created model.

Tab. 2: Model parameters of the model function to describe the test room for optimization

Model Parameters			
Constant Term [mV]	***Linear Effects*** $\left[\frac{mV}{mm^2}\right]$	***Square Effects*** $\left[\frac{mV}{mm^2}\right]$	***Two-way Interactions*** $\left[\frac{mV}{mm^2}\right]$
β_0=216.04	β_A = -30.06	β_{AA} = 0.38	β_{AB} = -0.29
	β_B = -1.31	β_{BB} = 0.32	β_{AC} = 2.89
	β_C = -19.79	β_{CC} = 0.07	β_{AD} = 0.26
	β_D = 9.98	β_{DD} = -0.31	β_{BC} = -0.23
			β_{BD} = -0.05
			β_{CD} = -0.11

The other factors are then optimally set using the One-Factor-At-Time method. For each parameter, the value range is scanned over ten measuring points and determined using problem-appropriate modelling.

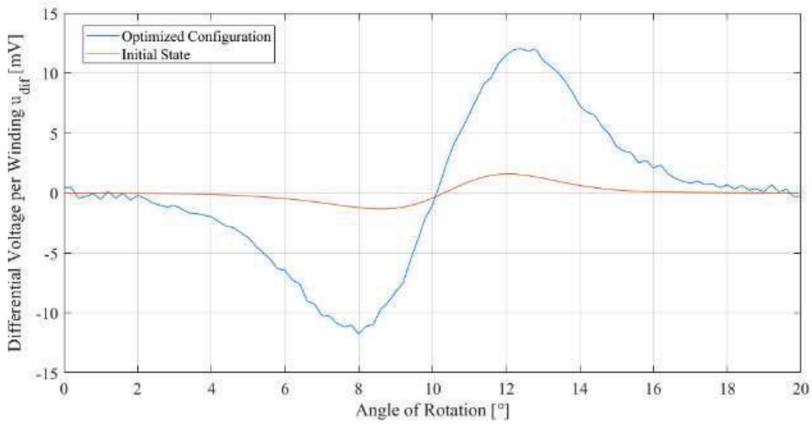

Fig. 2: Difference signal formed from the induced voltage signals of the two gear wheel configurations examined via the angle of rotation

E. Comparison with the Original System

After the main optimization the examined factors are optimally adjusted to the application. The difference signal calculated from the induced voltages for the gear wheel configurations used in this optimization is shown for the initial state and for the optimized sensor via the angle of rotation of the gear wheel in Fig. 2.

The diagram clearly shows the significant improvement in the sensitivity of the sensor upon changes in the air gap. The target size of the simulation study could be improved by a factor of 9. This increase in sensitivity enables an improvement in the monitoring of rotating components and enhances the interference immunity of the system. The clearly increased induced voltage signal can be adapted to the measuring electronics by modifying the number of coil turns.

E. Comparison with the Original System

To prove the improvement of the sensor on the basis of the field simulations, the simulation model was first validated using reference conditions on the test stand. A laser scanner serves as a reference, which is used for modelling in the simulation. After the successful validation of the basic model, the new sensor was built in the optimized dimensions. For the acquisition of the data, an evaluation electronics is used, which acquires the coil signals in parallel and in real time. The pre-amplification can be significantly reduced due to the significantly increased voltage changes and amplitudes. In the field tests, the output system on the one hand and the optimized system on the other were attached to the drum. This allowed a direct comparison to be made between the two sensors. In the field tests, the wear of the drum was tested to the limits, so that both a non-worn and a completely worn drum were recorded. This allows the analysis of the improvement over the entire measurement range. The gain-compensated improvements from the simulation studies could be proven and shown in the field measurements. In particular, in the areas of advanced wear where the sensitivity of the overall system is reduced due to the lower magnetic flux, changes in the teeth can now be reliably detected due to the adjustments in the sensor design. By reducing the necessary amplification of the individual coil signals, it was also possible to reduce the signal-to-noise ratio (SNR). Thus, the optimization based on electromagnetic field simulations could be proven in reality by means of field tests.

Conclusion

In this work three-dimensional magnetic field simulations were used to optimize an inductive sensor for real-time geometry of a rotating component during operation in agricultural machinery. The geometric dimensions of the sensor system were changed to improve the sensitivity of the sensor upon changes in the air gap between the inductive sensor and the ferromagnetic teeth. The most significant and most closely-linked factors were selected with the help of a Plackett-Burman test plan and theoretical considerations about possible interactions between the influencing factors and were optimally adjusted to the application using the Response Surface Method. The test plan for recording the support points was created from a Latin Hypercube Sampling. Thanks to the optimization the sensitivity of the inductive sensor was improved by a factor of 9. The improvements of the sensor could be proven in real field tests on the agricultural machine. This enables a finer resolution of the geometry monitoring and improvements in the interference immunity of the sensor system. In addition, the model created can support the effects of an installation space adjustment. The prediction of wear is improved by the optimization, as conditions with greater wear can also be precisely recorded.

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