SYSTEMATIC OPTIMISATION PROCESS FOR AN EBIKE DRIVE UNIT IN A HIGHLY VARIABLE ENVIRONMENT

Steck, Marco (1,2);
Husung, Stephan (2)

1: Robert Bosch GmbH;
2: TU Ilmenau

ABSTRACT

Drive units of eBikes are used in every type of bicycle and for different riding scenarios and riders. Due to the different riders and bike types, an enormous variety of influencing parameters and load spectra must be considered during the design process. Therefore, in this paper, a systematic approach for the optimization of the drive unit is presented, which adopts and combines several approaches from design theory. The focus is on efficient modeling and simulation of the relevant parameters and load spectra to minimize uncertainties in the design process.

Based on a system analysis, dimension-reduced parameter spaces are formed for the simulation of the system, meta-models are integrated into the simulation model and the results of the simulation are transferred into a data-based surrogate model to cover the parameter space in an efficient way with a minimum number of time consuming FE simulations. Furthermore, a coordinate-based evaluation method is presented for the FE model in order to form the input for the surrogate model, reduces the amount of data, and to allows a geometry- and mesh-independent evaluation to compare different models.

Keywords: Systems Engineering (SE), Simulation, Computational design methods, Lightweight design

Contact:
Steck, Marco
Robert Bosch GmbH
Germany
marco.steck2@de.bosch.com

Cite this article: Steck, M., Husung, S. (2023) ‘Systematic Optimisation Process for an eBike Drive Unit in a Highly Variable Environment’, in *Proceedings of the International Conference on Engineering Design (ICED23),* Bordeaux, France, 24-28 July 2023. DOI:10.1017/pds.2023.331

1 INTRODUCTION

Technical products must be developed in a way that the required properties are sufficiently fulfilled for the relevant applications and in the associated environments (Weber and Husung, 2016). For the optimization of demanded properties such as fatigue strength, it is crucial to consider the entire load spectrum resulting from the different applications in order to minimize uncertainties during the design process (Wolniak et. al 2021). For products that can be used in a wide range of applications, this results in increasingly complex load spectra that are hard to handle in computational analysis and testing. This can be particularly relevant for the optimization of sub-systems, where the load spectra must be considered not only in combination with the design parameters but also with a variety of other non-variable parameters of the overall system.

An increasingly important product with these challenges mentioned above is the eBike and their sub-system, the drive unit (DU). Given the novelty of the product, several challenges arise due to a lack of standards and experiences, which makes eBike DUs particularly interesting in the context of design research (Steck et al. 2022, Steck et al. 2023). Due to their function as sub-systems, which are used in all various bike types and accordingly in a variety of user scenarios, multi-layered and diverse load spectra with numerous influencing parameters from the overall bike system and design parameters from the engine itself arise. Figure 1 shows the integration of the DU into the eBike system and potential variations across the system.

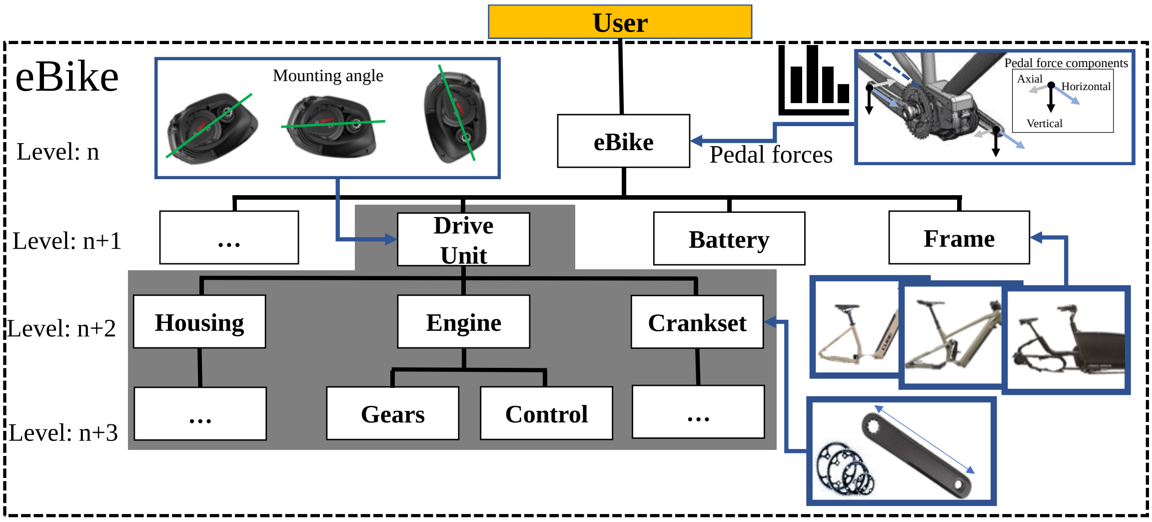

Figure 1. Overview of the drive unit and its influences

As a result of the large number of different bike types, the market demands DUs that can reliably withstand as many installation positions and application scenarios as possible. To obtain a more competitive product, a design optimization method must be developed that can evaluate the design response to different bike types and user behaviours. In this context, the most important parameter for optimisation is the durability of the mechanical structures in relation to the component weight. Although other influences such as the NVH behaviour or the thermal properties of the drive are other important development goals, the focus in this paper will remain on durability as the fundamental objective. However, to minimize uncertainties for the fatigue calculation, all possible combinations of DU-dependent design parameters must be considered together with the load spectrum and all eBike system configurations available on the market (see Figure 1). Consequently, numerous calculations of FE simulations are necessary, which results in an immense computational effort for each optimization loop.

In order to solve this problem, this paper describes a method for developing a simulation model of a sub-system that efficiently accounts for the load spectrum in conjunction with other influence and design parameters. In addition, a strategy for efficient computation of the entire parameter space is presented.

For this purpose, existing methods from engineering design research, such as system theory, scenario analysis, metamodeling, and sensitivity analysis, are used and applied to the eBike DU. In this context, the paper addresses the following research questions:

https://doi.org/10.1017/pds.2023.331 Published online by Cambridge University Press

- How can a model of a drive unit be developed for the optimization of durability which considers the influence of all relevant parameters of the whole eBike system?
- What methods can be used to minimise the computational effort for the simulation of the immense variance of the whole eBike system?

2 STATE OF THE ART

For optimisations of multi-level systems, the first step should be the modelling of the functional structure of the system, followed by the decomposition of the system into individual sub-systems. (Zerwas et al. 2022). Based on this, the dependencies between the individual sub-systems can be identified. For setting up the optimisation problem, the overall system and the interaction of the entire sub-system involved must be determined in relation to the relevant target variables. Thus, the starting point for any optimisation or modelling is a suitable system analysis as the indispensable basis. In previous publications, many methods have been presented that can be used for the analysis and general description of system architectures and their interactions. Example models to identify an abstract functional structure of a multi-level or multi-dimensional product are described for example in (van Keulen and de Wit 2010, Albers and Wintergerst 2014, Yildirim et al. 2017, Weber 2005, Husung et al., 2022).
In the work of van Keulen (van Keulen and de Wit, 2010), the procedure for the decomposition of multi-level system is described in general. With this analysis, both bottom-up and top-down relationships between levels of the system hierarchy and at the same level can be considered to describe the interactions of the individual sub-system. Subsequently, objective functions and constraints can be formulated for each sub-system, which can then be used for the setup of the optimisation problem. Thereby, the previously identified dependencies, responses and constraints of the neighbouring sub-system are used in addition to the variables of the individual sub-system. This scheme can be seen in Figure 2.

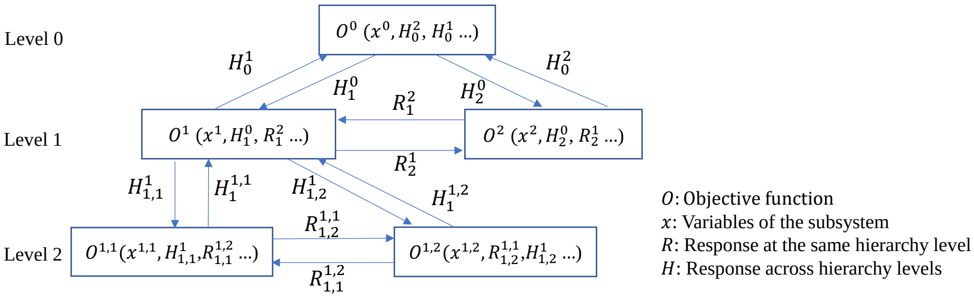

Figure 2. The procedure of the system decomposition (van Keulen and de Wit, 2010)

Applying this method to obtain the objective function of a sub-system can, of course, lead to a large number of influencing parameters that can either only be evaluated with enormous computational effort or cannot be integrated into the model of the sub-system at all. Especially for the consideration of uncertainties due to statistically scattering influences and their necessity to consider them holistically for the robust design increases the parameter scope significantly (Wolniak et. al 2021). Therefore, several methods were proposed to find ways of reducing the number of simulations or to solve the optimization problem with less computational effort. The most common techniques used are the sensitivity analysis and metamodeling.
Typically, a sensitivity analysis will be used to identify the most influential input factors for the optimisation in order to limit the design variables to the significant ones. Examples of such analysis can be found in (Jiang et. al, 2018, Stangl et al., 2013). Metamodels, on the other hand, are used to reduce computation time, whether through physical or data-based solutions. Here, either the entire system or only parts of the system can be represented as a metamodel. Depending on the individual system and the optimisation task it must be decided whether the entire system or only interfaces to individual sub-systems or components will be replaced by meta models. Nowadays, many metamodels are built from the inputs and outputs of complex numerical computations in a data-based approach, in order to make projections about a target variable by regression or classification methods without performing further time-consuming computations. In the current literature, there are already several methods and case studies for developing metamodels, such as the Respond Surface Method, linear Regression, Kriging,

https://doi.org/10.1017/pds.2023.331 Published online by Cambridge University Press

Radial Basin Functions and more recently Machine and Deep Learning approaches. More detailed insights and a summary of the state of the art in this domain can be found in (Kudela and Matousek 2022, Koeppe 2021). At this stage, it is not possible to recommend a general method for the formation of the surrogate model. Therefore, a suitable approach must be determined depending on the specifications of the model. However, all model approaches have in common that they achieve good results for the interpolation tasks but are less suitable for the extrapolation. Also, generally better results can be expected if only parts of the model are considered instead of the whole model. (Hoffer, J.G et all. 2021) For the creation of the surrogate models the use of simulations with a suitable sampling of the influencing parameters is necessary. Therefore, methods like Latin Hypercube Sampling (LHS) or Monte Carlo Simulation (MCS) are used, which are described for example in (Most and Will, 2008). Despite the given limitations, recent studies have shown not only on theoretical examples but also on industrial and practical applications that surrogate models can be efficiently used to analyse a system with variable influence parameters. (Kudela and Matousek 2022, Koeppe 2021)
The analysis of the state of the art reveals promising approaches and methods that can be used to address the challenges in DU optimization. As a result, a methodological approach based on these impulses is proposed in Section 3, which is subsequently applied to the DU in Section 4.

3 METHODICAL PROCEDURE FOR THE OPTIMIZATION

In order to optimize the sub-system, two essential points have to be fulfilled. First, an efficient model of the sub-system must be developed, which can calculate not only the influences within the sub-system but also any possible change of parameters in the overall eBike system. After that, a strategy is needed to efficiently investigate the parameter space of the whole system formed by the superposition of the DU and eBike parameters with the load spectrum. The focus for this strategy is therefore on reducing the computational effort and minimizing and handling the amount of simulation data. This is especially important, because it must be ensured that in each iteration of the optimisation no critical load case is overlooked and all possible parameter combinations are considered and identified. Once such a model is created, well-known and industrially used methods such as topology and shape optimisation (based on the critical load cases) as well as parameter optimisation (by including design parameters in the parameter space) can be used to obtain an efficient mechanical structure. A more detailed description of the methodical procedure for building an efficient model of the sub-system based on the system analysis as well as the key strategical tasks for the computationally efficient calculation will be given in the following. The developed procedure is shown in Figure 3.

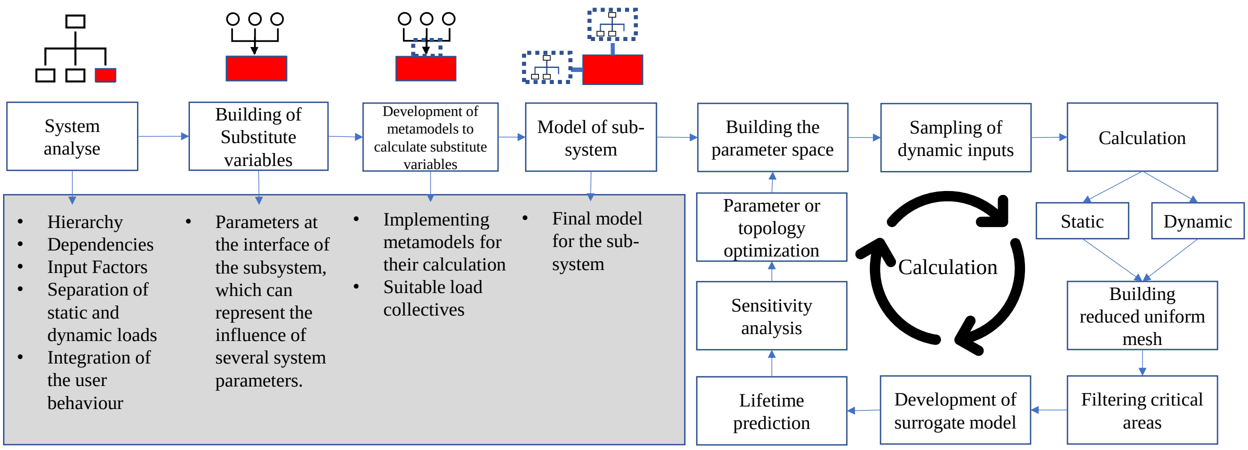

Figure 3. Methodical procedure for generating and calculating an efficient model for the optimization of a sub-system

3.1 System analysis

The first step for modelling the sub-system in the given context is to identify the relevant parameters and their dependencies within the sub-system and the overall system. For this purpose, the already existing methods for a top-down and bottom-up system analysis of the system hierarchy are applied (van Keulen and de Wit, 2010, Husung et al., 2022). In this context, it is particularly important to also

https://doi.org/10.1017/pds.2023.331 Published online by Cambridge University Press

include the user behaviour in the analysis to correctly transfer the user-dependent load collectives across the entire system to the sub-system.

Based on this system analysis, substitute parameters are established within the physical boundaries of the sub-system, to which all parameters of the overall system can be referred. These substitute parameters can be calculated through metamodels that describe the relevant system behaviour based on the identified dependencies. By using this approach, all possible values of the parameters of the higher-level system can be represented by different expressions of the substitute parameters in the subsystem. Most importantly, this significantly reduces the number of influencing parameters in the model of the sub-system. Consequently, a dimensionally reduced model for the calculation of the complex FE analysis can be developed. Since the dependencies of the individual system parameters towards the substitute parameters within the sub-system are known, the sensitivity of the system parameters can be recalculated. Therefore, there is no loss of information even though the dimension of the influencing variables has been massively reduced.

For further reductions, it can be investigated whether the loads caused by certain influence parameters must be calculated coherently or can be considered independently of each other. Especially for mechanical target values like the durability, loads can be grouped into static or quasi-static and dynamic parts. This allows the formation of two independent and dimension-reduced parameter spaces for the static and dynamic load condition. Since these can be calculated independently and combined afterwards by superimposing stress states, this again leads to a significant reduction of the parameters and load combinations to be calculated. For the optimization of a mechanical fatigue strength, this separation is indispensable and allows an independent calculation of the loads in separate models

3.2 Simulation strategy

As a first basic step for the calculation of the system, the parameter spaces for the static and dynamic model of the sub-system must be determined. Here it is important to consider the hierarchy and the known limits of the system. To reduce this number of combinations, discrete levels or classes can be assumed for suitable parameters.

Especially for the parameter space of the dynamic load, many possible operating points can be expected due to the variable user behaviour. Thus, it is reasonable to create a data-based substitute model for the FE model of the dynamic load to cover the reduced parameter space with the lowest possible number of simulations. This allows the determination of the load conditions based on the regression analysis of the system behaviour determined by the surrogate model in the post-processing of the FE calculation. Here, the decisive factor is the previous dimension reduction of the parameter space, which enables a more efficient sampling and a mapping of the parameter space with a smaller number of FE simulations. The resulting multitude of combinations in this dimensionally reduced parameter space can then be compensated by the surrogate model. Of course, this also applies to the calculation of the static parameter space. Regarding the formation and application of a surrogate model, however, the following problems must be considered for the calculation of the fatigue strength:

- Since the fatigue strength must be considered over all possible loads and their frequencies rather than based on one static load, a direct prediction of the fatigue strength or damage is impractical.
- By separating out independent loads, differently meshed models are created, which must be combined for the calculation of the local concept.
- Since several loading situations have to be considered in a local concept for the fatigue calculation, the reasonable target value for the prediction and interpolation of the surrogate model is the stress state at each node of the simulation.
- Due to the FE meshing, enormous amounts of input and output data are generated for each element and its results.

To solve the problem of the non-uniform and above all overly detailed discretization of the FEM mesh, a uniform broader discretization must be found. For this, a suitable balance must be found between loosing too much information and the aggregation of as many data points as possible. Therefore, constantly, or less loaded areas are subdivided into larger divisions to reduce the number of inputs for the surrogate model. In order to analyse the data from the FE model into a uniform and automated scheme, across multiple loops and geometry changes, the FE results are divided into a geometric grid. Starting from the maximum component dimensions, a specific grid of cubes with constant edge length is formed, which are then refined step by step (see Figure 4). The refinement is performed using an algorithm that identifies local maxima as a function of the gradient and the difference between the highest and lowest equivalent stress in that cube. If there is more than one local maximum in one of the observed cubes, the cube is refined by half the edge length. Then, the values of this maximum are assigned to the respective cube. To avoid the inclusion of numerical errors and divergence points in the calculation, outliers can be determined by looking at suspicious element volumes, the gradient and the standard deviation as well as the percentiles. Of course, this algorithm takes into account the stress states of all calculated loads to achieve an overall suitable refinement.

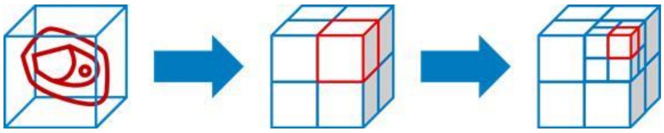

Figure 4. Schematic representation of the clustering process

In addition to an enormous data reduction (without relevant loss of information), this approach also allows the combination of differently meshed models for static and dynamic load cases. Thus, the results of the input parameters can be efficiently assigned to a concrete output value which enables an automatic procedure. In this way, it can be ensured in each loop that no critical load or location is missed. Since this method is independent of the exact geometry in the design space, comparisons can be made between different stages of the design, even if the geometry changes in different loops due to changes in the design parameters. Obviously, this also allows the method to be applied to other products or only specific parts of the geometries.

For the calculation of the surrogate models, the parameter space is partitioned and simulated by a suitable sampling method such as the LHS and MCS. Then all these simulations are evaluated and the minimum discretization for all operating points is determined.

Now, an estimation can be made which cubes, due to a relatively high stress in one of the simulation samples, are relevant for the formation of the surrogate model. Therefore, it is assumed that the sampling is sufficient to detect possible critical points. Since the formation of the surrogate model generally only allows the interpolation of the results, the derivation of the critical points based on the sampled data is seen as a reasonable assumption. Thanks to this additional filtering, the input data for the surrogate model can be reduced yet again.

Finally, this surrogate model enables the representation and calculation of all influencing parameters and the entire load spectrum. Most importantly, this method enables the calculation of design-relevant (output) parameters and their sensitivity to all possible inputs at all locations which have been identified as relevant. Thereby the clustering and filtering helps to compensate the main problems for the analysis of a highly variable parameter space where no clear target value or location for its evaluation is yet known

4 APPLICATION AT THE EBIKE

In order to better illustrate the discussed method, its application is presented in the following chapter using the eBike DU as an example to demonstrate the most important steps.

4.1 System analysis

As a summary of the results of the system analysis, the force, energy and information flows for the basic architecture of an eBike are presented in Figure 5 This architecture shows the interaction of the relevant sub-systems and the user behaviour centred around the critical input for the durability calculation, the loads acting on the housing.

As the user behaviour is on the one hand the starting point for the direct DU load and on the other hand also related to the general eBike and frame setting, this has to be investigated in more detail as part of the system analysis. Besides the obvious dependency of the user behaviour to the driving loads, it is assumed that certain riding situations can only occur in combination with a certain type of bike. At least this can be derived from the general eBike specifications released by the bike manufacturers. For example, downhill rides and jump situations are not permitted for trekking bikes. This correlation allows further parameter combinations to be excluded from the calculation of the possible parameter space and is therefore important for the following procedure. But this is only possible if the load spectra are determined modularly and can be related to suitable driving situations, so that suitable load spectra can be formed for each bike setup. In this case, the load spectra were obtained by measurements of pedal

https://doi.org/10.1017/pds.2023.331 Published online by Cambridge University Press

forces in typical riding situations. For this purpose, riding situations were defined by a classical full factorial DOE that included parameters like the pedal type, the position of the driver and the motor assistance level. More detailed information can be found in (Steck et al., 2022).

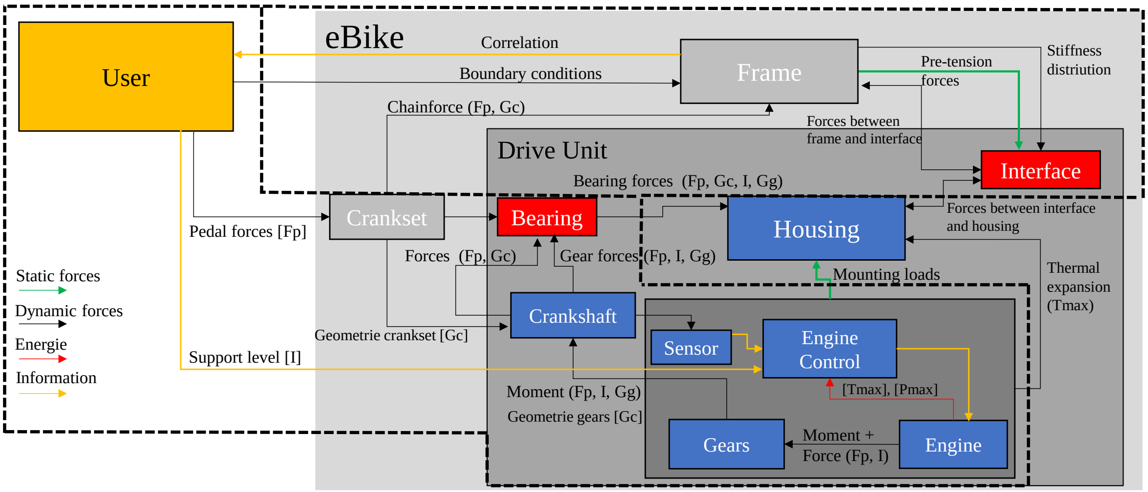

Figure 5. Overview of the power, energy and information flows of the DU.

4.2 Building of substitute parameters

To find suitable substitute parameters, a parameter within the sub-system must be identified that contains the effects of several other eBike or DU parameters. From the system analysis, it becomes clear that the bearing forces perform exactly this role, as they are dependent to both the external and internal influence parameters of the DU. A similarly broad mode of action can be observed for the frame interface, as it is associated with forces and boundary conditions and defined by the stiffness distribution. Therefore, it is reasonable to define the bearing forces and the frame stiffness as the desired substitute parameters, which can be calculated by the aggregation of the other related influence parameters.
For the remaining static or quasi static loads (including external loads, thermal loads and mounting loads), no substitute parameters have to be defined, as they can be represented directly at the subsystem. In addition, they do not have to be considered in combination with the dynamic parameters based on the user behaviour.

4.3 Metamodel for substitute variables

4.3.1 Bearing forces

As the functions within the DU sub-system can be described with a high level of detail, the interaction of the sensors for detecting the torque and force of the driver and the subsequent motor control based on the selected level of assistance are known. As a result, the torques and forces from the gears and the engine can also be calculated based on the determined load spectrum for the respective driving situation. In combination with relevant geometric data (pedal length, chainring diameter, mounting angle...) from the eBike setup, the bearing forces can then be calculated for all combinations of the relevant parameters and pedal forces of the load collective. Thus, many influencing parameters of the overall system can be transferred to the bearing forces and their orientation, which can be directly included in the FE Model (Abaqus) as the bearing pressure.

4.3.2 Frame stiffness

With regard to the modelling of the frame stiffness, the real boundary conditions of a cycling motion must also be taken into account. For the case of normal cycling, the system's boundary conditions can be derived from user behaviour, as riders must apply a counter-torque to the handlebars to compensate for pedalling forces. Accordingly, a fixed mounting on the front axle and a purely translational fixation on the rear axle of the bike frame must be implemented. This fixation is also already included in the norm test of the frame and can be seen in Figure 6 (DIN EN 15194, 2017).

https://doi.org/10.1017/pds.2023.331 Published online by Cambridge University Press

Taking this boundary condition into account, a static condensation can be used to form an equivalent stiffness matrix for the reference points at the interface of the DU and at the front and rear wheel axles. This allows the sub-system to be coupled with the real frame stiffness and a real boundary condition.
In addition, the chain forces can also be included in this substitute model as a moment on the rear axis to correctly represent the load situation. Similarly, forces in the DU due to external frame loads caused by bumps and obstacles or heavy braking can be calculated and implemented. Investigations on different frames have shown that large differences in the stiffness matrix occur, primarily for different frame types. Therefore, not all possible frame stiffnesses are considered, but only a characteristic stiffness matrix for each bicycle frame type. This stiffness matrix can then be used as a fixed parameter representing the bicycle frame of a specific bike type in the parameter space for the dynamic calculation. (Steck et al., 2023)

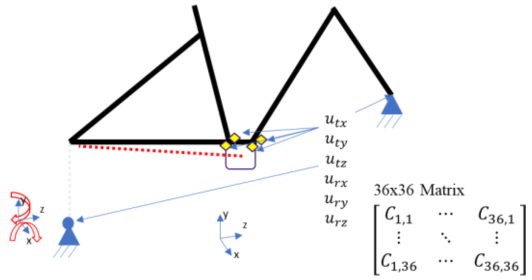

Figure 6. Simulation model for the calculation of the frame metamodel (Steck et al., 2023)

4.4 Models of the sub-system

At the end of the modelling process, several models can be created based on the separation of static and dynamic loads and their influence parameters. As a result, a model is created for the representation of the dynamic user-dependent parameters and individual models are created for the calculation of the static load parameters. Due to the following uniform partitioning, different meshes of the FE models can be used, which allows an easy adoption of models from different loading situations.

5 CALCULATION PROCEDURE

This chapter will not describe the entire calculation process. For this paper, the focus will be on the problem-specific steps of the method, the formation of the parameter space and the clustering method to analyse and reduce the input and output of the simulation.

5.1 Parameter space

As a basis for the formation of the surrogate model and the required sampling of the input data, the parameter space must be captured for all possible combinations of the load collective and the DU and eBike parameters. The bike type related constraints can then be used after the formation of the surrogate model to determine the type of specific load and the durability.
The added value of this dimensionally reduced view can be demonstrated by examining the bearing forces of the DU as an example. Figure 7 shows the possible bearing loads that result from various gear, pedal, chainring and housing geometries combined with the entire load spectrum.

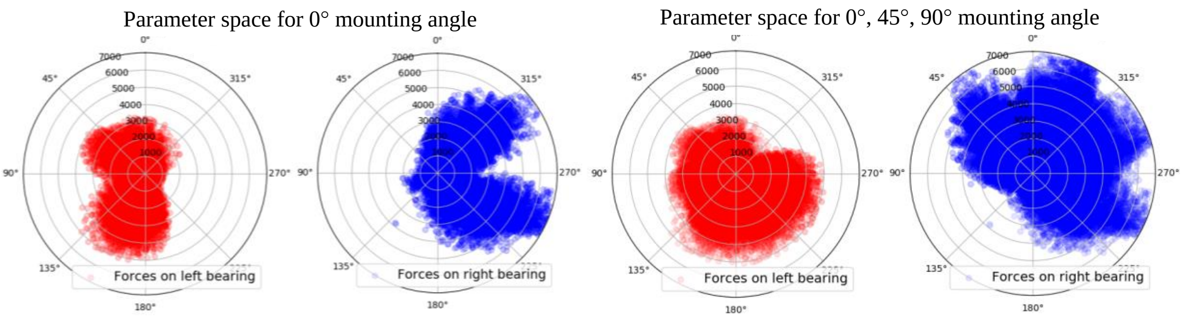

Figure 7. Orientation and amplitude for the bearing forces for a certain user load collective, all crank set variations and different mounting angles

https://doi.org/10.1017/pds.2023.331 Published online by Cambridge University Press

When looking at this parameter space, it can be observed that the variation of all possible input parameters partially causes similar or identical load situations. Especially the variation of the mounting angle of the DU leads to an enormous overlapping of the parameter spaces. This shows the potential for a reduction of the simulation tasks by aggregating the influences and calculating an entire parameter space instead of each individual combination. Nevertheless, the parameter space still contains to many load points, which requires the calculation of a surrogate model for a more efficient computation. Especially since this parameter space still has to be varied with the stiffnesses of different frame types.

5.2 Clustering

For the test of the clustering method, 100 sampled load and parameter combinations and 2 static load states with a different mesh were examined for uniform discretization. Each of the models in that test had over 800.000 elements and more than 7 million node values. This amount of data could be broken down to a uniform network of about 30.000 cubes. In total edge lengths of 16 to 1 mm were obtained for that test. The relevant convergence condition for the maximum tolerated difference of the Mises equivalent stress across all nodes of a cube was set to two MPa.
Additional filtering for elements that have at least half the yield strength of the material for one of the calculated setups was selected. This reduced the remaining number of input data for the training of the surrogate model to 1500-2000 datasets. The plotted result of the remaining cubes can be seen in the following Figure 8. This method as well as the whole postprocessing and data management is programmed in python.

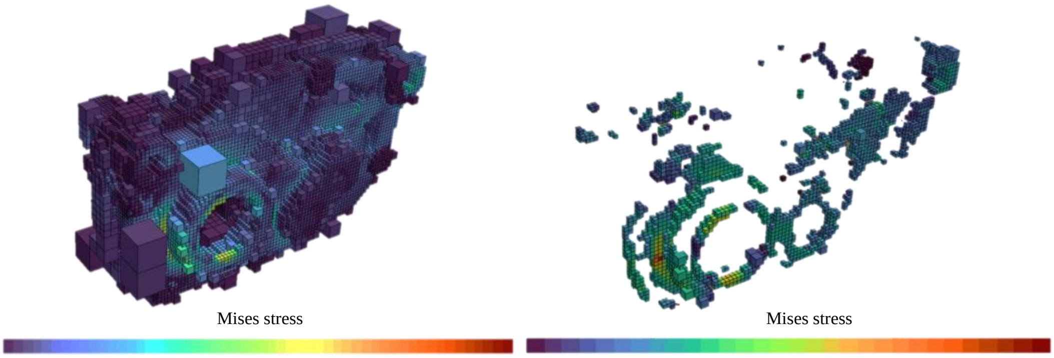

Figure 8. Results of clustering: on the left, uniform reduced meshing on the right filtered according to maximum stress values

6 CONCLUSION AND FURTHER STEPS

In this paper, a methodological approach for modelling an eBike drive unit in the context of variable system conditions was presented. Thereby, many already existing methods in the environment of the design research were used. It was shown how the influencing variables of the overall system can be successfully broken down to suitable substitute parameters. On the one hand, this enables a modelling of the sub-system that can also consider influences from the entire eBike system and, on the other hand, an enormous dimensional reduction of the parameter space that has to be calculated. These dimensionally reduced influence parameters provide the basis for the generation of efficient surrogate models which was identified as the important methodical approach to efficiently represent the uncertainties due to the enormous variance of the load collective.
In addition, a method was presented, which can form an improved input dataset set for the surrogate model by reorganizing and condensing the data structure of the FE output. Thus, the required reduction of the simulation data could be realized. This helps in the formation of the surrogate model and in the combination of the dynamic and static loads that were calculated independently to reduce the possible combinations. Finally, this method allows an efficient and automated calculation of all relevant mechanical loads and ensures that no critical load case or location is missed. Due to the uniform grid, the damage in certain regions can also be calculated for different design parameters and geometry changes. This enables a robust parameter optimization of the sub-system as well as the definition of a limitation of the possible eBike system parameters.
In addition to parameter optimization, the critical load cases and locations can be determined for the use of topology optimization. Then the method can be applied again to the new geometry to evaluate

https://doi.org/10.1017/pds.2023.331 Published online by Cambridge University Press

the design changes. In general, the major advantage is that the enormous number of possible load combinations can be efficiently calculated and evaluated. As this method can be focused on any target variables of the FE output, further considerations are possible in addition to the fatigue strength calculation, where e.g. displacements at the bearings of the gears and motor axis are considered to support an analysis of the NVH behaviour or the gear design.

The further steps are the calculation of the existing geometries and the formation and validation of the surrogate model as well as a sensitivity analysis of the influencing parameters. This should provide product-specific solutions as well as fundamental insights for the design of eBike DUs that have only been roughly investigated so far.

REFERENCES

Albert de Wit and Fred van Keulen F., de Wit A. (2010) "Overview of Methods for Multi-Level and/or Multi-Disciplinary Optimization", *51st AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, https://doi.org/10.2514/6.2010-2914

Albers, A. and Wintergerst, E. (2014) "The Contact and Channel Approach (C&C2-A): Relating a System's Physical Structure to Its Functionality", in: *An anthology of theories and models of design: Philosophy, approaches and empirical explorations*, London, Springer, pp. 151–171.

DIN EN 15194, (2017) "Fahrräder – Fahrräder –Elektromotorisch unterstützte Räder –E-PAC" (15194:2017)

Hoffer, J.G.; Geiger, B.C.; Ofner, P.; Kern, R. (2021), "Mesh-Free Surrogate Models for Structural Mechanic FEM Simulation: A Comparative Study of Approaches" *Applied Sciences.* 2021*; 11(20):9411.* https://doi.org/10.3390/app11209411

Husung, S., Weber, C., & Mahboob, A. (2022). "Integrating Model-Based Design of Mechatronic Systems with Domain-Specific Design Approaches" *Proceedings of the Design Society, 2, 1895-1904.* https://doi.org/10.1017/pds.2022.192

Jiang J.,Ding G., Zhang J., Zou Y., Qin S., (2018), "A Systematic Optimization Design Method for Complex Mechatronic Products Design and Development", *Mathematical Problems in Engineering*. https://doi.org/10.1155/2018/3159637

Koeppe A. (2021) *Deep learning in the finite element method*, Dissertation RWTH Aachen University, Aachen https://doi.org/10.18154/RWTH-2021-04990

Kudela, J., Matousek, R. (2022), "Recent advances and applications of surrogate models for finite element method computations: a review", *Soft Computing 26, 13709–13733,* https://doi.org/10.1007/s00500-022-07362-8

Most, T. and Will, J. (2008), "Sensitivity analysis using the Meta-model of Optimal Prognosis – An automatic approach for variable reduction and optimal meta-model selection", *Weimarer Optimierungs-und Stochastiktage*, Weimar.

Stangl T., Walter M., Wartzack S. Schneyer T. (2013) "Robust design proposal by the use of structural topology optimization considering uncertainties of input parameters and boundary conditions", 19th International Conference on Engineering Design (ICED13)

Steck M., Husung S., Hassler J., (2022)" Determination and systematization of load situations for eBike drive units as basis for their design and optimization", *8. IFToMM-D-A-CH Konferenz* https://doi.org/10.17185/duepublico/75445

Steck M., Husung S., Hassler J., (2023)" Determination and characterization of the influences of the bike frame on eBike drive units as the basis for their design and optimization", 9. IFToMM-D-A-CH Konferenz https://doi.org/10.17185/duepublico/77395

Weber, C. (2005) "CPM/PDD - An Extended Theoretical Approach to Modelling Products and Product Development Processes", *2nd German-Israeli Symposium on Advances in Methods and Systems for Development of Products and Processes*, Fraunhofer-IRB-Verlag, pp. 159–179.

Weber, C., Husung, S. (2016). "Solution patterns- their Role in innovation, practice and education" *14th International Design Conference*

Wolniak, P., Cramer, J., & Lachmayer, R. (2021). "Robust multi-objective optimization in product development with respect to user-scenario and manufacturing uncertainties", 23rd International Conference on Engineering Design (ICED21), https://doi.org/10.1017/pds.2021.520

Yildirim U., Campean, F. and Williams, H. (2017) "Function modeling using the system state flow diagram", *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, vol. 31, no. 4, pp. 413–435.

Zerwas, Thilo, Georg Jacobs, Julia Kowalski, Stephan Husung, Detlef Gerhard, Bernhard Rumpe, Klaus Zeman, Seyedmohammad Vafaei, Florian König, and Gregor Höpfner. (2022). "Model Signatures for the Integration of Simulation Models into System Models" *Systems* 10, https://doi.org/10.3390/systems10060199