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Research paper

Numerical identification of position-dependent friction coefficients from measured displacement data in a bolt-nut connection

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ABSTRACT

Friction is a complex system affected by microscopical effects and multidisciplinary phenomena. Coulomb's simple friction model with a constant friction coefficient cannot account for all these tribological effects. Nevertheless, this model is still widely utilised for calculations of mechanical applications. In order to reflect the importance of friction as a parameter for functionality, we need more realistic and sophisticated calculations. This is particularly relevant for bolt-nut connections, which serve as motivating example for our study. Our approach is to introduce position-dependent friction coefficients by dividing the contact surface into different friction areas, each characterised by a constant friction coefficient. These coefficients are then adapted to measured displacement data. To this end, we develop a numerical parameter identification tool. The tool combines calculations in Ansys Mechanical, an established Finite Element software, and Microsoft's Visual Basics for Applications for optimisation purposes. We verify the parameter identification tool using the simple model of a block on a planar surface. Within this test scenario, the algorithm converges and provides a good approximation of the friction coefficients. Subsequently, we apply parameter identification to the model of a bolt-nut connection. We perform optical measurements to acquire experimental displacement data. The parameter identification tool demonstrates its functionality. Finally, we discuss future modifications of the procedure, that will enable more realistic and reliable results.

1. Introduction

Mechanical applications are generally limited by friction mechanisms in contacting surfaces. The mechanisms are related to friction laws. The law most commonly found in practical applications is Coulomb's friction law: The friction force, which acts against the relative motion of contacting surfaces, is proportional to the normal force with the so-called friction coefficient μ being the proportionality factor. The friction coefficient is assumed to be constant, depending only on the material pairing. In mechanical engineering, friction is regarded as an important parameter for functionality. Various applications are designed to minimise friction (e.g. bearings, railways, chains). Conversely, certain applications aim to maximise friction (e.g. vehicle brakes or belt drives). Bolted joints are a combination of the two: As a preloaded bolt joint, they require high friction to prevent unintentional loosening. However, this friction, along with the friction in the bolt head, must be overcome during the tightening process. Consequently, a substantial proportion of the force applied during tightening needs to be invested overcoming friction rather than achieving the intended preload force of the bolted joint. Literature provides practical tables for the maximum load for particular bolt sizes, depending on the grade of steel of the bolt material. Yet, no analytical dependence of the mechanism is described [1].

Influences of friction coefficients in mechanical applications can be observed in bolt-nut connections. In a M10 joint with a friction coefficient of 0.1 approximately 82% of the tightening torque can get lost because of the friction in head, thread, and nut contact [2]. A part of this friction energy is needed to protect the connection against self-loosening. In guidelines for the calculations of bolt-nut connections additional safety factors are included. An example is a factor of approximately 20% to prevent slipping in the interface of clamped bodies [3]. Furthermore, there are many microscopical effects in a tribological system that influence the stability of the system. If we look closer at the bolt-nut connection, we find many frictional forces appearing under ten-

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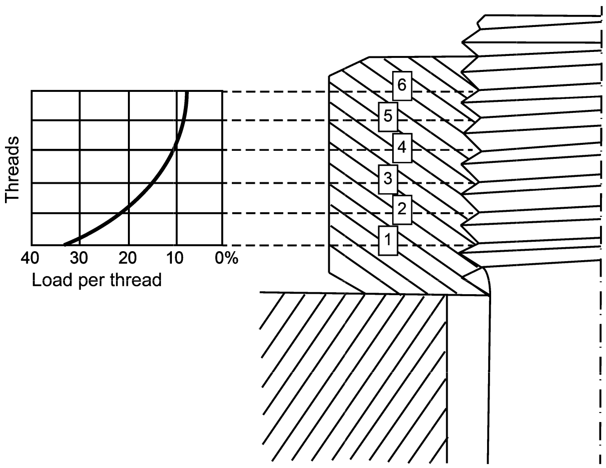

Fig. 1. Load variation over threads of the nut based on [2].

sile load which e.g. cause the nut to a radial stretching [2]. This effect causes a decreasing contact area between bolt thread and nut thread and is therefore a critical factor for the durability of the joint. Another critical point for the calculation of a bolt-nut connection is that the load over a thread contact varies in axial direction. The load decreases from the first thread to the last thread in the typical manner, see Fig. 1.

The friction force can, upon further inspection, not be modelled by one constant friction coefficient. Moreover, there are a few phenomena that influence the in-contact behaviour such as sliding velocity, micro-contacts, and contact pressure. Modern simulation software integrates many of these phenomena. Still, it is hardly possible to estimate a global friction coefficient for a body-to-body contact simulation or calculation which considers all these tribological effects. The complexity of the system "friction" with its micro-structure dependencies and multidisciplinary phenomena shows that there is, beside all, a lot to comprehend. From a simulative point of view, there are many processes associated with the energy balance during friction that cannot be represented by a model and must be estimated. Examples are deformation processes or chemical processes [4,5]. These effects appear on the micro-level of friction and are largely ignored by Finite Element simulation programs. A position-dependent friction coefficient, which is used in this study as an adjusting tool, is a way to improve simulation results in the described context.

In engineering practice, bolt-nut connections are typically configured using tabulated standard values with large safety factors. Our goal is to reduce these safety factors by employing more sophisticated calculations. Precise calculations can greatly benefit various applications of bolt-nut connections, such as the maintenance of bolted joints in wind turbines. These joints are particularly large, difficult to access and subject to high environmental stress. Efforts in this area focus on accurately predicting maintenance intervals and reducing costs. A case study on the loosening of bolted joints, discussed in [6], emphasises the importance of accurate prediction of the preload force through tightening torque. Achieving an accurate calculation of this tightening torque requires knowledge of friction coefficients. In our study, we explore a very first approach that combines experimental, modelling and computational aspects. Using Ansys Mechanical, we develop a computational model based on Coulomb's friction law. In this model, the surface of the contact object is divided into distinct areas with different friction coefficients, represented by the orange-framed windows in Fig. 2. Due to the hidden contact zone, the friction coefficients can normally not be determined by experiments. Instead, we use a special experimental setup to optically measure displacement data, see black-framed window "Experimental data" in Fig. 2. We then identify the friction coefficients numerically. To that end, an optimisation algorithm minimises the difference between the measured and the simulated displacement data, compare green-framed window in Fig. 2. In doing so, the searched model parameters are determined, see red "Exit" in Fig. 2. The optimisation process, depicted by the arrows in Fig. 2, iteratively refines the model parameter.

The article is organised as follows: In Section 2 the measurement techniques as well as the approach to the numerical identification of the frictional parameters are explained. The implementation of our algorithm and its coupling with Ansys are in the focus of Section 3. We present and discuss the results of the measurements and of our approach on the identification of the frictional parameters for two different examples in Section 4. Finally we draw some conclusions and give an outlook to future work.

2. Experimental setup and mathematical methods

In this section, first we present the used measurement techniques and the corresponding experimental setup. The following part is devoted to the algorithmic background of the numerical parameter identification.

2.1. Optical measurement of the displacement

The experimental data set was generated by a tensile test and an ISO 4014 M20 x 120-bolt with a property class of 5.6. The nut has the same configuration as the bolt. In this experiment displacement data were recorded by an optical measuring system (GOM Aramis 3D) at defined areas of the test setup. The test setup consists of two plates (plate 1 and plate 2) that are connected to the tensile testing machine, two jaws for blocking the nut against rotation as well as a M20 bolt-nut connection with a cut-out section (see Fig. 3 and the area between the two detected nut surfaces in yellow). This is necessary to be able to measure optically in the effective zone of the bolt and at the same time to obtain a significant change in the stress state. However, the cut-out section should be as small as possible to minimise the disturbance compared to real displacement conditions of a loaded bolted joint. This seems to be the best compromise to get experimental data. The framed picture on the right in Fig. 3 shows optically detected faces in different colours. Displacement measurements from these areas serve as input data for the parameter identification.

In unloaded condition, the bolt head rests loose on plate 2 and the nut rests loose on plate 1. In loaded condition the tensile testing machine moves plate 1 further in positive y-direction (see green arrow of coordinate system in Fig. 3) and the tensile force creates a contact between plate 1 and nut and also plate 2 and bolt head. As a consequence, the bolt holds the nut and presses it onto plate 1 in consequence of plate 1 going upward in positive y-direction. The displacements of the bolt-thread-flanks within the joint are visible at the cut-out section of the nut. In the following investigations we use the measured y-displacements of the first two flanks of the bolt as basis for the parameter identification. In Fig. 6, a section of the test setup is shown, displaying the 10 validation points on these two flanks of the bolt. As a comparison to the measured points, one can see in Fig. 7 the y-displacements of optically detected surfaces resulting from the applied tensile force.

2.2. Parameter identification

The commonly used simple computation rules and friction laws do not meet the requirements of complex systems such as bolt-nut connections. Basic calculations for bolted joints (e.g. those performed according to [3]) are only rough estimates. Observations and measurements show that we cannot assume the same friction coefficient for the whole contact surface. Thus, we divide the contact surface into areas with different friction coefficients. Physical considerations should be the basis for a first division of the contact surface. Both the division of the surface

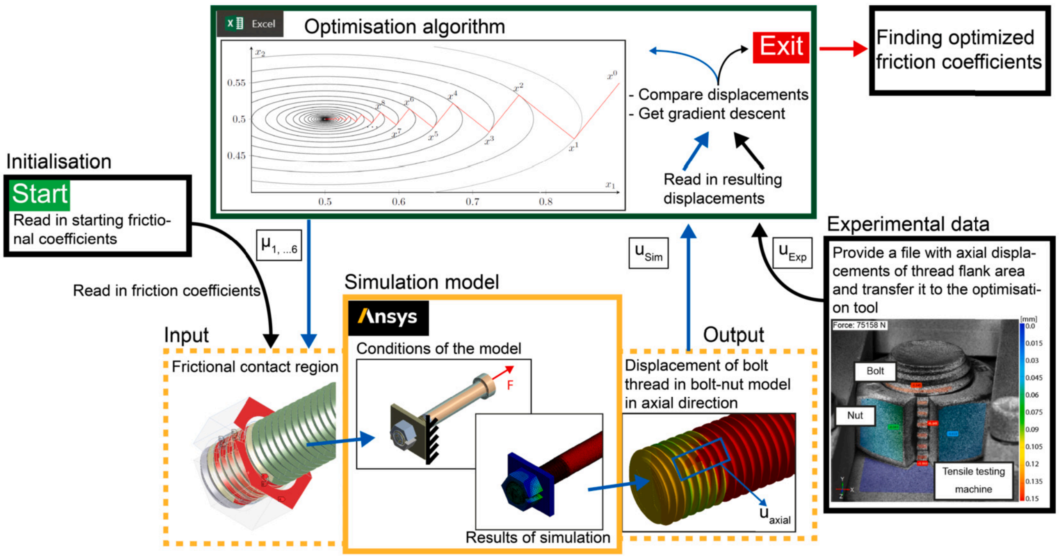

Fig. 2. Scheme of the processes during parameter identification including the simulation model with in- and output, the optimisation algorithm for the friction coefficients in excel, and the experimental data.

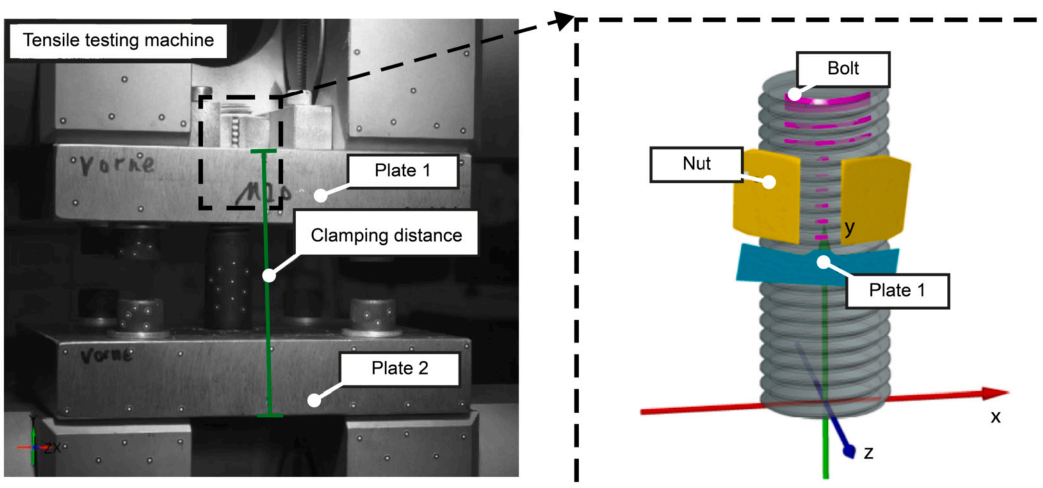

Fig. 3. Experimental setup for optical measurements of the displacements (left) and optically detected faces in detail (right).

and the choice of the different friction coefficients are highly relevant factors for finding a more realistic model for e.g. bolt-nut connections.

A mathematical model of a system, e.g. describing a physical process, consists of equations, assumptions and constraints. The model is expressed in terms of constant model parameters, independent variables, and dependent variables, so-called states. A classical direct problem is given if the model of a system in a certain domain is known as well as all the model parameters. The task is then to calculate the states. Generally, dynamic processes are modelled with ordinary or partial differential equations and corresponding initial and boundary conditions. Then, the direct problem is the solution of the differential equation. A wide range of appropriate mathematical models exists in order to describe processes from science and engineering. Sometimes, the basic model is known, but not all of the model parameters. This results in an inverse problem. Given that the states can be measured in experiments, it is important to determine model parameters allowing us to reproduce the measured data with theoretical calculations. The task of finding the best possible parameters is called "parameter identification".

Let $f(x,p)$ represent a function that associates the state y with a combination of independent variables x and parameters p. The function f allows to predict the state up to some disturbing terms ε. These terms, such as errors, arise from inaccuracies in the model or measurement. Thus, we can express $y = f(x,p) + \varepsilon$. We define the term $\Psi(p)$ as a measurement for the difference between the function output for a specified choice of parameters and measured states y:

$$\Psi(p) = \|f(x,p) - y\|^n = \|\varepsilon\|^n ,$$

where n is a reasonably chosen constant and $\|\cdot\|$ represents an error norm. The function $\Psi(p)$ is referred to as the objective function for the parameter identification. Additional constraints, stabilisation, and penalty terms (here summarised as $\Phi(p)$) can be added to form a new objective function. With the aim of reducing the error between measured and calculated states, the aforementioned considerations lead to the minimisation problem

$$\min J(p), \quad J(p) := \Psi(p) + \Phi(p).$$

Thus, parameter identification problems involve the selecting of the best objective function and the optimising of the objective function. For more information, see [7–9]. Parameter identification problems can also be interpreted and solved as optimal control problems. A detailed introduction to this topic can be found e.g. in [10].

In the application of bolt-nut connections, we aim to improve displacement calculations by dividing the contact surface into areas with different friction coefficients for the Coulomb friction. We are able to measure the displacements in the thread-nut contact in an experiment. Finding friction coefficients that reproduce the measured displacements is a parameter identification problem. In our case, the displacements are the states and the friction coefficients are the parameters. We chose a simple norm of the difference between calculated and measured values as the objective function Ψ. In this study, we do not consider any further constraints or penalty terms, thus $\Phi(p) = 0$.

The minimisation of the objective function usually has to be solved numerically. There is a large range of algorithms available for solving various optimisation problems (see e.g. [11] or [12]). Iterative methods are well-suited for nonlinear optimisation problems. The idea behind these methods is to start with an initial guess and iteratively improve the values until a stopping criterion is met. One approach is to start at the current iterate and follow a so-called search direction that reduces the function value. The step size specifies how far to move along this direction until a sufficient reduction of the function value is achieved. Methods that employ this technique are known as descent methods. One option is to move in the direction of the steepest descent, which is the opposite direction of the gradient at the current point. This method is called the gradient descent or steepest descent method. The method does almost always converge, but sometimes very slowly. The choice of the step size greatly influences the convergence properties. However, determining the optimal step size is highly computational expensive or even numerically impossible. Instead, one must find a step size that leads to a sufficient reduction of the function value [13]. This can, for example, be ensured by the Armijo-condition.

For the gradient descent method, the gradient of the objective function needs to be determined. If analytically differentiation is not possible, it must be performed numerically. For the bolt-nut connection, we use the numeric method of forward difference quotients to approximate the directional derivative of f in direction q by

$$\frac{f(x, p + \delta q) - f(x, p)}{\delta}$$

with a small parameter $\delta > 0$. The size of δ is a critical parameter of the algorithm and has to be chosen carefully. If it is too large, the approximation of the gradient may become worse. Conversely, if it is chosen too small, round-off errors can affect the calculation.

3. Simulation and parameter identification setup

The details of the used contact model in Ansys are discussed in the subsequent section. Furthermore, we present some details on the implementation of the parameter identification algorithm.

3.1. Modeling frictional contact in ansys

Ansys provides a wide range of contact interactions based on several contact models. In this study, we consider contact interaction between two flexible bodies with elastic deformation behaviour. We use pair-based contact definitions, where a contact and a target side have to be selected [14]. Subsequently, it is determined between which elements on the respective side interaction occurs. Interaction properties are exclusively specified on the contact surface. Therefore, it is only necessary to divide the contact surface into different areas and define the corresponding friction parameters. Furthermore, we use augmented Lagrange formulation to describe the frictional contact interaction. This formulation provides a balance between accuracy and computational efficiency at high robustness and is therefore useful for any type of contact behaviour when simulating contact behaviour in Ansys. The implemented contact elements are linked with a surface-to-surface contact and symmetric contact behaviour. For many settings, we adhere to the defaults in Ansys. However, we deviate from them for certain settings to achieve better convergence of the two models (bolt-nut connection and block on surface). These adjustments include a symmetric contact behaviour, no small sliding option, a normal stiffness factor of 0.05 and the nodal projection choice as detection method. To increase convergence speed, it is also important to identify highly stressed or even distorted areas and then adjust contact definitions and local mesh configurations.

3.2. Implementation of the parameter identification algorithm

The aim of this study is to show that an optimisation can be a promising approach for improving the calculation of complex contact systems like the bolt-nut connection. We intentionally did not yet exploit the full potential of this approach and will discuss weaknesses and ideas for further improvement later in this section and in Section 5.

In this first study, we use a well-developed tool for modeling and solving problems with frictional contact with the help of finite element techniques. Ansys is such tool and provides us with a variety of options during the built-up of the geometry and for the calculations. As described above (see Section 3.1) we are able to compute strain or displacement for a defined geometry and with given friction parameters. We want to estimate friction coefficients that reduce the error between the computed strains or displacements and the measured values. With the help of toolboxes, parameter studies can be performed directly in Ansys and further implementations can be integrated into the Ansys setting. However, the extension, which we have in mind, is not possible to realise in Ansys directly. Hence, we develop an alternative approach in this study. Our work is based on the ideas presented in [15].

We perform the parameter identification with the method of gradient descent introduced in Section 2. A sketch of the complete process of parameter identification and the interactions between different softwares is shown in the overview of the parameter identification tool, see Fig. 2. In order to be able to access calculations results from Ansys and provide parameters for the calculations, we make use of the interface between Ansys and Microsoft Excel. We implement the optimisation algorithm in Visual Basic for Applications (VBA), a script language to code macros in Microsoft Office applications. This limits us immensely, especially in terms of computational time as parallelisation is hardly possible in VBA. The VBA code needs a set of starting values for the friction coefficients (e.g. extracted from a table as given in [3]) and the measured strain or displacement data as input, and provides us with a set of friction coefficients as output. These friction coefficients reduce the error between the results of the FEM computations and the measured values for strain or displacement according to a given stopping criterion. During the computation, Ansys is called several times to perform computations of strains or displacements for various friction coefficients: for the numerical determination of the gradient, during the determination of the Armijo stepsize, and for the computation of the next iterate of the gradient descent method.

4. Results and discussion

In this section, we discuss two different examples to test our approach to parameter identification. The first one is a simple test case to verify our code. The second one is based on a real application. Here, the measurement of the occurring displacements in the experiment is of particular interest to obtain reliable results.

4.1. Model of a block on a planar surface

Testing the implemented parameter identification tool is what we are aiming for in this study. Only when verified in a test setting, the transfer of the parameter identification tool to a real problem is possible. Consequently, we apply the parameter identification tool to a simple simulation of a block on a planar surface. Fig. 4 shows the model construction with a cubic block in contact with the surface of a planar plate. In Ansys workbench this model is built as a static structural simulation. Two materials are used in this study, aluminum and epoxy,

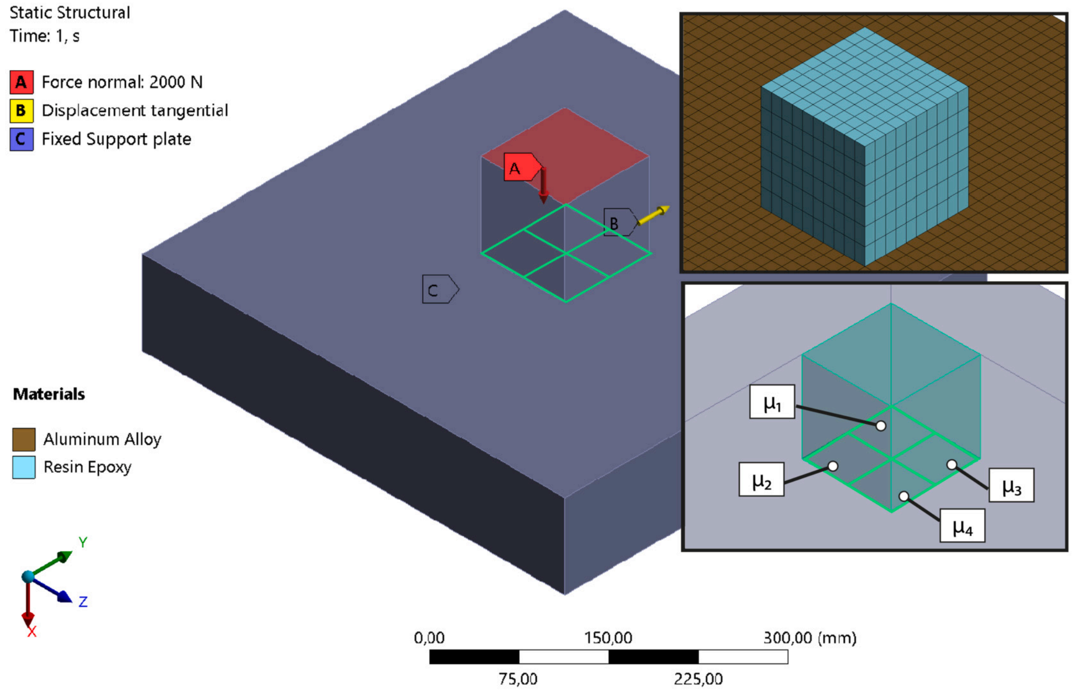

Fig. 4. Model construction with a cubic block in contact with the surface of a plate.

which are included in the Ansys materials library. This material combination provides a high imprint and big strain values in the contact region. The block is selected as contact side and the planar surface as target. Randomly, we divide the contact surface into four different areas, each with an independent coefficient of friction. The cube is pulled in y-direction with a displacement of 2 mm and also constantly pressed on the surface of the plate with 2000 N.

Instead of using measured values to compare to, we predefine the goal data for friction and strain. The set of goal friction coefficients for the four areas (μ) consists of randomly chosen entries between 0.1 and 0.5. Using the Ansys model, we compute strain data ε corresponding to these friction coefficients and define them as reference strain data set for the parameter identification. Thus, we generate a test setup in which the parameters we are aiming to find with the parameter identification are known in advance. By doing so, we are able to test the performance of our parameter identification tool.

We then perform the parameter identification with a set of starting friction coefficients $\mu^{(0)}$. Based on the range of goal friction coefficients, we start with a friction coefficient of 0.1 on each area of the contact surface. The iterative optimisation algorithm is run with the goal of finding friction coefficients that reduce the error between corresponding strain data and the reference data. Beginning with the starting values, the friction coefficients and corresponding strain data are modified in each iteration. Then, if the optimisation terminates, the modified strain data fulfill the stopping criterion and the modified friction coefficients approximate the goal coefficients sufficiently well.

As a first result, we observe a termination of the parameter identification. That means, we are able to reduce the error between calculated and reference strain data so that the stopping criterion is fulfilled. This is achieved reasonably fast. For a more detailed analysis, we consider the relative error of the strain $\varepsilon^{(k)}$ after k iteration steps of the optimisation, $\|\varepsilon^{(k)}-\varepsilon\|/\|\varepsilon^{(0)}-\varepsilon\|$, which is plotted in Fig. 5 (red line). It corresponds up to a scaling factor to the objective function of the parameter identification. In contrast to real-life problems, the goal friction coefficients are known in this test setup. Therefore, we additionally observe the development of the friction coefficients throughout the optimisation. A good approximation of the goal friction coefficients is achieved at the termination of the parameter identification. The errors of the friction

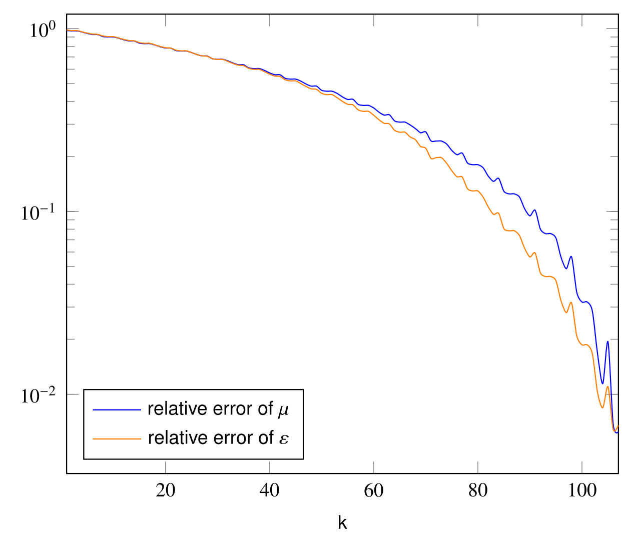

Fig. 5. Development of the relative errors during parameter identification for the test setting of the block model. We consider the relative error of the friction coefficients $\|\mu^{(k)}-\mu\|/\|\mu^{(0)}-\mu\|$ and the relative error of the strain $\|\varepsilon^{(k)}-\varepsilon\|/\|\varepsilon^{(0)}-\varepsilon\|$ at iteration step k.

coefficients $\mu^{(k)}$ after k iterations of gradient descent in relation to the error of the starting coefficients $\mu^{(0)}$ are determined: $\|\mu^{(k)}-\mu\|/\|\mu^{(0)}-\mu\|$. They are also presented in Fig. 5 (blue line). Both relative errors behave in a similar way. Initially, there is a gradual decrease in error during the early iterations, followed by a more rapid reduction in error after approximately half of the iteration steps. However, the numerical calculation of the gradient becomes more involved when the algorithm approaches the minimum. This behaviour leads to the oscillations and the local increase of the errors. At this point, the numerical stability of the algorithm needs improvement. Altogether, the presented approach leads to a convergent iteration and we verify the algorithm as well as the implementation.

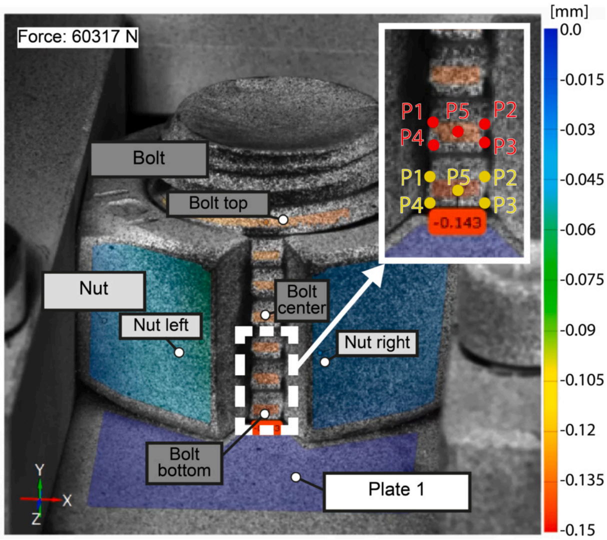

Fig. 6. View on the test setup with the details of some measuring points and the reference points for simulation (P1,. . . ,P5).

4.2. Optical displacement measurements

After setting up a parameter identification tool and testing it on the simple model of a block on a planar surface, the next step is to try this tool on a more realistic problem. For this purpose, measurement data has been generated by an optical measurement system, see Fig. 6 and 7. The measurement procedure was described in Section 2.1. The measurement results show at a first glance an increase in the displacements of predefined reference surfaces (nut, bolt, plate) when the force is increased. Since the measurement axis was defined against the direction of displacement, we obtain negative values for the displacements, see Fig. 7. The brown line shows the current point in time and the associated force. This force was used as a reference value for the static mechanical simulation part of the optimisation. The displacement values at this time can clearly be assigned to the different areas of the specimen (nut and bolt). Resulting effects of a bolt-nut connection under load, such as the axial load distribution in the bolt thread, can be observed by the increasing clearance of the areas bolt bottom, bolt center, and bolt top towards high force values. A set effect can be seen at the beginning of the force application in the bolted joint. After that, the displacement values increase linearly with the applied force.

The measurement data of the y-displacements of the first two thread flanks in the defined measurement points (P1,. . . ,P5) are used as reference values for the optimisation, see Fig. 6.

4.3. Model of a bolt-nut connection

Compared to the previously described model of a block on a planar surface, the following simulation involves more complex contact conditions. We consider the model of an M20 bolt-nut connection under tensile load. In this case, the contact surfaces are helical. The simulation setup with its contact, boundary, and meshing definitions is shown in Fig. 8. As in the previously described experiment, the nut presses against a plate due to the tensile force (B) and the engagement of nut and bolt. The plate is fixed with a fixed support command in the simulation (C). A movement of the nut is thus blocked in positive z-direction. In addition, the nut is blocked against rotation at two parallel faces of the nut (A). This is implemented in the experiment by the abutting jaws, compare Fig. 3.

The simulation is also used to observe how displacements in the cutout area are influenced by friction coefficients in the thread region. In addition to that, influencing factors on the simulation result e.g. material properties, contact algorithm formulations, and mesh quality are

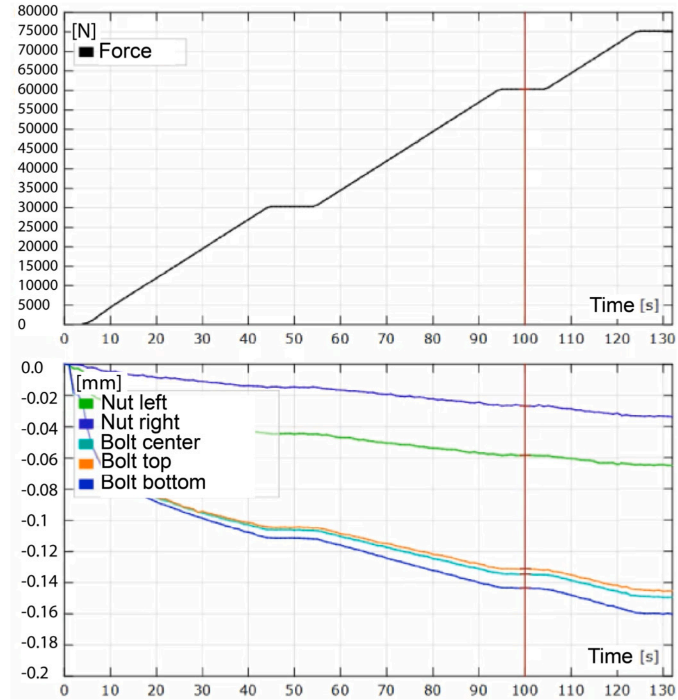

Fig. 7. The y-displacements (bottom) of some measuring points resulting from the applied tensile force (top). The current time point is marked with the brown vertical line.

not considered as variables with a big impact on this study. The bolt-side is selected as contact and the nut-side as target. The contact surface of the bolt (marked red in Fig. 8) is radially separated into two areas, one on the upper flank area and one on the lower flank area of the thread. This consideration assumes a radial variation of the friction in a threaded bolt-nut connection. Furthermore, we assume that there is also an axial difference in friction coefficients affected by the load variation, compare Fig. 1. Hence, we consider a split of the two contact areas on the different thread flanks into three axial sections, each. In total, the contact surface between bolt and nut is divided into six friction areas with different friction coefficients, see labels A to F in Fig. 8.

Additional friction occurs where nut and plate are in contact with each other. We considered a fixed friction coefficient of $\mu = 0.15$ at the contacting surface between plate and nut. All further characteristics of the model for the bolt-nut connection are adapted to the conditions and properties given by the tensile load experiment in Section 2.1. One adapted quantity is e.g. the support against rotation on two surfaces of the nut. The model setup of this study uses the default material data of Ansys Mechanical: construction steel.

As described in Section 2, we are able to optically measure the displacement data u of the bolt-nut connection. We use these data instead of strain data to perform our parameter identification. As a result, we find suitable area-dependent friction coefficients. The objective function for the parameter identification describes the distance between the measured displacements and the calculated values at the corresponding iteration step k of the optimisation $u^{(k)}$. The starting friction coefficients are estimated according to table A5 in [3]. We considered metallically bright surfaces and no lubrication and chose the value of $\mu^{(0)} = 0.1$, which is within the cited range of friction coefficient class B.

The realisation of the model of a bolt-nut connection in Ansys is far more complex than the one of the block model. Thus, the computation time for the calculation of the displacement data is longer. With a special export command, we obtain the nodal y-displacements of two flank areas of the bolt thread as output of the Ansys simulation. Each area includes five nodes, distributed on the flank-surface in reference to Fig. 6. These five points represent the movement of the flank area un-

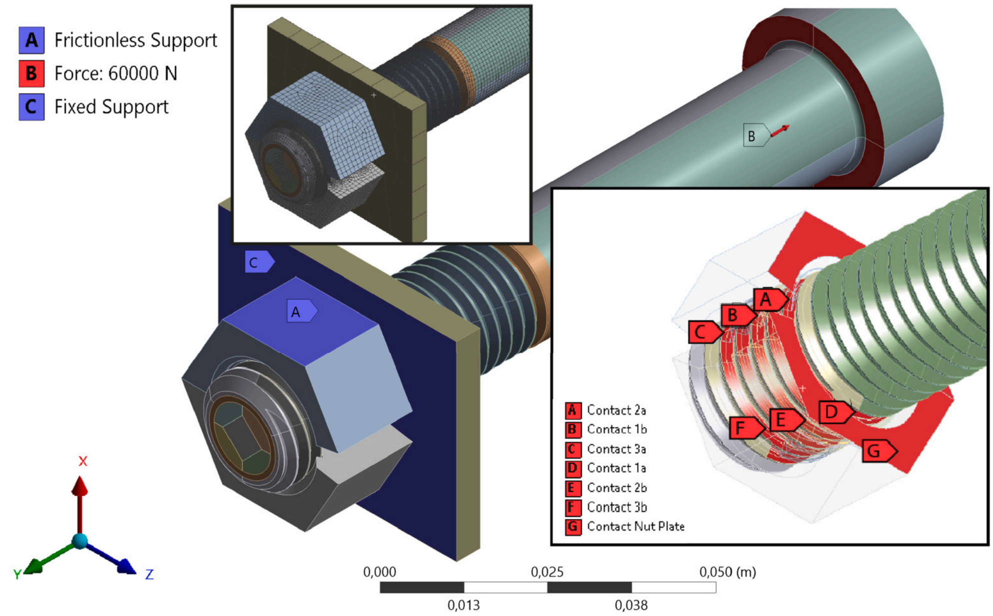

Fig. 8. Simulation setup of the bolt-nut connection model. The contact definitions of the model (A-G in red, right bottom corner), the legend of the simulation boundaries (A-C, left, top corner) and the meshing model (middle, top) are illustrated.

der tensile load. With this simplified description of the flank surface it is possible to compare simulation results and experimentally measured displacement data.

With the described setup we apply our parameter identification tool to the model of a bolt-nut connection. Due to longer computation times, we do not wait for the termination of the optimisation procedure, but interrupt it after approximately 20 iterations. In order to examine how the displacement data change throughout the parameter identification for the bolt-nut connection, we consider the relative error of the displacement after k iteration steps of the optimisation: $\|u^{(k)}-u\|/\|u^{(0)}-u\|$. Fig. 9 shows the changes of the relative displacement error throughout the iterations. Similar to the relative error of the strain in the model of a block on a planar surface, we observe an increase of the error at the beginning of the iterative process and fluctuations. We have a sudden drop of the error at the 5th iteration. For all following iterations, the resulting friction coefficients were negative for at least one of the friction areas. From a physical point of view that this seems illogical. Additionally, Ansys does not perform the calculations with negative friction coefficients, but sets negative values internally to a defined positive value. This means that the iterative process is interrupted in step 6 and thus only calculations up to this step are taken into account. To solve this problem, a penalty term for negative friction coefficients should be introduced to the objective function of the parameter identification (see Section 2.2).

Even with only few iteration steps, the parameter identification tool provides us with friction coefficients that lead to a reduction of the distance between computed and measured displacements. Based on the optical measurement system, we indeed obtain different friction coefficients for the six friction areas. Within this framework, we limit ourselves to this qualitative observation and do not evaluate the variation of the friction coefficients quantitatively.

5. Conclusion and outlook

The simulations conducted using the numerically identified parameters demonstrate an improved accuracy in the examples discussed in the article, substantiating the potential of our approach. A significant aspect of the study is the experimental measurement of the displacements in a bolt-nut connection. By matching the numerical simulations with different friction areas to these measured displacements, it becomes evident

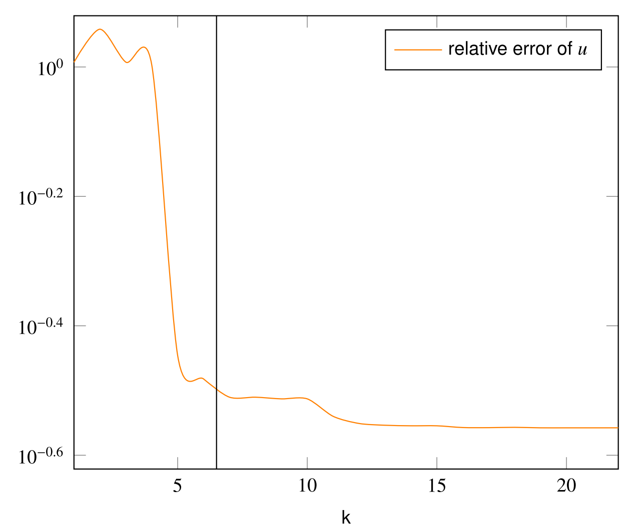

Fig. 9. Development of the relative error of the displacement ($\|u^{(k)}-u\|/\|u^{(0)}-u\|$) at iteration step k of the parameter identification for the model of the bolt-nut connection. The vertical black line marks where the iterative process is interrupted.

that a constant friction coefficient, as proposed in Coulomb's friction law, is not sustainable. This approach allows for the implicit inclusion of a wider range of tribological effects. Introducing position-dependent friction parameters into the simulations is a preliminary step towards a more precise description of friction.

However, we encountered some shortcomings of our method. The main challenge lies in the needed computation time. Since we are not able to determine the gradient analytically, we can only approximate it numerically. This costs us in terms of accuracy and also requires a lot of additional computation time. Here, more efficient implementations in one program with interlacing parts using suitable parallelisation approaches are our first approach to overcome these difficulties. The second point is the slow convergence of the gradient descent method and the non-physical friction parameters. In this case, Quasi-Newton methods could enhance the calculations, while penalty approaches ensure bounds on the parameters.

Further challenges lie in the modeling of the bolt tensile test. On the one hand, manufacturing tolerances and residual stresses from manufacturing have an influence on the numerical representation of the real bolted joint. On the other hand, measurement inaccuracies occur during the experiment due to e.g. dirt on the rubbing contact surfaces, a decentralised clamped bolted joint or an insufficiently optically detected measuring surface. These challenges can be met by more precise production of the parts and the test set-up or by prior measurement of the parts. In addition, supplementary measurements such as measuring the length of the bolt before and after a measurement can lead to a reduction in measurement errors.

Apart from the numerical improvements of our approach, we should consider the model itself as well as the parameter identification process. Further studies are necessary to further improve the computations of strain and displacement. These include e.g. the selection of smaller areas for the friction coefficients, the use of other friction laws or a better distinction of parts in the bolt-nut connection (e.g. nut, head, thread) which possess different friction properties.

CRediT authorship contribution statement

Dominik Hinse: Conceptualization, Data curation, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Magdalena Thode:** Conceptualization, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Andreas Rademacher:** Conceptualization, Methodology, Project administration, Supervision, Writing – review & editing. **Klaus Pantke:** Conceptualization, Methodology, Project administration, Resources, Supervision, Writing – review & editing. **Christian Spura:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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