Digitalized data access of DE material models and their parameters using an OBD(M)A approach

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ABSTRACT

Dielectric Elastomer (DE) transducers are characterized by their geometrical dimensions and in particular by the properties of the elastomer and electrode materials. Therefore, in addition to dimensions, it is advantageous to consider optimization of material properties to fulfill transducer requirements, such as blocking force, free stroke, or response time. A big challenge in describing the properties of DE materials deals with utilizing different but commonly used hyperelastic material models and their parameters, which differ in complexity and corresponding model errors. Thus, determined material parameters are not necessarily consistent. In addition, parameters are depending on the measurement method, its conditions and the samples themselves. All of this leads to heterogeneous datasets making data access more complicated and in certain cases impossible for users. To overcome this, OBDA (ontology-based data access) approaches have been proven to access these heterogeneous datasets individually and efficiently and to gain the relevant information with the help of an ontology. Within a research project funded by the Federal Ministry of Education and Research, an extended OBDA approach is developed: OBDMA (ontology-based data and model access) combines data access with model-based working steps. While the joint project considers four different smart material classes, this paper focuses on dielectric materials and their transducers, in particular the development of methods to handle hyperelastic material models and their parameters. The various possibilities of material models and parameter identification methods are discussed on the basis of a measurement curve. Finally, the working principle and the advantages of the OBDMA system are demonstrated by means of a representative DE use case.

Keywords: dielectric elastomer materials, ontology, digital data access, material models and parameters

1. INTRODUCTION

Dielectric elastomer transducers (DE) consist of thin dielectric elastomer films coated with flexible and conductive electrodes. When a voltage is applied, the transducer deforms.[1] Numerous modeling and characterization studies,[2,3] as well as material modification and optimization investigations,[4,5] are being conducted in the field of DE-transducers to characterize their mechanical and electrical properties.
One of the typical properties of elastomer materials is their non-linear elastic behavior, which can be represented by hyperelastic models. Hyperelastic material models are defined by an assumption for the strain energy density combined with a deformation assumption. Neo-Hooke, Mooney-Rivlin, Yeoh and Odgen are just a few examples of strain energy density modeling approaches that vary in complexity and accuracy.[6–8] In addition to the multitude of models, differences in measurement, identification, and storage formats,[9] as well as different manufacturing processes,[10] result in many possible parameters, leading to heterogeneous databases and complicating data access. However, easy data access is crucial for material design and optimization of DE-transducers. In this contribution, we discuss and extend an ontology-based data access (OBDA) approach, which is an efficient method for accessing data from heterogeneous databases via a homogeneous interface in form of a terminology (ontology).[11]

An ontology pursues the goal of modeling information in form of concepts and their relations.[12] In recent years, there have been various efforts to improve knowledge storage and access in engineering science domains

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using an ontology approach. For material science there are several investigations on the development and use of ontologies.[13] Among other investigations the European Materials Modelling Council (EMMC) is working to establish common standards and has developed the European Materials and Modelling Ontology (EMMO) in form of a top-level ontology.[14] While many material-specific ontologies, including EMMO, focus on storing knowledge at the ontology level, this study takes an OBDA approach, where knowledge is distributed across an ontology, mappings, and databases. By using mappings to connect data from different databases to the ontology, this approach allows flexible querying of heterogeneous databases.[15] Furthermore we considerably extend OBDA to the approach of ontology-based data and model access (OBDMA). OBDMA not only enables easy data access but also links to models (here mainly given by analytical functions). This method allows querying not only for data given by the database or inferred by the ontology, but also for data calculated with the help of these user-defined functions (UDF), providing flexible and application-oriented data access. For instance, one can analyze and model a stress-strain curve across the entire range of measured strain, or selectively over a range that is dependent on the specific application and based on the desired level of model accuracy and complexity. The basic principle of OBDMA is sketched in Figure 1.

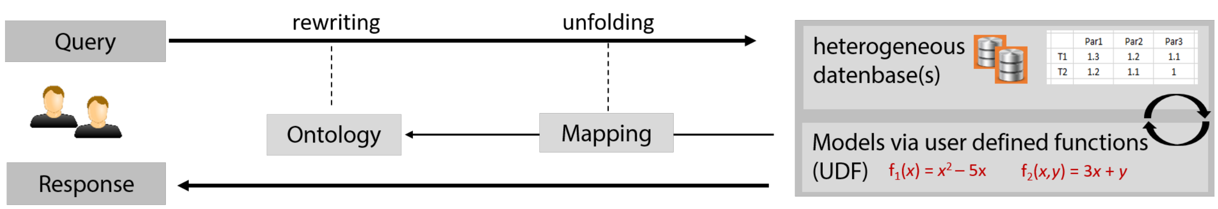

Figure 1. Basic principle of an OBDMA-system.

In the following two sections, the OBDMA approach's advantages are explained in the case of hyperelastic modeling of DE-transducers. For this purpose, hyperelastic material models are first presented and discussed in section 2, followed by a demonstration of the OBDMA-system using a simplified use case in section 3.

2. HYPERELASTIC MATERIAL MODELING AND IDENTIFICATION

The fundamentals and advantages of an OBDMA-system are exemplified by modeling and parameterizing elastic material properties. DE materials are characterized by their incompressibility and show a non-linear elastic behavior. The elastic stress $\sigma_{\mathrm{elast,i}}$ is defined by the stretch λ_{i}, the strain energy density u_{elast} and the hydrostatic pressure p:

$$\sigma_{\mathrm{elast,i}} = \lambda_{\mathrm{i}} \frac{\partial u_{\mathrm{elast}}}{\partial \lambda_{\mathrm{i}}} - p. \tag{1}$$

Depending on the assumption for the strain energy density and the deformation, a hyperelastic model can be derived from equation 1. There are three typical deformation assumptions: uniaxial, planar and biaxial, depending on the geometry and boundary conditions.[16] Various assumptions about the strain energy density model are available for different DE applications, varying in complexity and accuracy.
When considering stress models, it's important to differ between the true and technical stress. The true stress $\sigma_{\mathrm{elast,i}}$ refers to the deformed area A and the technical stress $\sigma_{\mathrm{tech,i}} = \sigma_{\mathrm{i}}$ to the undeformed area A_0, respectively. Equation 1 refers to the true stress and equation 2 shows the link of the true and technical stress.

$$\sigma_{\mathrm{i}} = \frac{\sigma_{\mathrm{elast,i}}}{\lambda_{\mathrm{i}}},\ A_0 = A\lambda_{\mathrm{i}} \tag{2}$$

For this analysis, the measured stress-strain curves are stored in the database using the technical stress, geometry, and boundary conditions, making the data independent of the deformation assumption.

Table 1. Exemplary elastic models

model	deformation	equation
linear Hooke	no	$\sigma_{\mathrm{x}} = Y\varepsilon_{\mathrm{x}},\ \lambda_{\mathrm{x}} = 1 + \varepsilon_{\mathrm{x}}$
Neo-Hooke	uniaxial	$\sigma_{\mathrm{x}} = 2C_{10}\left(\lambda_x - \frac{1}{\lambda_x^2}\right),\ Y = \frac{C_{10}}{6}$
Neo-Hooke	planar	$\sigma_{\mathrm{x}} = 2C_{10}\left(\lambda_x - \frac{1}{\lambda_x^3}\right),\ Y = \frac{C_{10}}{6}$
Yeoh	uniaxial	$\sigma_{\mathrm{elast,x}} = 2\left(\lambda_x - \frac{1}{\lambda_x^2}\right)\left(C_{10} + 2C_{20}\lambda_{\mathrm{uni}} + 3C_{30}\lambda_{\mathrm{uni}}^2\right),\lambda_{\mathrm{uni}} = \left(\lambda_x^2 + \frac{2}{\lambda_x} - 3\right)$
Yeoh	planar	$\sigma_{\mathrm{x}} = 2\left(\lambda_x - \frac{1}{\lambda_x^3}\right)\left(C_{10} + 2C_{20}\lambda_{\mathrm{pl}} + 3C_{30}\lambda_{\mathrm{pl}}^2\right),\lambda_{\mathrm{pl}} = \left(\lambda_x^2 + \frac{2}{\lambda_x^2} - 2\right)$

This contribution presents the linear Hooke model and two hyperelastic models (Neo-Hooke and Yeoh) to demonstrate the manifold of parameter identification. However, the analysis can also be applied to other model assumptions. Table 1 gives an overview of the considered elastic models applied with two deformation assumptions using the technical stress.

Various parameter identification techniques are presented in this study to show the range of possibilities depending on the assumed model, identification range, and methodology. The results are discussed based on a stress-strain curve measured on a sample with the geometry shown in Figure 2, where uniaxial deformation can be assumed.[16]

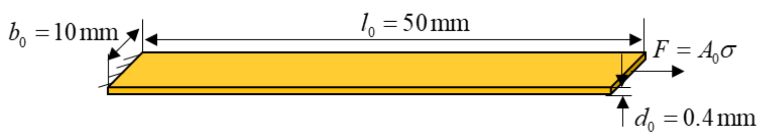

Figure 2. Sample geometry.

The measured strain range is $\varepsilon_{\mathrm{mes}} = 0 - 200\%$. Besides the different model approaches, there are also different identification methods. Two identification methods are considered here: initial slope and minimizing an error over a specific identification strain range $\varepsilon_{\mathrm{ident}}$.

Table 2. Two exemplary identification methods.

method equation	
intial slope	$Y = \frac{\sigma_0}{\varepsilon_0}$
minimize R	$\min\limits_{C \text{ or } Y} R$

For this analysis, the error is defined as the mean normalized error according to the equation 3 and for the initial slope method the initial strain is fixed to $\varepsilon_0 = 5\,\%$

$$R = \frac{1}{N}\sum_{i=0}^{N}\frac{|\hat{\sigma}_{\mathrm{i}} - \sigma_{\mathrm{i}}|}{\sigma_{\mathrm{i}}} \tag{3}$$

In some cases, however, the root mean square error may be more appropriate. Different error definitions affect the accuracy for different strain ranges and thus depend on the application conditions. Consequently, several parameters can be determined for a model approach depending on the three criteria of identification method, range, and error definition. An example variation is shown in the next two steps to demonstrate the importance of having access to different models and different identification options.
In a first step, the model approach and the identification method are varied using the measured strain range as the identification strain range $\varepsilon_{\mathrm{ident}} = \varepsilon_{\mathrm{mes}} = 0 - 200\%$. For the linear Hooke and Neo-Hooke model, the two

identification methods shown in Table 2 and for the Yeoh model only the minimization method are investigated. The five results are shown in Figure 3.

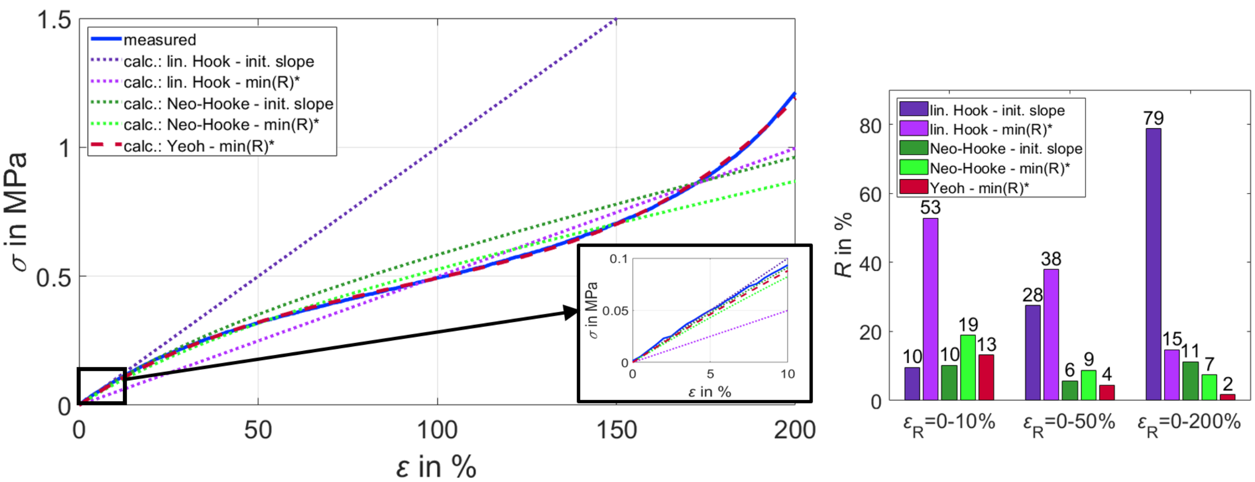

Figure 3. Comparison of different model approaches and identification methods: stress-strain curves (left) and mean normalized error over different error ranges ε_{R} (right).

The left diagram shows the measured stress-strain curve in blue compared to the five model fit curves. The right one indicates the mean error R over a particular error strain range ε_{R}, which is used to determine the error R. Considering the linear Hooke model with initial slope as the identification method, it shows the best results in the range $\varepsilon_{\mathrm{R}} = 0 - 10\%$, but for a strain range of $\varepsilon_{\mathrm{R}} > 10\%$ the error becomes high. The error over the entire measurement range $\varepsilon_{\mathrm{R}} = 0 - 200\%$ can be optimized using the minimization method over the measured strain range. However, the error is significantly higher for the lower strain range of $\varepsilon_{\mathrm{R}} = 0 - 10\%$ for this identification method.

The Neo-Hooke model has only one material parameter like the linear Hooke model, but the non-linearity allows lower error values for a wider strain range. Up to a strain range of $\varepsilon_{\mathrm{R}} = 50\%$, the error is relatively small, and the model is suitable for many DE applications. The Yeoh model is necessary if low error values are required over the entire measured strain range of $\varepsilon_{\mathrm{R}} = 0 - 200\%$. While the low error over a wide strain range is advantageous for the Yeoh model, the model complexity is disadvantageous.

When a simple model is required, as is often the case in control applications, another way to identify parameters is to restrict the identification range $\varepsilon_{\mathrm{ident}}$ according to the application domain. This limitation enables minor errors over the application range. However, a more significant error is expected for out-of-range applications.

The identification range is varied to demonstrate its influence. For this purpose, a working point $\varepsilon_{\mathrm{WP}}$ is defined and the identification range is created around the working point according to equation 4:

$$\varepsilon_{\mathrm{ident}} = \varepsilon_{\mathrm{WP}} \pm 5\%. \tag{4}$$

For the analysis, the working point is varied with 10%-steps, and for each identification range the Young's modulus is determined. The results are compared to the identification range of $\varepsilon_{\mathrm{ident}} = 0 - 200\%$ in Figure 4. The top left diagram shows the stress-strain curves. The results for the variation of the identification range are plotted for the identification range and the working point is marked. The top right diagram shows the Young's modulus over the different working points. The mean normalized error is demonstrated in the bottom diagram determined for the error strain range $\varepsilon_{\mathrm{R}} = \varepsilon_{\mathrm{WP}} \pm 5\%$.

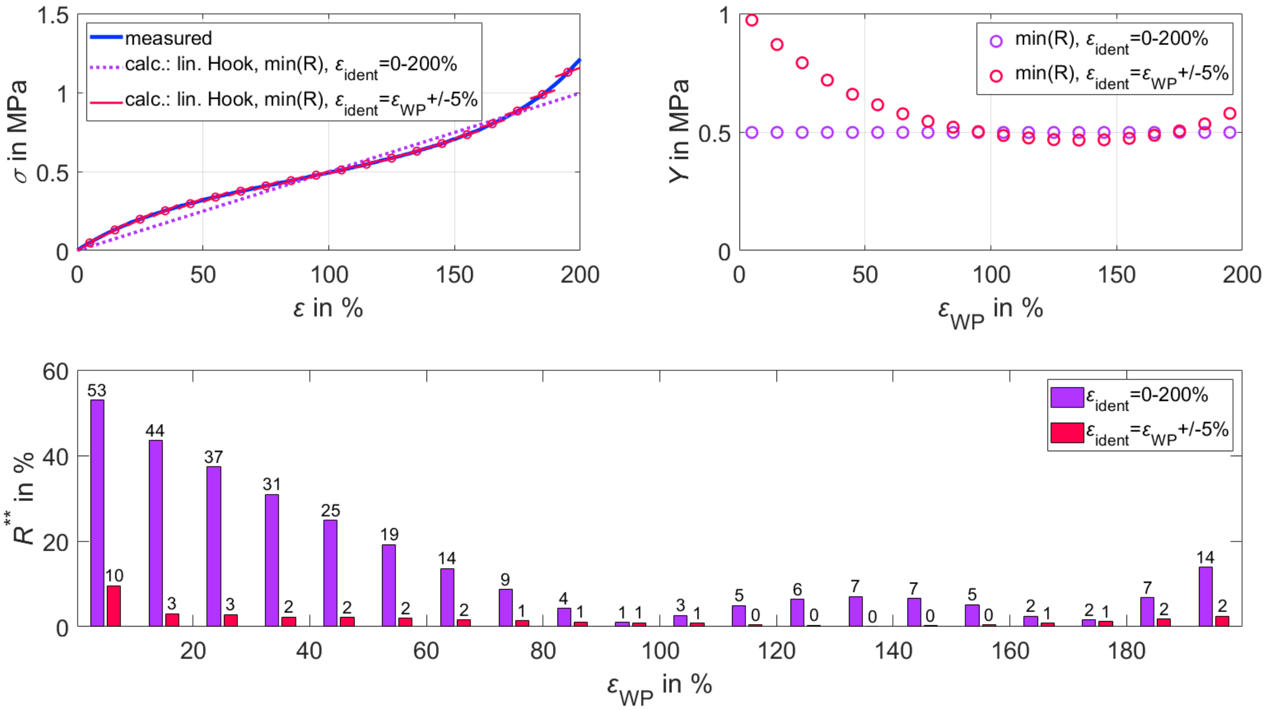

Figure 4. Comparison of different identification strain ranges $\varepsilon_{\mathrm{ident}}$ for the linear Hooke model: stress-strain curves (top, left), Young's modulus over the working point $\varepsilon_{\mathrm{WP}}$ (top, right) and the mean normalized error with the error range of $\varepsilon_{\mathrm{R}} = \varepsilon_{\mathrm{WP}}\ +/-\ 5\%$ (bottom).

As expected, the parameter identification with the small identification range leads to lower error for the considered error strain range. It should be noted that with this method, higher errors are expected outside the valid range. Thus, the error can be reduced by considering a limited range, but this limitation must be taken into account for the application.

The previous analysis demonstrated the importance of choosing the right model approach, identification method, and range for the considered application, and consequently, various data sets of elastic parameters are needed for an application-oriented development of DE-transducers. The OBDMA-system provides easy access to these various data and models and is introduced in the next section.

3. OBDMA-SYSTEM

OBDMA (ontology-based data and model access) is an extension of the OBDA (ontology-based data access) approach. A user can specify a query using the vocabulary of the given ontology. The basic query language is SPARQL, a W3C* recommended language for the semantic web and linked open data that provides convenient language constructs. A user interface can be specified, so that the SPARQL query is generated in the background.[17] The SPARQL query is automatically rewritten - in order to capture the implications of the ontology - and then automatically transformed (using the mappings) to a query (usually SQL) that can be answered over the backend database. For OBDMA, UDFs (user-defined functions) are also stored in the database, enabling new data to be calculated on-the-fly.
Figure 5 gives an overview of the functional principle of the OBDMA-system explained based on a query about elastic parameters.

*https://www.w3.org/TR/rdf-sparql-query/

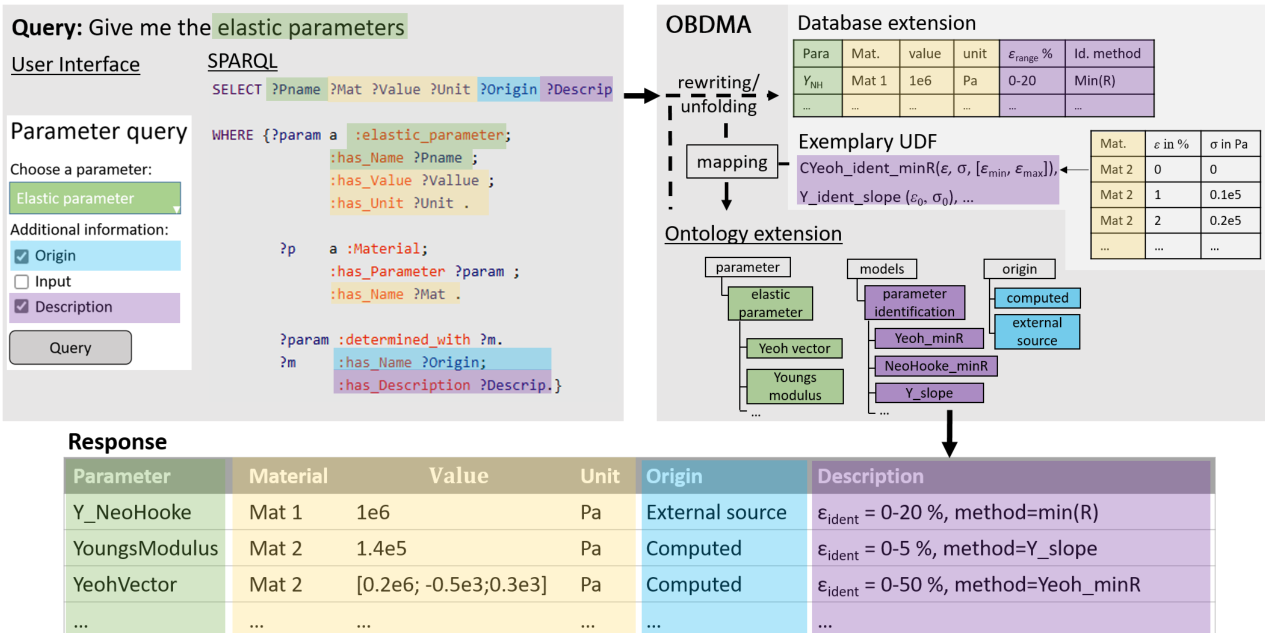

Figure 5. Functional principle of the OBDMA-system explained by means of an exemplary query.

The OBDMA-system consists of the rewriting and transformation algorithms as well as declarative artifacts in form of the database, the mappings, and the ontology. The input to the OBD(M)A-system is a SPARQL-query. It is stated by the user either directly as a SPARQL-query or indirectly with the help of some user interface whose input however is directly translated into a SPARQL-query. In detail, the query in Figure 5 asks for the values and units of all elastic parameters, the corresponding material, their origin and description of the origin. The origin indicates whether the parameter was calculated internally in the system or stored as a value in the database and determined in an external source, such as a data sheet or paper. In the case of a internal calculation, the input parameters of this calculation can also be queried (not done in this example). The description includes some specifics about the origin, e.g., for elastic parameters, the information about the identification method and the strain range. The user neither need to have any information about the internal structure of the database nor ontological information, e.g., which parameters actually count as elastic parameters to state such a query.
In this SPARQL-query, first via rewriting, the ontological information is incorporated. Though, in OBDA (and thus also in OBDMA), only a restricted ontology can be modeled, it enables to increase the expressivity of the query. In the example, the ontology incorporates the information that e.g. the Yeoh-vector and the Young's modulus are both elastic parameters. Without this information, the user would have to state the query for each of this parameters on its own, with this information, the query is extended in the rewriting step to incorporate all these variants (thus, the query "give me the elastic parameter" changes to "give me the parameters which are an elastic parameter or a Yeoh vector or a Young's modulus or …"). The rewriting is independent of the database, thus, the ontology is not restricted to one specific use-case based on one database but can be exchanged and reused. To connect the rewritten SPARQL-query with an actual database, a mapping is needed, it contains rules converting the SPARQL query to a SQL query. In this unfolding step, each element of the rewritten query is mapped to some values of the database. As in the ontology, it is also possible in this step to incorporate background information. Beside the actual "translation" of the SPARQL- into the SQL-query, especially the model access is done in this step. A query asking for the value of the Young's modulus is then on the one hand mapped to values already given in the database from some external source, e.g., a measurement. On the other hand, in the mapping a rule is given including the information how the value can be calculated based on parameter values and a function given in the database. This rewritten and unfolded query can then be queried over the database and an result is returned to the user. In this example, for Mat 1, information about the

Young's modulus for the Neo-Hooke model Y_{NH} is stored in the database, the knowledge that this is an elastic parameter is given in the ontology. For Mat 2, a stress-strain curve is given in the database and combined with the two UDFs, the Yeoh vector and Young's modulus are evaluated.

In this example, only a simple SPARQL-query has been described. It is possible to extend these queries, e.g., with filter operations. For example, the user can first query which elastic parameters are available. In the next step, the user can query only a specific parameter, e.g., the Yeoh vector, with further information like value and description. Next to this, it is possible to get more information about the calculations done, e.g., querying input parameters of a model or the equation used for a calculation. In section 2 different possibilities of hyperelastic models and methods for parameter identification were demonstrated. The presented OBDMA system allows the handling of all these models and parameters and offers an application-oriented approach.

4. CONCLUSION

Especially in young research areas, such as DE-transducers, material data and models are often available in heterogeneous form. For example, the parameter identification for an application-oriented determination is quite individual. The diversity and the large number of possible values for elastic material parameters were demonstrated in the first section and are essential for developing and optimizing DE-transducers. OBDMA is a system that provides easy access to such heterogeneous data and models, where the database can be flexibly modified and extended. In this paper, OBDMA is explained for DE materials as an example, but it can also be used for other applications. For example, in the SmaDi collaborative project, four different smart materials are being considered for the development of an OBDMA-system, of which DE materials are only one. The principle of OBDMA has been demonstrated in the previous section with a simple example, although the advantages better come into play with large and diverse databases.
When using SPARQL as a query language, filter options allow application-oriented response containment. For example, parameter identification can be limited to a specific range, or Young's modulus can be queried only for a specific range of values. In summary, the principle of the OBDMA-system was presented, and its advantages were demonstrated using the example of parameter identification for elastic models for DE-transducers. Furthermore, collecting and implementing existing parameter values and models are prerequisites for a broad application and enable optimized and application-oriented material development for DE-transducers.

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