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Self-Optimization In Gear Manufacturing And Assembly For Automotive Electric Drive Production

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Abstract

Due to the trend of electrification in the automotive industry, the economic production of electric drives with high acoustic quality requirements is a crucial factor to stay competitive in the global market. Low noise levels in the interior are an important criterion for the perceived quality of electric vehicles. Consequently, the noise generated by mounted gear components within integrated electric drive topologies must be minimized. Gears with unavoidable manufacturing deviations are usually randomly assembled, leading to random non-defined gear-related acoustic properties of the assembled electric drive. Furthermore, parameters of the gear manufacturing machines do not dynamically adapt to unknown changes in the production system leading to non-ideal quality output. To address these challenges, this paper presents a self-optimization concept in gear manufacturing and assembly in the production of electric drives by cognition enhanced control. A digital twin is developed which estimates the transmission error based on in-line measurements. Through optimization, an optimal selection of gear pairs is achieved. Based on quality predictions, adaptive control of the gear manufacturing process can be implemented, leading towards a closed-loop self-optimization of the production system. The concept is developed and validated using an exemplary use case from the commercial vehicle industry.

Keywords

Self-Optimization; Cognitive Control; Digital Twin; Gears; Electric Drive Production

1. Introduction

With the ongoing global focus on electromobility and the increasing demand and requirements, efficient and effective processes for manufacturing and assembling of components take on a decisive role in international competition. Due to the absence of the combustion engine's sound in electric vehicles, the overall noise level decreases significantly, bringing previously unnoticed noise sources such as ancillaries or the electric drive train into focus [1]. Consequently, new product requirements arise in the production of drive train components, including gears. Today quality-related backward loops are used in electric drive production, enabling a detection of noise related cause-effect relationships and consequently an implementation of counter measures in gear manufacturing [2]. However, since this process is carried out reactively, it could lead to a considerable delay in the use of information and hence in a waste of energy and resources due to production of scrap parts or loss in quality. Additionally, the random assembly of gear components is leading to undefined acoustic properties of the individual gearbox, caused by typical manufacturing deviations. With the ongoing digitalization in the context of Industry 4.0, self-optimizing systems in manufacturing and assembly show high potential to overcome these issues by integrating control systems with real time quality predictions in the production system. This publication therefore presents a self-optimization concept for model-based control by parameter optimization in gear manufacturing and selecting optimal gear pairs in the series production of electric drives, complementing the conventional quality backward loop. The paper is structured as follows: In section two, the state-of-the-art of self-optimizing production systems is described. Section three outlines the proposed concept to optimize the overall efficiency of the production system through self-optimization. Exemplary results are shown in chapter four followed by chapter five with a summary and outlook.

2. State of the art

Self-optimizing systems are control systems, which autonomously adapt their objectives based on internal decisions to achieve a certain result and therefore extend the capabilities of classical adaptive control [3]. Due to the potential to learn autonomously, self-optimization is closely related to the term cognition [4]. By processing and utilizing information from the production process, cognitive systems can adapt to their environment, allowing them to serve as a central component in a self-optimizing production system [5]. The enhancement of production systems with cognitive and adaptive capabilities is considered as paradigm shift [6], [7]. On a conceptional basis cognition enhanced control systems can be integrated in multiple levels within the production process [8]. Nonetheless, use-cases mainly focus on the optimization of process steps in either manufacturing [9], [10], [11] or assembly [12], [13], [14], [15], primarily aiming to optimize a parameter of that process step or a functional key characteristic (FKC) of the product to improve overall efficiency. Although a combined integration of adaptive control loops in manufacturing and assembly show potential to reduce overall production costs [16], [17], a simultaneous integration of selective assembly and adaptive manufacturing in cognition enhanced control systems has not yet been considered. With new acoustic quality requirements in gear production for automotive electric drives, manufacturing processes reach a technological limit. In complex serial production unknown environmental influences can cause a high number of possible failure states of the finished drives. Cognition enhanced control systems are able to adjust the parameters of the production system autonomously to changing environmental influences and thus have the potential for a self-adaptive optimization of tolerance chains in the production process [18]. In the following chapter the proposed self-optimization concept for cognitive control in manufacturing and assembly is introduced.

3. Self-optimization through cognitive control in manufacturing and assembly

Within this chapter a concept for a self-optimizing system based on a cognition enhanced quality control in manufacturing and assembly is introduced. The controller can adapt the objectives autonomously based on the current state of the production system and retrieve optimal gear manufacturing parameters as well as optimal gear pairings. The developed concept for a cognition enhanced quality control is shown in figure 2 with focus on adaptive manufacturing and assembly pairing strategies. Manufacturing deviations are unavoidable and can cause quality deviation of the final product. Therefore, inspections assure that individual components are within defined specifications. After storage the individual components are assembled to the final product. Further quality tests at the end of line ensure the specified quality fulfilment of the final product.

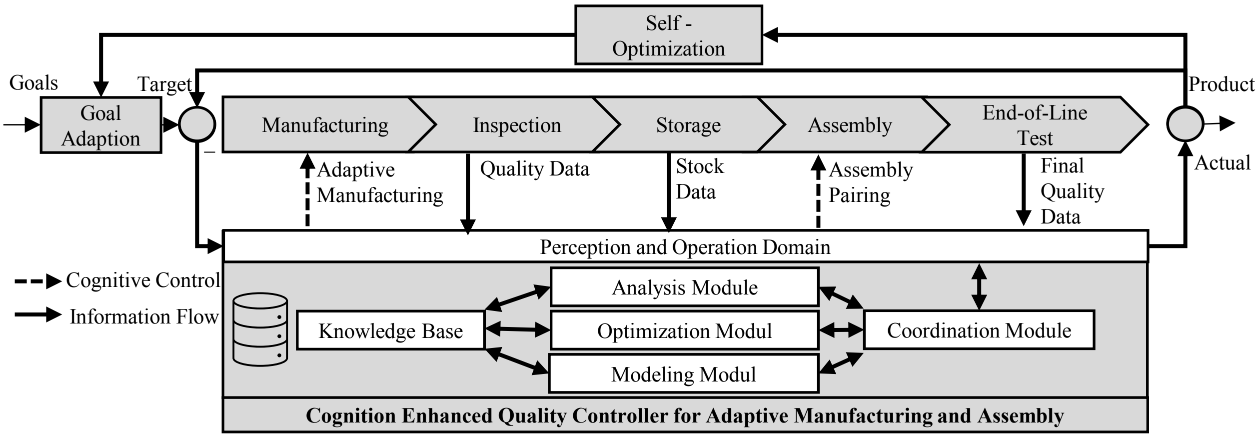

Figure 2: Self-Optimization through cognitive control in manufacturing and assembly.

In the bottom of Figure 2, the concept for a cognition enhanced quality controller is shown. The individual elements of the controller are related to the self-optimizing cognitive control according to [18]. The controller perceives the environment based on production data in near real time and monitors the current state of the production system. The controller retrieves measurement data from inspection in manufacturing as well as final quality data from end-of-line tests and traces the location of components and subassemblies in stock and upstream manufacturing processes. Considering external economic, environmental, as well as quality related boundary conditions, the cognition enhanced controller can take multi-criteria target values into account, which are used to autonomously find an optimum operating point for its production processes [10]. Based on the defined external objectives such as quality requirements, costs or throughput, internal objectives of the system can be derived [19]. Within the proposed concept internal objectives aim to optimize manufacturing by adaptive parameter adjustments and tool control, as well as selection strategies for the optimum component pairing for assembly. Based on function-oriented quality predictions and optimization ideal adaptive control parameters for manufacturing and assembly can be derived and fed back into the production system. Further information about function-oriented product models for quality predictions as well as the proposed control strategies for manufacturing and assembly are outlined in the following chapters.

3.1 Function oriented modelling approaches for predictive quality

To implement cognition enhanced control strategies, functional models need to be developed to enable the quality controller to predict the FKC of the final product based on the measured properties of the individual components. The objective is to model the relationship for each component of the assembly, described as a set of component related parameters $x_1,\dots,x_n$, to the FKC $f(x_1,\dots,x_n)$ measured at the end-of-line testbench at a quality critical operating point. The development of a function-oriented product model can be achieved by using different approaches including simulation or data driven advanced statistical approaches depending on the availability of accurate simulation models or sufficient level of information in the available measurement data. Since quality predictions based on simulation can be time consuming and thus not suitable for real time quality predictions, functional surrogate models can be developed and integrated in the knowledge base of the cognition enhanced controller. For the development of those models a calculus of variations can be used, incorporating the parameter space of possible production related tolerance distributions $\varphi(x_{i,j})$ for each parameter of a component as well as the simulation results of the FKC $f(x_1,\dots,x_n)$. In order to validate the simulation results, an evaluation with experiments is necessary [10]. Based on the simulation results regression-based surrogate-models can be trained and used for quality predictions in the controller. Next to simulation-based approaches, data driven approaches can also enable a functional model building for near real time quality predictions using measurements from the process. The model building in this regard is based on in-process measurement data and FKC quality data. Machine-Learning based approaches such as

Neural Networks, *Random-Forests*, *Support-Vector-Machines,* or other regression techniques can be used. The selection of an appropriate simulation- or data-driven approach finally depends on the ability to accurately predict the quality critical FKC of the assembled product with given boundary conditions of the production process. The integration of predictive models into the cognitive controller enables cognitive control strategies in manufacturing and assembly which are described in the following chapter.

3.2 Cognition enhanced quality control in manufacturing and assembly

Based on developed functional models near real time predictions enable the control system to select optimum parameter settings in manufacturing as well as ideal gear pairing strategy in gear assembly. The controller is therefore able to select an optimal option based on a set of possible solutions in terms of selective assembly or optimize its parameters and tools in manufacturing, see Figure 3.

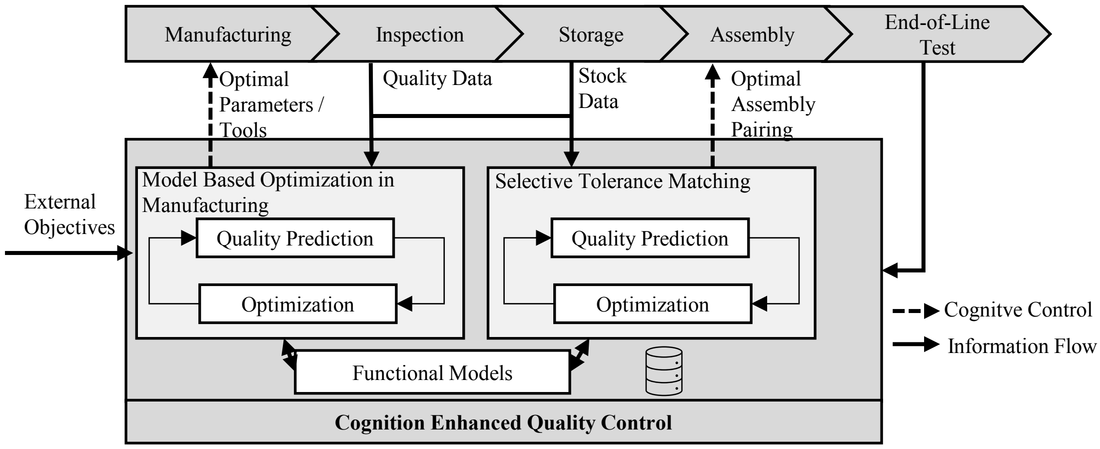

Figure 3: Cognition enhanced control in manufacturing and assembly based on function-oriented product models.

The focus of selective assembly is often on partitioning components in classes of certain width [20].The pairing of components without partitioning based on measurement values is called individual assembly [16], [21] or tolerance matching [12], [22]. The selective matching of parts with individual tolerance values based on the external objectives of the cognitive controller is referred to as selective tolerance matching in the following. One major element of selective tolerance matching is the ability of the controller to precisely predict FKC of the product based on the model $f(x_1,\dots,x_n)$, developed in chapter 3.2. The developed model gets incorporated into the knowledge base of the cognition enhanced quality controller. Given a set of component related in-line measurements for each part of an assembly $x_1,\dots,x_n,$ and the developed meta-model, the controller is able to virtually assemble possible part combinations and assess the corresponding FKC $f(x_1,\dots,x_n)$ through quality predictions. By using the optimization module of the controller, the best match for a set of components is then selected regarding the defined strategies and external objectives.

With reference to [9] a model-based optimization of the manufacturing process can be achieved. Based on functional models the system compares the predicted and the targeted process result which eventually leads to a set of internal objectives such as parameter adaptions. A further example for the proposed cognition enhanced control in manufacturing is a dynamic process for tool selection. Since the characteristics of a certain tool are known, the system can predict the expected quality output of each tool and evaluate its accuracy regarding the actual quality output of the currently used tools. The decision to change a tool finally depends on the ability to optimize the overall efficiency production system defined by multiple external objectives, e.g., in a quality, yield and costs. In the following chapter the concept of cognition enhanced control is applied to an automotive gear manufacturing and assembly process for electric drive production.

4. Industry case study

The presented concept is validated on an automotive gear manufacturing and assembly process for electric drive production focusing on the improvements of noise and vibration characteristics of the electric drive through cognition enhanced control strategies.

4.1 Production process of highly integrated electric drives

The considered electric drive is highly integrated containing the stator, rotor, inverter, gearbox, and bearings in a central housing unit, see Figure 4. The electric machine is classified as an electrically excited synchronous machine. The gearbox consists of a two-stage gear reducing the rotational speed of the electric drive to the desired speed of the tires.

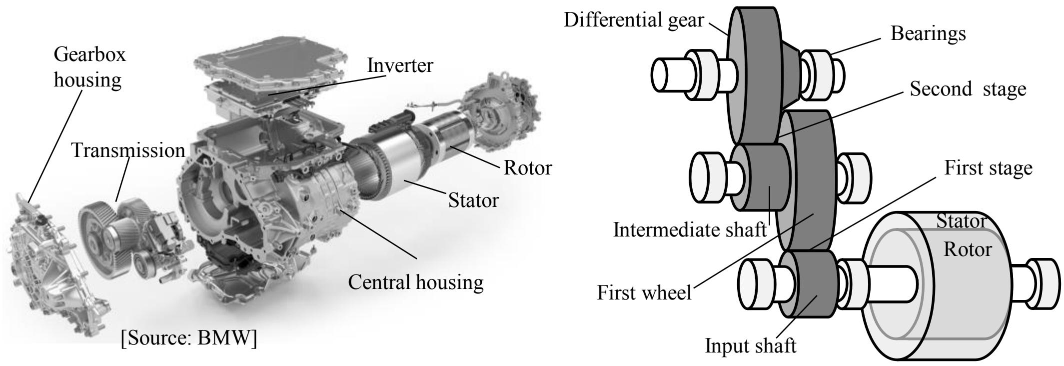

Figure 4: The considered automotive electric drive (left) and its schematic gearbox (right).

Within this case study the first stage of the gearbox has been evaluated. The manufacturing process of these gear components consists of multiple steps including turning, hardening and a final hard finishing step, optimizing the profile quality of the teeth before assembly. Based on a tactile coordinate measurement machine the profile of the gears is measured. Gear components are randomly assembled. Afterwards, the gearbox is assembled along with other components to a finished drive. At the end of the assembly process, the drive is tested for functional characteristics including acoustics. In this measurement step, structure-born noise is measured at certain speed ramps and loads using accelerometers at the housing. The permissible noise-levels are restricted by tolerance limits derived from customer requirements and vehicle tests. Applying the concept presented in chapter 3, the process is controlled by a conceptional cognition enhanced quality controller, see Figure 5.

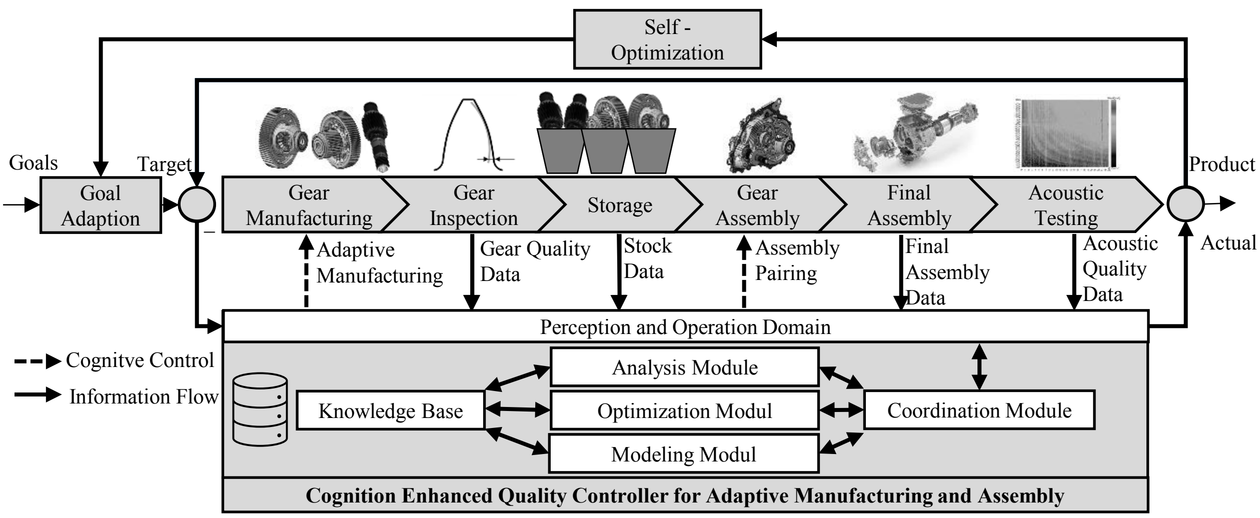

Figure 5: Self-Optimization through cognitive control in gear manufacturing and assembly for automotive electric drive production.

Due to manufacturing deviations caused e.g., by tool wear in gear finishing, systematic shifts in the final acoustic properties of a produced lot might occur. This can lead to critical noise at specific operation points of the engine and therefore to higher production costs due to rework, scrap parts, as well as waste of energy and material. Through a continuous analysis of the acoustic quality data, critical frequencies, speeds, and loads can be retrieved and optimization objectives can be adjusted. By means of cognitive control in gear manufacturing, parameters of the gear manufacturing process can be adjusted, or relevant tools can be changed. Based on the defined objectives and available measurement data, specific gear pairing strategies through quality predictions based on the individual topological properties become possible. Therefore, functional models need to be developed. The development of functional surrogate models is described in the following chapter.

4.2 Function oriented modelling

The objective of functional modelling in this case study is to model the relationship for each gear of an assembly, described as a set of gearbox related parameters $x_1, \ldots, x_n$, to parameters $f(x_1, \ldots, x_n)$ which correlate to gearbox related frequencies measured at the end-of-line testbench at a quality critical operating point. Therefore, a functional surrogate model is developed. A Monte-Carlo-Simulation (MCS) has been run, varying the gear micro geometry of the gear pairs in a defined range with a uniform distribution. Based on the variation of the gear pairs micro geometry, the peak-to-peak transmission error (TE) has been simulated at the quality critical speed and load, using the commercial CAE software *SMT MASTA*, see Figure 6.

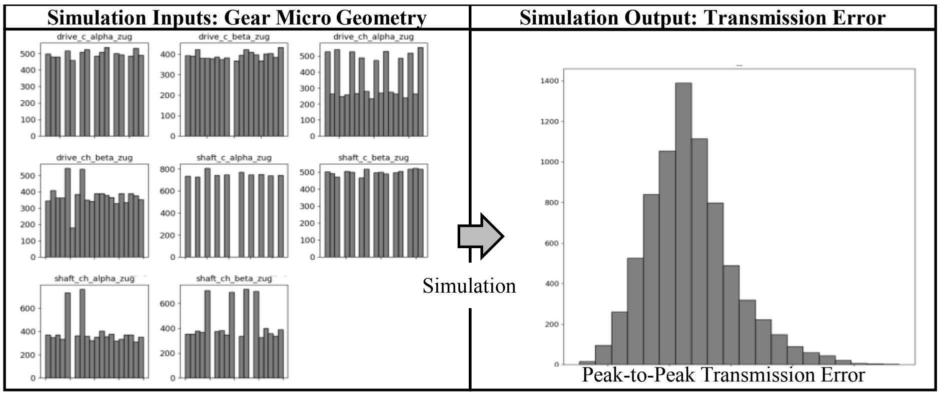

Figure 6: Gear micro geometry (left) and simulated peak-to-peak TE (right) using MCS.

Overall, 7500 variations have been calculated. The parameter range was chosen to cover typical manufacturing deviation in serial production. Since simulations are time consuming and thus are not suitable for in-process optimizations and quality predictions, the simulation results shown in Figure 6 have been used to develop a surrogate model. To find a surrogate with good precision for the simulation, different machine-learning algorithms were tested. After pretesting the scikit-learn implementations of *Histogram-based Gradient Boosting Regression Tree* [23], *Bagging Regressors* [24] and a *Random-Forrest* [25] were chosen for further optimization. Hyperparameters of these algorithms were tuned using grid search cross validation with ten folds. Therefore, the simulation results were split into a random training set containing 80 % of the samples and a test set containing 20 % of the samples. The best algorithm in training was defined by having the highest coefficient of determination, R^2, see Formular 1, The metric represents the proportion of variation in the dependent variable, which is predictable by the independent variables. To check the algorithms' ability for generalization, these surrogate models were used to predict the peak-to-peak TE based on samples of the test set. The mean squared error (MSE) was also calculated for the test sets. The results of these predictions can be found in Table 1.

Table 1: Accuracy results of the surrogate model with highest R^2 in randomized cross validation on train and test data

Algorithm	Hist. Gradient Boosting		Bagging Regressor		Random-Forrest	
Data set	Train	Test	Train	Test	Train	Test
R^2	0.86	0.88	0.79	0.80	0.79	0.80
MSE	---	0.0006	---	0.001	---	0.001

A mathematical definition of the metrics R^2 and mean squared error (MSE) can be found in Formula 1-2:

$$R^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{1}$$

$$MSE(y, \hat{y}) = \frac{1}{n}\sum_{i=1}^{n-1}(y_i - \hat{y}_i)^2 \tag{2}$$

With n being the number of samples, y the actual value of a sample, $\bar{y}$ the mean of actual values in the dataset, $\hat{y}$ the predicted value. Since the *Gradient Boosting* algorithm performs best on the training set and generalizes well on the test-set, the model with the identified hyperparameters was chosen and stored in the knowledge base of the controller for further quality predictions, see chapter 4.3.

4.3 Cognition enhanced control through selective tolerance matching

To obtain a realistic scenario, a discrete event simulation was modelled in python simulating the fine finishing manufacturing process of the input shaft and the wheel, a measurement step at gear inspection, the storage of the components, as well as the gear assembly process in a virtual environment. The cognitive controller has also been implemented in this virtual production environment. It extends the ideas of adaptive control loops in cyber-physical production systems [16] by means of cognition enhanced control, see Figure 7.

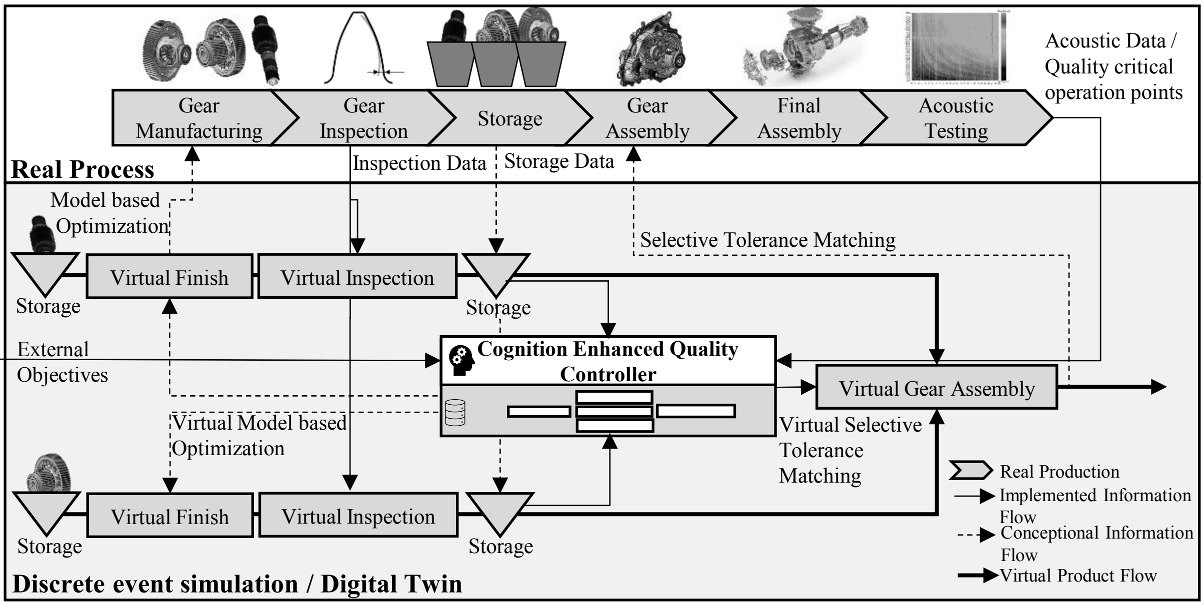

Figure 7: Schematic representation of the virtual implementation of cognitive control in a discrete event simulation.

The measurement values of the virtual inspection were retrieved from a real-world inspection of the gear components. Afterwards the virtual components are stored in a virtual storage. At each time step the virtual controller monitors locations of the components within stock and corresponding measurement values. Therefore, the virtual controller can simulate optimization strategies for the real production in a virtual environment. By using selective tolerance matching based on the model developed in chapter 4.2, gear pairings in current stock can be selected which minimizes the TE. The virtual assembly process has been run twice to compare the predicted results of random assembly with selective tolerance matching, see Figure 8.

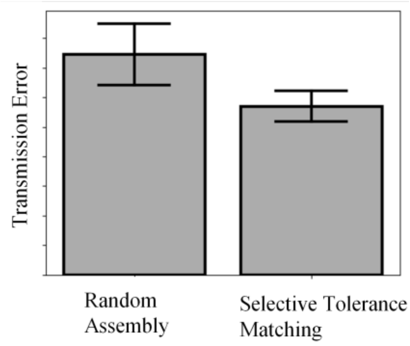

Figure 8: Comparison of the predicted TE with selective tolerance matching and random assembly.

The results of the predicted peak-to-peak TE with selective tolerance matching show a reduced standard deviation and mean compared to the random assembly. Since the TE is considered as a primary source of gear noise and vibration [26], the concept has the potential to optimize acoustic properties of the produced drives, and therefore reduce costs and waste. Current limitations of the concept are discussed in the following chapter.

4.4 Limitations

The presented concept for cognitive enhance quality control has limitations, which have not been considered due to simplification and scope within the use-case. To obtain a more realistic scenario, the use-case can be extended by adding the full topology of the gears to the simulation, adding the second gear stage including both flanks and simulating multiple speeds and loads. Optical in-line measurements can be used to obtain higher information density in the measurements [27]. Also, functional models can further be optimized to obtain higher prediction accuracies. Currently only the gears micro geometry has been considered. In real-world serial production however multiple other sources, e.g., misalignment of the shafts through tolerance deviations of the housing can also influence the acoustic properties of the drive, which have not been considered yet. Even if some studies show a correlation between the TE and noise [28] the direct relationship between TE and level of gear whine is considered as unrevealed [26]. Functional models should be integrated predicting the actual structure-born noise. This will enable the cognitive quality controller to realistically predict scrap parts and thus also estimate costs and sustainability indicators using actual tolerance limits in the virtual assembly. Finally, a combined validation of the concept in serial production incorporating both methods of model-based optimization strategies in manufacturing and selective tolerance matching is necessary.

5. Summary and outlook

In this publication a self-optimization concept based on cognitive quality control in manufacturing and assembly processes has been presented and validated in the gear production of automotive electric drives. The proposed concept incorporates model based control in manufacturing as well as selective tolerance matching for an optimal selection of components in assembly using function-oriented quality predictions. Within an industrial use-case a discrete event simulation was developed incorporating the cognition enhanced controller. On a simulation basis it was shown that the proposed method lowered the predicted peak-to-peak TE for the first gear stage and thus has the potential to improve acoustic characteristics of the electric drive. However, to increase the potential of cognition enhanced control in gear manufacturing and assembly for electric drive production, further research is required to overcome the discussed limitations of the current concept leading towards the goal of self-optimized cognition enhanced production systems.

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Biography

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