Sensorless Coil Temperature Measurements using Neural Networks for Voltage Control

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Abstract: Voltage and current measurement data based deep learning as a method to conduct sensorless coil temperature prediction of an embedded linear induction actuator is being proposed and validated in this work. Generated numerical data from Finite Element field simulations are used to train a neural network which in turn predicts temperatures at non-accessible places e.g. at an embedded coil. The network is demonstrated and the comparison to experimental data shows the potential of virtual sensing. Even though the number of physical sensors have increased enormously in the last decades, the measurement of desired temperatures at certain locations is limited by accessibility and by the application itself, for example, if a coil is used as a moving part in an actuator. This work proposes an indirect method based on measurable quantities in the device, such as voltage and current, to quantify precisely temperatures and hot spots in sensitive parts of the device. As high temperatures can have a huge effect on the device's performance, a controllable voltage to compensate the performance reduction instantaneously is desired. Applications based on the principle of an inductive linear actuator show a strong performance dependency on the temperature of the conducting material or coil. The authors present an Artificially Intelligent voltage controller to achieve the desired performance based on measurable variables in the device and supported by sensorless methods like temperature prediction with Artificial Intelligence (AI).

1 INTRODUCTION

Induction actuators cover a wide range of applications such as arc suppression, high-speed mechanical switches and hybrid DC circuit breakers where very fast operating cycles are required (Vilchis-Rodriguez et al., 2019). Different concepts exist using the advantages of coils and repulsion disks. The characteristics of such processes are a very short energizing time and fast movements within milliseconds. In DC circuit breakers, current pulses are created by the discharge of a capacitor. With the generation of eddy currents, a repulsive force drives a rod up and down to ensure the stability of power grids, in case of voltage drops or power failures (Dong et al., 2011). The induction actuator is a standard concept for switches such as circuit breakers. By using a circuit breaker, the load can be disconnected. This leads to the occurrence of electric arcs. The inductive linear actuator's principle is attractive as it allows simple designs and high speed actuation while providing reliability and stability (Lim et al., 2013).

An induction actuator based application with iterative cycles is investigated for a wide range of applications and thermal conditions. The repetitive periods during operation can lead to overheating of the system. Due to the excited coils and induced eddy currents, the temperature rise in the coils is huge and therefore affects the resistance of the coils. The temperature levels in a fast repetitive mode typically require active cooling. For further heat reduction, a voltage controller is needed to define the voltage charging level of the capacitor during every cycle. The measurement of the temperature in an embedded coil is very difficult due to limited space and would lead to fast failure of the sensor due to high temperatures and forces. Instead of the temperature other properties such as current and voltage can be measured and based on these data, the demperature can be determined. There are many applications that use AI for integrating virtual sensors to determine complex

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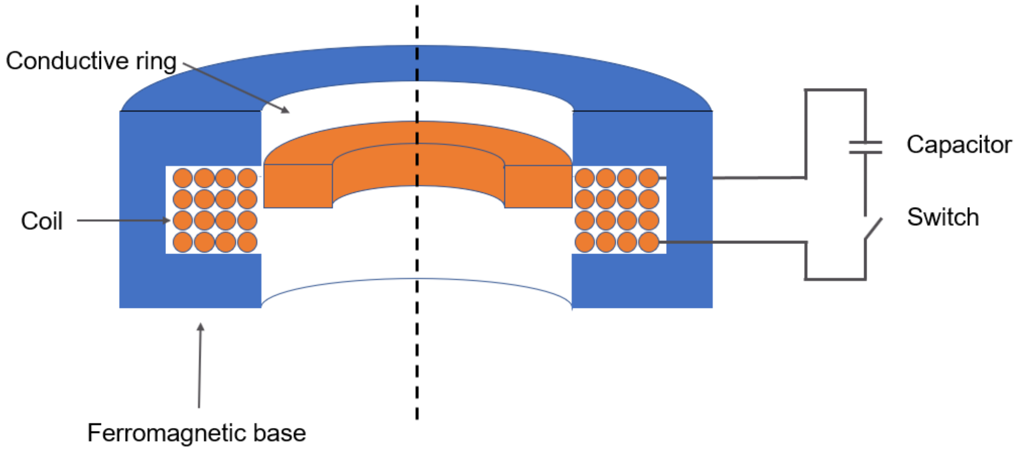

Figure 1: Linear induction actuator.

variables using already existing sensor data. Some authors (Gonzaga et al., 2009) use a feed-forward artificial neural network for the design of a soft sensor to estimate the PET viscosity in real time and then control the polymerization process. Neural networks as well as Kalman filters are suitable methods to determine the temperature for highly non-linear systems such as batteries (Charkhgard and Farrokhi, 2010).

2 LINEAR INDUCTION ACTUATOR

In Fig. 1, the design of the induction actuator is shown in detail. The system consists of a coil surrounded by a stator which guides the magnetic field closely through the coil. The conductive ring is placed inside the coil guided by a shaft. When the switch is turned on, the loaded capacitor is discharged through the coil. The current in the coil causes a time varying magnetic field and induces eddy currents in the conductive ring in the opposite direction to the coil current. Due to the magnetic field and the current in the coil and conductive ring, a repulsion force is generated between the two conductors and the ring moves away. The capacitor is charged with an energy E_{max} and generates a current pulse that reaches a maximum value I_{max}. The main target of this system is always a constant desired kinetic energy of the conductive ring, regardless of the frequency of repetitive loadings. Under operating conditions with several cycles per minute, the accompanying heat generation leads to a significant temperature rise, which results in a limited performance as the temperature directly influences the coil resistance. The time interval in Fig. 2 consists of two different segments. On the one hand, the stroke period P_s, on the other hand the waiting period P_{wait} in which the system expects new input. For the control of cooling and the capacitor's input charging voltage, the measurement of the temperature is required and a relationship between this temperature and the kinetic energy must to be known. The full system was previously optimized to achieve the desired performance even at the end of its lifetime, e.g. the conductive ring will still have sufficient kinetic energy. Consequently, the capacitor is oversized. However, this oversizing leads to excessive kinetic energy, high forces and wear, which in turn cause the coil to break earlier. Additionally, too much kinetic energy would overload the system and lead to faster failure and shorter life time.

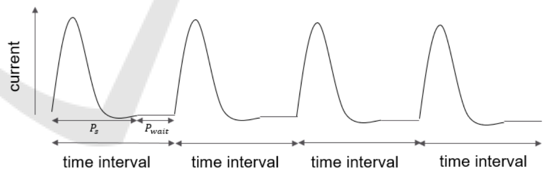

Figure 2: Repetitive cycles during operation.

Temperature sensors are widely used due to their low price, but reach their limits with limited installation space and offline calibration. In addition, other problems such as own heat development, contamination by ions or damage during the process become apparent (Charkhgard and Farrokhi, 2010). In the case of the investigated induction actuator, a sensor for temperature measurements would have a big impact on the physical behaviour and performance of the system as the fill factor of the coil is important to stay high and the initial position between the coil and conductive ring has to be precise at the beginning of a cycle. Further, high accelerations and forces would destroy the sensor quickly.

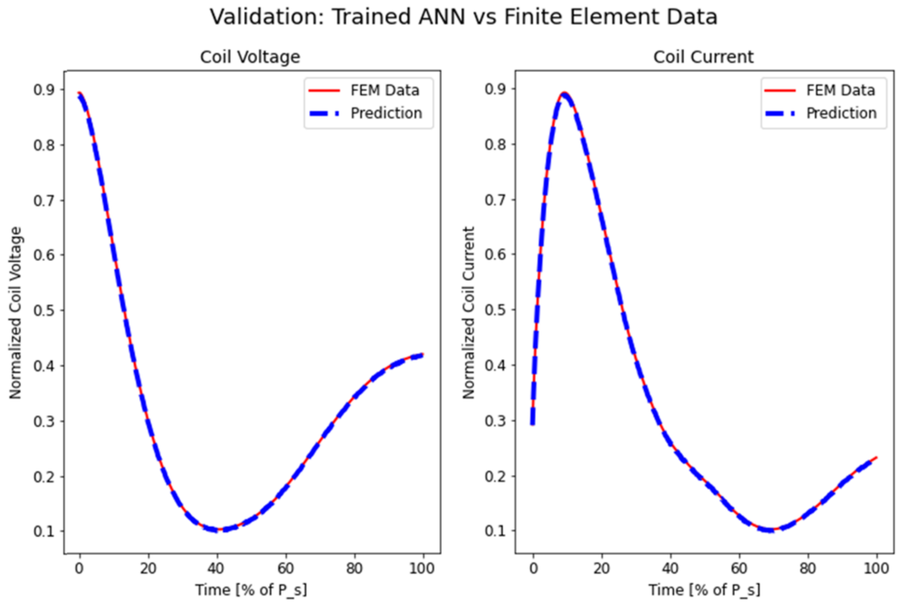

Figure 3: The neural network precisely represents the FEM curves.

Virtual sensors have evident advantages over real physical sensors in terms of cost and implementation. In addition, certain installation places can also lead to rapid sensor failure. Regarding virtual temperature measurements, (Guzm et al., 2018) use a CFD model and a model based on transfer functions to predict the real time temperature of a greenhouse from real sensor data. (Boulandet, 2016) introduces a lumped-parameter model of an electric circuit to predict the front-side acoustic radiation impedance of a loudspeaker using the measured electric impedance of the loudspeaker and additional parameters defined by experimental data using curve fitting. As alternative to transfer functions, simplified models and regression methods as well as neural networks get more and more attention as precise, fast and reliable methods. (Hussein, 2018) shows a sensorless way to estimate the surface temperature and the battery cell's terminal voltage using ANNs with current measurements as input.

3 MODELLING

3.1 Finite Element Method (FEM)

Due to the complexity of the electromechanical system involving eddy currents and changing inductance caused by a flying ring, the induction actuator is simulated with FEM. This numerical method offers a precise model and captures all relevant effects that cannot be implemented and modelled so far with methods such as system identification. By varying relevant system parameters, e.g. lifetime dependencies of the capacitor, thermal influences such as the coil resistance, the conductive ring resistance and voltage of the capacitor, many different data points with different voltage and current curves of a predefined geometric concept are simulated. Subsequently, the voltage can be used to regulate the kinetic energy of the flying conductive ring to achieve the target performance. The key parameters are:

- Capacitance of capacitor C_{cap}
- Resistance of the capacitor R_{cap}
- Voltage of the capacitor V_{cap}
- Resistance of the coil R_{coil}
- Resistance of the conductive ring R_{cu}.

Using these input parameters, the corresponding transient currents, voltages in the coil and the forces acting on the conductive ring are calculated by using FEM. The idea of this sensorless measurements is based on the following equations from a coil's electric circuit, modelled by an inductance and a resistor, using Faraday's law (Galili et al., 2012).

$$u = iR + \frac{d\Phi}{dt} = iR + \frac{d\int_A B(t)dA}{dt} \qquad (1)$$

In the coil, the inductance is changing with the position x of the conductive ring and the current of the coil. The inductance is a highly complex term that cannot be calculated in advance. As the magnetic field is a result of the changing current and the position influences the changing area A directly, the flux linkage is defined as $\lambda(...)$.

$$u_{coil} = i_{coil}R_{coil} + \frac{d\lambda(i_{coil},x)}{dt} \tag{2}$$

$$u_{coil} = i_{coil}R_{coil} + \frac{\delta\lambda(i_{coil},x)}{\delta i_{coil}}\frac{di_{coil}}{dt} + \frac{\delta\lambda(i_{coil},x)}{\delta x}\frac{dx}{dt} \tag{3}$$

$$R_{coil} = \frac{u_{coil} + \frac{\delta\lambda(i_{coil},x)}{\delta i_{coil}}\frac{di_{coil}}{dt} + \frac{\delta\lambda(i_{coil},x)}{\delta x}\frac{dx}{dt}}{i_{coil}} \tag{4}$$

The voltage and the current of the coil depend on the constant resistances and varying inductances. Calculating the resistance from the varying parameters is complex and leads to numerical instabilities such as divisions by zero. However, these equations are simplified engineering equations which are included in a weak form in the finite element solver model. Using variables such as position, voltage and current, neural networks are applied as a regression model that predicts any output for any combination of inputs in a very fast way.

After predicting the resistance, the temperature can be defined by $R_{coil} \sim \rho_{coil}$:

$$R_{coil} = \frac{\rho_{coil} * l}{A} \tag{5}$$

$$\rho_{coil} = \rho_0(1 + \alpha * (T - T_0)) \tag{6}$$

$$T = \frac{1}{\alpha}(\frac{\rho_{coil}}{\rho_0} - 1) + T_0 \tag{7}$$

3.2 Neural Network Integration

Due to the fact, that neural networks are able to learn highly complex dependencies, they are ideal to solve non-linear relationships between input and output variables. Its properties make it relatively easy to solve the complicated induction equation. As mentioned in (Kumar et al., 2020), physical data can be used in both predictive directions, using a forward and an inverse model. Due to the physical equations shown above, the dataset generated by FEM includes the scalar values (input) and the time dependent voltage and current curves (output).

3.2.1 Forward Model

The forward direction can be used to investigate the system dynamics from the five scalar inputs described in 3.1 and integrate the outputs such as current and

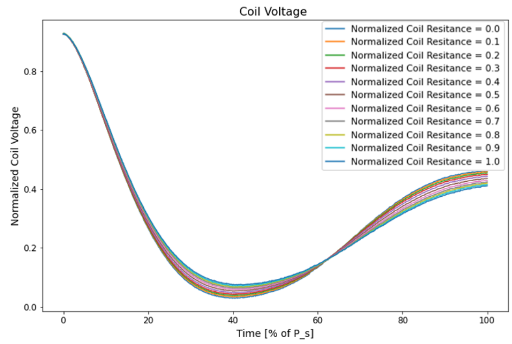

Figure 4: Varying coil resistance influences the voltage curves.

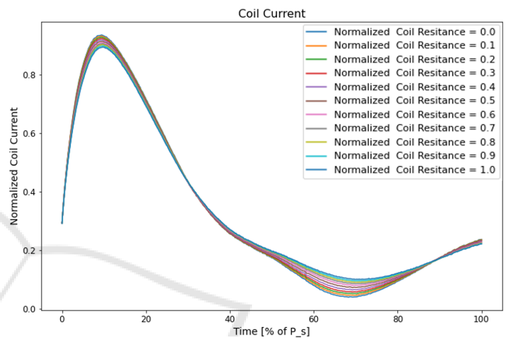

Figure 5: Varying coil resistance influences the current curves.

voltage curve in a system simulation procedure. This forward model is realized by a feed-forward neural network, which is trained on the FEM-data of 600 data points created with Latin-Hypercube sampling to cover a homogenous range of variables. As the FEM model is being developed over several years and has an error of less than three percent to experimental results, it can be used for validation as seen in Fig. 3. The required accuracy is obtained with three layers of 2'000 neurons each. The use of dropout and three folds of cross-validation reduces the risk of overfitting. A trained neural network, using the scalar inputs mentioned above, is able to capture the effect of resistance in the coil as seen in Fig. 4 and Fig. 5. The coil and current pulses are scaled over the stroke period P_s. The heat generation in the coil results in higher resistances and therefore has a significant impact on the current pulse. This forward model can be used later in a system simulation for predicting various operating cycles within a few milliseconds instead of various hours for one cycle using FEM simulations.

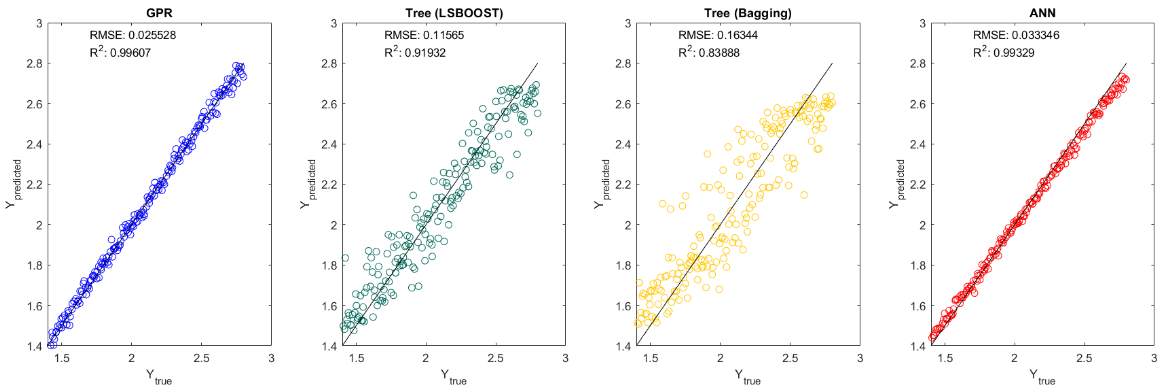

Figure 6: Predicted and true data responses of ρ_{coil} comparing GPR, Trees (Boosting and Bagging) and ANN.

3.2.2 Inverse Model

For the prediction of the temperature, an inverse model is necessary. Current and voltage curves serve as input to predict the coil resistance. By using all these data points, a neural network is trained to find the coil resistance's influence on the current and voltage curve.

The neural network is constructed with several hidden layers using Rectified Linear Units (ReLU) as the activation function. The convergence algorithm Adam, a stochastic gradient descent algorithm available in the Python library Tensorflow, turned out to be the most suitable. A wide range of different neural network configurations was trained and analysed, taking into account parameters as the number of hidden layers, the number of neurons, dropout, and batch normalization. Fig. 6 shows the comparison of using different Machine Learning methods for the prediction of the coil's resistivity ρ_{coil}. GPR and ANN both achieve high accuracy results on noisy input data. The comparison was done using five cross folds and doing hyperparameter optimization for each model. Additionally, white noise was added on normalized input data to get the problem robust also for experimental and predicted data. By applying white noise with a maximum amplitude of 3% on the input data, each model was optimized by training the hyperparameters, e.g. the learners and number of leafs for decision trees, standard deviation and kind of kernel for GPR and hidden layers and number of neurons for neural networks. Three percent noise on normalized data is used so that this model can be also applied to experimental data.

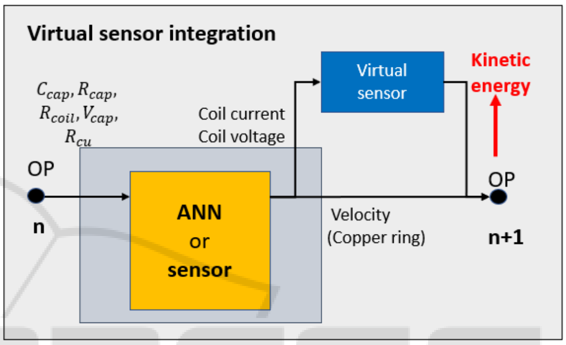

Figure 7: Potential applications of a virtual sensor are a system simulation models using data predicted by ANN and a real integration on a microcontroller using sensor data.

4 USE CASES

Our proposed virtual sensor can be either applied to a real induction actuator application and monitor the temperature of the coil using real sensor measurements or it can be integrated into a system simulation as seen in Fig. 7.

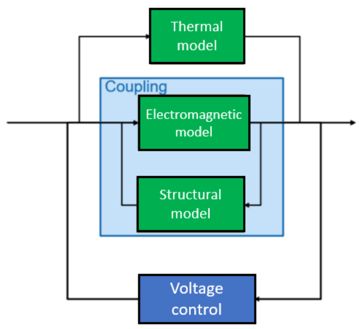

Figure 8: System simulation model with integrated voltage control.

In this work, the AI-based system simulation of this process is realized as shown in Fig. 8. The temperature behaviour is represented by a thermal lumped parameter model predicting the input energy with Gaussian Process Regression (GPR) during one operation cycle and then solving the ordinary differential equation for each cycle. The electromagnetic coupling is described by the neural network based forward model. For performance regulation voltage control is introduced. The purpose of the system simulation is to investigate the system's performance under different operating conditions.

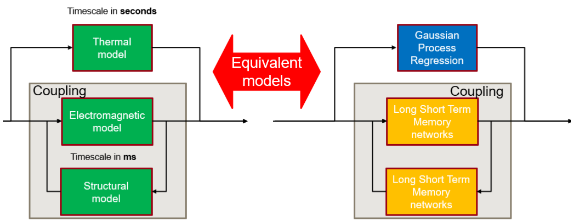

Figure 9: Physical models represented by machine learning techniques.

As seen in Fig. 9, a system simulation procedure is created by implementing time series neural network as fast and accurate representation of the time-consuming finite element calculations. Long Short Term Memory (LSTM) networks are used in a coupled way to predict the forces of the conductive ring to calculate the kinetic energy.

5 VALIDATION

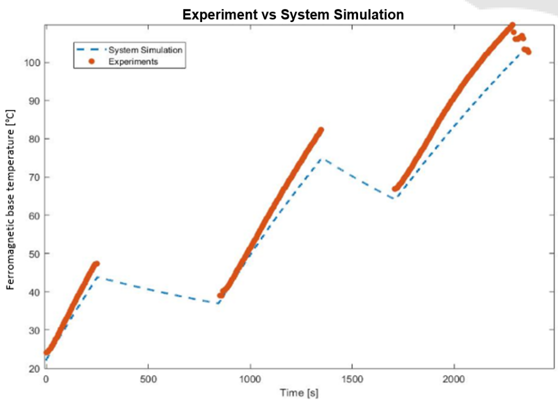

Figure 10: Validation of the thermal model using the temperature of the ferromagnetic base.

In a system simulation procedure, the performance control can be tested. As seen in Fig. 10, the system simulation is validated with experiments by executing more than 200 operation cycles in a laboratory and comparing them to the simulation results. As the temperature in the coil cannot be measured, it is compared to the measurements of the ferromagnetic base. Although the system simulation assumes a homogenous temperature of the ferromagnetic base, it clearly captures the trend. The temperature of the ferromagnetic base is measured radially outside the base. The performance of the virtual sensor can be compared with the validated system simulation, Fig. 11. It is shown that after every operation cycle the initial temperature can be predicted based on the voltage and current of the coil.

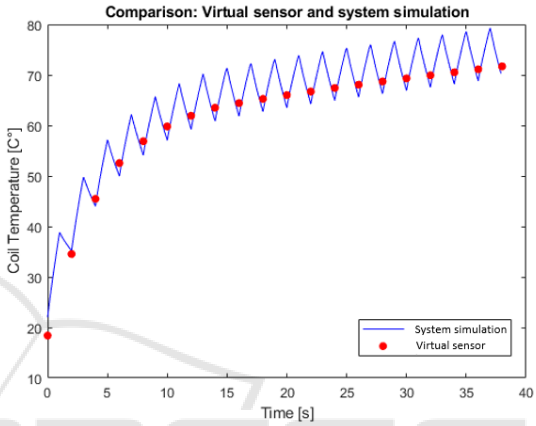

Figure 11: Comparing the coil temperature of the thermal model in the system simulation with the virtual sensor.

6 VOLTAGE CONTROL

By predicting the force of the conductive ring, its velocity can be derived and the kinetic energy is calculated. For a desired kinetic energy at an optimal performance point, the input voltage of the capacitor can be regulated with a controller in a system simulation model. Due to the knowledge of decreasing lifetime parameters of the capacitor and the temperature measurements, the expected performance of the system is predicted and a controller can adapt the input energy. Based on the FEM data, artificial intelligence is used once more in form of GPR to predict the corresponding input voltage of the capacitor for the above defined input parameters. For this voltage control, a real time thermal model is necessary to monitor the transient behaviour of the coil temperature over time and use it as new input for the machine learning model. After every operational cycle, the voltage control gets the lifetime and thermal input parameters and predicts the needed voltage for a desired input energy. In Fig. 12, the influence of voltage control is shown. For the investigated device with an operational time interval of two seconds, the heat gener-

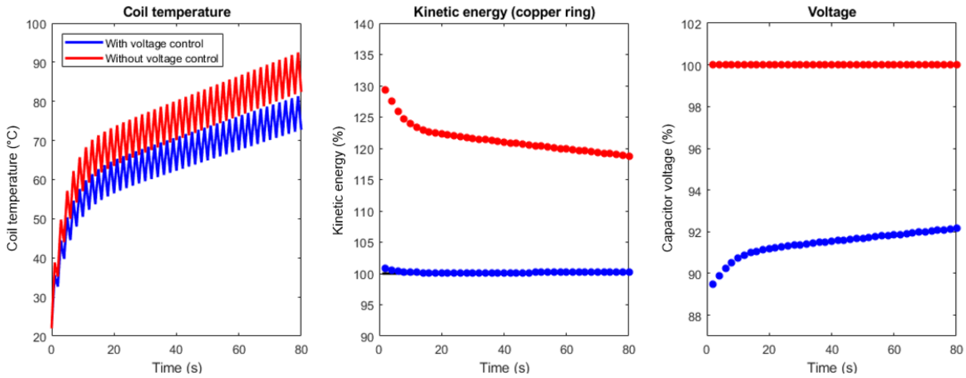

Figure 12: During 40 operation cycles, voltage control has a significant influence on the heat generation in the system. It leads to a continuous character of the kinetic energy and requires less energy in the capacitor.

ation in the system leads to increasing coil temperatures, although the system is already cooled. By using a constant input voltage of 100% to make the system reaching 100% kinetic energy of the conductive ring even at the end of the lifetime, a lot of energy is unnecessarily invested leading to longer charging times in the capacitor. If voltage control is included, less voltage is needed and the system can adapt to temperature changes and decreasing capacitance due to abrasion of the capacitor. The optimal performance at 100% kinetic energy is achieved with errors of less than 2% and, therefore, makes the whole system more efficient and achieves reliably the desired optimal performance point.

7 CONCLUSIONS

A virtual sensor is proposed for the temperature determination in the coil of an induction actuator to control its performance. Beside the introduced system simulation model, the sensor can be used for predicting the temperature of a coil when physical hardware sensor measurements of the coil current and voltage are available. A validated and highly accurate FEM model is used to generate training data for an AI-based virtual sensor. The electromagnetic FEM model takes hours to calculate the system response of one single operation cycle. In contrast, a trained ML model predicts the temperature of the coil within milliseconds in places where no sensor can be integrated without reducing the performance. When considering thousands of working cycles, excessive computing equipment would be needed to describe the temperature accurately and efficiently with FEM models. The virtual sensor therefore not only allows measurements in places that are difficult to reach, but also enables a fast and very accurate calculation method.

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