**Abstract**

Our tool provides an intuitive workflow that imports and processes raw unfiltered shape memory alloy mechanical (tensile/compression), thermal (DSC), or thermomechanical (tensile/compression with environmental chamber) data to produce customizable figures and systematically derived material data. This toolset can extract data from multiple inputs such as tensile test data and external thermocouples and automatically synchronize them onto the same time series. With raw force and displacement data, the SMA REACT can calculate strains and stresses based on various sample geometries. Coupling temperature, stress, and strain data, this tool can apply customizable filters and remove systematic errors within the dataset, periodically prompting the user for filter approval. The refined data is then iteratively calibrated to best fit a Lagoudas-Hartl constitutive model. The program is open-source allowing for other features and SMA models to be added. The focus on automated and intuitive generation of figures and model fitting greatly assist experimentalists, modelers, and designers to iterate on novel shape memory alloy materials and applications.

**Introduction**

Shape memory alloy actuators have found uses in the fields of aerospace, biomedical, civil, robotics, and more by virtue of their high actuation energy density and solid-state operation [1]. The inherent complexity of SMAs is an opportunity for more space- and weight-efficient assemblies, but a challenge from a design perspective. A notional process for developing a shape memory alloy engineering system could be divided into six stages (detailed graphically in Fig. 1). Step 1 requires identifying one’s system requirements which entails discerning a suitable range of material requirements (i.e., stiffness, actuation strain, transformation temperatures). These material requirements directly drive step 2, i.e., choosing the precise SMA composition. Finding relations between composition and material properties have recently been streamlined with NASA’s SMA database tool [2], [3].

The arduous journey of turning a material concept into a reality involves the many iterations between Steps 3-5, i.e., processing, characterization, and model fitting. Processing differences during manufacturing can affect the material properties, such as reducing an ingot into a wire or tuning print parameters for additively manufactured SMAs [4]. Characterization enables the simultaneous assessment of the new processing techniques and responses to loading conditions (i.e., tension, compression, or torsion). Rigorous engineers may seek to validate the behavior of a new material within the original system requirements. This can be done by fitting the characterization data to a model that captures the full thermomechanical constitutive response (i.e., the relationship between temperature, stress, and strain). With a calibrated constitutive model (such as the Lagoudas [5] or Brinson [6] models) engineers can design the system to confirm the behavior of the unique nonlinearities inherent of SMAs. Iteration of these steps will likely occur multiple times to reach requirements. Once the constitutive model accurately represents the SMA behavior and the material satisfies requirements, the SMA device can then be integrated into the engineering system.

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Figure : The typical SMA development process involves many discrete steps. This work provides an easy constitutive model calibration tool, the Rendering of Experimental Analysis and Calibration Tool, to enable SMA component design.

Such design processes involve many disciplines and can be a daunting endeavor for small teams or new adopters of SMA technology. Characterization hardware is complex; due to the various external state variables that govern shape memory material behavior, extracting a stress-strain-temperature history often requires synchronization of multiple metrologies (i.e., thermocouples, load cells, and strain gauges). Development requires significant time and effort, but the greater SMA community has developed tools to expedite certain stages.

The composition-processing-property space for SMAs is becoming well understood, and many recently developed tools enable quick discovery of new alloys [nasa][7], [8], [9]. ASMADA, the Automatic Shape Memory Alloy Data Analyzer, identifies heating and cooling cycles of SMAs and extracts SMA material properties according to ASTM standard E097 [10], [11], [12]. The Shape Memory Materials Analysis and Research Tool (SM2ART), also known as SMAnalytics, provides an extensive open-source database of tested shape memory alloys and their standard properties [2], [3]. Many research groups have published user material models (i.e., UMATs) to interface with open-source and commercial finite element solvers [13], [14], [15], [16]. [20]-focused

In this work, we detail a streamlined open-source, GUI-based tool to help both material scientists and design engineers analyze their thermomechanical data and calibrate an appropriate SMA constitutive model. We deem this tool REACT, for the Rendering of Experimental Analysis and Calibration Tool. REACT provides an intuitive workflow that imports and processes raw unfiltered shape memory alloy mechanical (tensile/compression), thermal (DSC), or thermomechanical (tensile/compression with environmental chamber) data to produce customizable figures and systematically derived constitutive models (depicted schematically in Figure 2). For iterative calibration, REACT allows the user to choose bounds and lock-in values to further increase speed and accessibility. The tool is written in python but requires no programming experience to use; it is available on GitHub under the GNU General Public License [x]. Two modules accomplish the essential tasks of data processing and constitutive model calibration.

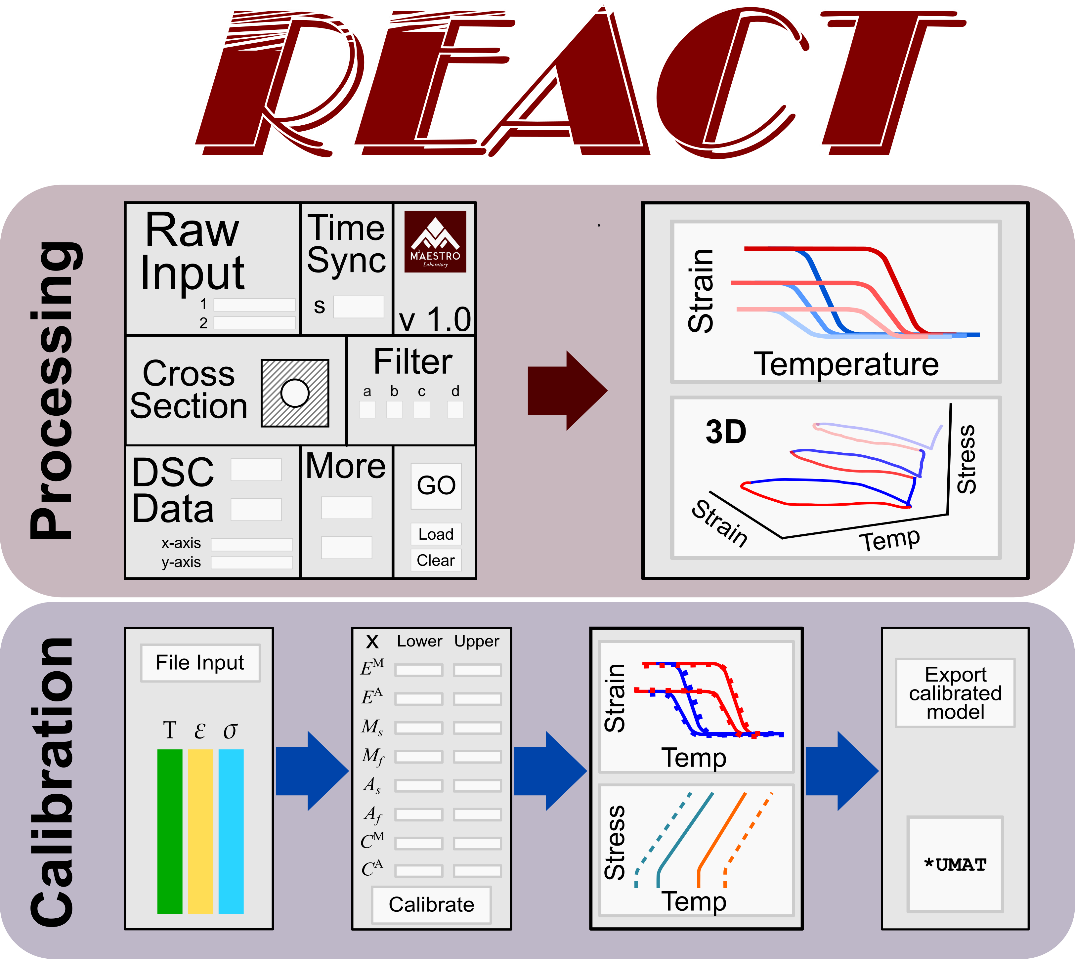


Figure : SMA-REACT allows the user to load their own data, specify known model parameters, and find an optimal calibration that best approximates experimental response.

**Method description**

(Add some meta-text of what this section is, and why it’s different than documentation). Full code documentation of the processing module can be found online [link to your cool wiki].

**Data Processing Module**

Shape memory alloy characterization requires acquisition of at least stress, strain, and temperature histories. Sometimes these histories rely on different telemetries and must be synchronized into a single data file. The SMA REACT processing module extracts data from multiple inputs such as a load frame and external thermocouples and automatically synchronizes them onto the same time series. With unfiltered force and displacement data, REACT can calculate strains and stresses based on various sample geometries. Coupling temperature, stress, and strain data, this tool can apply customizable filters and remove systematic errors within the dataset. The program then produces various figures to help visualize the complex shape memory alloy material behavior. Users can export this processed data to the next module of the tool, Model Calibration.

**Model Calibration Module**

For many applications, selecting a particular SMA component based on transformation temperature and maximum transformation strain is insufficient; the transformation temperatures and actuation strain in the *operating stress regime* must be well characterized and predictable. this intended

A deterministic amount of data can allow for derived closed-form analytical expressions for simple models [17], [18]. However, when the operating stress regime of the SMA spans many stress regions and requires multiple (> 3) experimental tests, these analytical methods become overdetermined. Numerical optimization must be employed to find the combination of model parameters that best fit experimental data, demonstrated within [19], [21], [22], [23]. These approaches help to speed the process, but exist as purpose-built codes and are have limited applicability outside the authors’ specific application or research group.

Given filtered and synchronized experimental data from the processing module, the model calibration module finds the best fit of constitutive model parameters (martensitic elastic modulus, austenite start temperature, etc.) based on the Lagoudas one-dimensional constitutive model. The developed calibration routine leverages hybrid optimization to minimize error between model prediction and experimental data. Hybrid optimization comprises a global optimization (i.e., a genetic algorithm) to identify a starting point for a local gradient-based optimization (i.e., SLSQP). Our tool enables the user to customize the optimization routine as well as the model parameters to be optimized (e.g., bounds and free variables). Outputs from the calibration routine include a set of model parameters to be used in future analyses (i.e., material properties for FEA) and a thermodynamically consistent phase diagram based on calibrated model parameters.

Our tool leverages the genetic algorithm NSGA-II [24], [25] for the global search and then SLSQP implemented in SciPy [26] for the local search, although the tool is modular and can be modified to use other optimization algorithms. For all example calibrations in this text, we specify the population size and number of generations to be 100 and at least 10, respectively for NSGA-II. We restrict SLSQP to 100 maximum iterations. Though REACT calibrates for only one SMA model at the moment, the developed framework in REACT can be expanded to consider other constitutive models, higher dimensional models (e.g., 3D models with anisotropic effects), and different loading modes (e.g., superelasticity).

**The One-dimensional Lagoudas SMA Constitutive Model: A brief primer**

The Lagoudas shape memory alloy constitutive model uses the Gibbs' free energy to derive a thermodynamically consistent relationship between stress and strain. In this work, we leverage the temperature- and strain-driven implementation of this model for wider applicability in standard finite element suites. In this section, we will omit a full model derivation (see Lagoudas et al. [5] for more information) , but rather highlight the seventeen unique but dependent model parameters that need calibrated and their effects on constitutive behavior.

Table :The one-dimensional reduction of the Lagoudas SMA constitutive model requires calibration of 17 unique but dependent parameters.

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Mathematical Symbol** | **Units (SI)** |
| **Thermoelastic properties** |  |  |
| Elastic moduli |  | Pa |
| Coefficient of thermal expansion |  | 1/K |
| **Transformation properties** |  |  |
| Transformation temperatures (at zero-stress) |  | K |
| Stress-influence coefficients |  | Pa/K |
| **Transformation strain properties** |  |  |
| Minimum transformation strain |  | m/m |
| Maximum transformation strain |  | m/m |
| Critical stress at which transformation strain manifests |  | Pa |
| Transformation strain rise time |  | 1/Pa |
| **Smooth hardening properties** |  |  |
| Smooth hardening coefficients |  | - |

The Lagoudas one-dimensional constitutive model comprises four interdependent parameter groups.

1. **Thermoelastic properties** include the elastic moduli for each material phase ( and for austenite and martensite, respectively) and the coefficient of thermal expansion . Note this model formulation assumes the coefficient of thermal expansion is constant with respect to material phase; this allows the use of simpler nonlinear solution methods (i.e., Convex Cutting Plane [27]).
2. **Transformation properties** include zero-stress transformation temperatures and stress-influence coefficients . Zero-stress transformation temperatures define the start and end of transformation at zero stress (denoted by the character for the material phase and the subscript for the start and end). Stress-influence coefficients define how transformation temperatures change with respect to stress and are assumed to be constant with respect to material phase; the slope of the stress-temperature phase diagram at the *calibration stress[[1]](#footnote-3)* gives these two values.
3. **Transformation strain properties** define the evolution of transformation strain with respect to stress and are crucial to understand if the material exhibits sufficient transformation strain at the design stress. The transformation strain is approximated as an asymptotic exponential function, where and are the minimum and maximum transformation strain, defines the critical stress at which transformation strain manifests, and is the *rise time*, or how quickly the transformation strain increases from to .
4. **Smooth hardening coefficients** () define the smoothness of the transition between elastic response and transformation, or vice versa. They are bounded between 0 and 1 and are ordered from one to four, corresponding to a hot-to-cold actuation loop (i.e., ).

As mentioned earlier, the seventeen material properties that define shape memory alloy constitutive response are unique but interdependent. For example, a change in smooth hardening coefficient will cause a change in the corresponding zero-stress transformation temperature. Herein lies a crucial nuance of calibrating the Lagoudas constitutive model: the model defines the transformation temperatures as the point at which transformation begins (i.e., the state where the transformation criteria are activated), rather than the tangent (which is the definition used in ASTM E3097) [11].

Many other material properties are interdependent; a change in transformation strain properties will be reflected in both the strain-temperature response and the shape of the transformation surfaces. While the stress-influence coefficients are single numbers for each phase, they are only one part of the mathematical expression to define the transformation surface in stress-temperature space (see Lagoudas et al. for more information [5]). For these reasons, calibration must leverage numerical optimization to ensure a robust fit of experimental data.

**Calibration via numerical optimization**

Mupdatingthe 17 model parameters to find a best fit to experimental data is a tedious and process.The REACT model calibration module instead uses numerical optimization to find the best fit. Further, the user can specify material property bounds or property values. Prior knowledge of certain properties (e.g., Young’s moduli from tensile tests), will greatly minimize error between model prediction and experiment by varying all other material properties.  Depending on the size of the dataset, each calibration process can execute in less than 10 minutes, and even those who are not innately familiar with the Lagoudas SMA constitutive model can easily digest the results. In this way, our tool provides a high-throughput, low-barrier-to-entry calibration method that hope to increase the adoption of SMA solutions.

**Implementation example**

To show the utility of SMA-REACT, we discuss a sample dataset and calibrate the Lagoudas SMA constitutive model both analytically and numerically using the GUI. We detail an iterative tuning process to refine the calibration, demonstrating the ease of the GUI.

**Experimental data**

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Figure : To demonstrate the utility of SMA-REACT, we will calibrate a constitutive model to fit published experimental data [28].

To calibrate an accurate SMA constitutive model to capture actuator behavior, *n* constant force thermal cycling tests are needed, where *n* is preferably greater than 4. Each test requires stress-strain-temperature histories. We use an experimental dataset for a Ni50.5Ti27.2Hf22.3 alloy from Bigelow et al [28]. The six different constant force cycles, non-zero coefficients of thermal expansion, and nonlinear relationship between applied stress and transformation strain make this data set a great calibration example. Add a tie-in sentence here.

**Identifying material property bounds**



To produce an accurate calibration using SMA-REACT, the optimizer must be provided with bounded material parameters. The better the bounds, the more likely the optimizer will not get stuck in a local minima. To this end, we will calibrate select parameters analytically and discuss rules of thumb for other parameters.

The most important property bounds are the transformation temperatures. If the transformation temperatures are incorrectly bounded, the optimizer may converge to non-physical results (i.e., a phase diagram where martensite temperatures are higher than austenite temperatures) in an attempt to minimize error between model and experimental data. Transformation temperatures for each tested stress level can be estimated via the tangent method or similar (see Figures 5 a) and b)). If a “zero-stress” isobaric test (i.e., 7 MPa or lower) was performed, the transformation temperatures found for this test can be taken as the zero-stress transformation temperatures. Otherwise, each zero-stress transformation temperature can be found via the x-intercept of a linear regression of the transformation temperatures as a function of stress. This estimate is equivalent to a Lagoudas model calibration with smooth hardening parameters set to . Bounds for each transformation temperature are typically 10-20 K around each parameter (i.e., for an estimated of 150 K, the lower and upper bounds would be 130 K and 170 K, respectively).

The average slope of the martensite and austenite transformation surfaces for martensite and austenite for a specified stress range about the user-determined *calibration stress* can be taken as the stress-influence coefficients ( and ). Note that the stress-influence coefficients should not be derived from the average slope from estimated transformation temperatures at all stress levels; most shape memory alloys exhibit a nonlinear change in transformation temperature with respect to stress (see Figure 3(b) in [27]), and the Lagoudas model compensates for this via the transformation surfaces (), where the stress-influence coefficients at the calibration stress are a contributing factor. The stress-influence coefficient bounds are then set to vary by 1 MPa/K in each direction.

Austenite elastic modulus can also be estimated from constant-stress force cycling data by extracting the total strains and a temperature well above at each tested stress level. Then, by designating this temperature , Hooke’s law becomes:

Austenite elastic modulus is the best-fit linear coefficient from this equation (see Figure 5 c)).

Estimating the rest of the material properties (Martensite elastic modulus, transformation strain properties, coefficient of thermal expansion, smooth hardening coefficients) is a more involved process that requires a nonlinear curve fitting routine; see the Appendix for more details. In practice, the estimating the properties detailed above and applying best practices for the remaining properties results in a sufficient calibration.

|  |  |  |
| --- | --- | --- |
| a) Constant-stress force cycling data for five distinct stress levels. | b) Estimates for zero-stress transformation temperatures and stress-influence coefficients at the calibration stress are extracted directly from CFTC data. | *c) Austenite elastic modulus are found via Hooke's law at the reference temperature, which is a model parameter defined by the analyst.* |

*Figure 5: Given constant-stress thermal cycling (CFTC) data for several stress levels, the Lagoudas SMA constitutive model can be calibrated using local curve-fitting routines. However, this method still relies on many manual iterations to find smooth hardening coefficients (not shown above). In each subfigure above, the parameters found are displayed in the grey box in the lower-right corner.*

Table 2 shows typical bounds for a preliminary calibration. As mentioned previously, Austenite elastic modulus, transformation temperatures, and stress-influence coefficients can be easily estimated via linear regression. Martensite elastic modulus is commonly lower than the austenite elastic modulus, so common practice entails setting a lower bound equal to one-half the estimated austenite value. Relatively low bounds for the coefficient of thermal expansion are suggested for preliminary calibration to properly restrict the optimizer to find reasonable values for transformation properties. These bounds can be modified based on material response; inspecting the slope of the strain-temperature response in either martensite or austenite can help guide the analyst.

Transformation strain properties are the most difficult property group to accurately estimate during a preliminary calibration. This is due to the exponential nature of the transformation strain function (see \_\_\_) and the large sensitivity of transformation strain properties on overall calibration error. A calibration that accurately predicts all other properties will drastically underperform a calibration that incorrectly predicts thermoelastic and transformation properties but accurately predicts transformation strain properties. Commonly either the minimum transformation strain or critical stress at which transformation strain manifests , or both, are set to zero for preliminary calibrations. Setting both of the aforementioned parameters to zero is indicative of a material that exhibits no two-way shape memory effect.

Finally, smooth hardening coefficients are typically the last parameters to be refined. As we do in the next section, typically, these parameters are set to 1 for preliminary calibrations to reduce the number of active design variables. When thermoelastic properties and transformation strain properties have converged, the smooth hardening coefficients and transformation temperatures are refined.

Table 2: Common starting bounds for each parameter of the Lagoudas constitutive model. Note that these are guidelines and should be modified after a preliminary calibration.

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Mathematical Symbol** | **Bounds (SI)** |
| **Thermoelastic properties** |  |  |
| Austenite elastic modulus |  | Eq. 2, Figure 5c) |
| Martenite elastic modulus |  |  |
| Coefficient of thermal expansion |  |  |
| **Transformation properties** |  |  |
| Transformation temperatures (at zero-stress) |  | Figure 5b) |
| Stress-influence coefficients |  | Figure 5b) |
| **Transformation strain properties** |  |  |
| Minimum transformation strain |  | [0, 0.01] |
| Maximum transformation strain |  | [0.01, 0.05] |
| Critical stress at which transformation strain manifests |  | [0, 50E6] |
| Transformation strain rise time |  | [1E-8, 1E-6] |
| **Smooth hardening properties** |  |  |
| Smooth hardening coefficients |  | [0, 1] |

Some material properties are estimated and can inform the bounds during optimization. For example, the estimated austenitic elastic modulus of 55 GPa informs the upper and lower bounds of 50 GPa to 80 GPa, respectively. This allows the optimizer to start in the neighborhood of feasible solutions, but gives it freedom to explore for a better performing result. To fully capture the true strain-temperature response, iterative calibration of each smooth hardening coefficient is necessary until a satisfactory fit is accomplished. Due to the interdependencies highlighted earlier, each change of smooth hardening coefficient will need to be accompanied by a change in the associated transformation temperature and perhaps stress-influence coefficient (i.e., a change in will need to be accompanied by a change in and ).

The global numerical calibration of REACT includes a preliminary genetic algorithm followed by a gradient-based algorithm. Then, based on the values to which the optimization converged, the parameters that converged to the bounds were further inspected, bounds were widened, further improving the calibration accuracy. This process of inspecting the converged results and comparing to the optimization bounds was repeated three times until each parameter converged to a value well within the set bounds. Thus, a local optimum is found. With a large enough initial population in the genetic algorithm, one can be confident that this is near the globally optimal calibration for this model formulation. One can see the improvements in iteration in Table 2.

Table : Estimating bounds via simple rules allows the optimization enables a calibration within 2% error. SMA-REACT enables quick parameter tuning to further improve the calibration.

|  |  |  |
| --- | --- | --- |
| **Calibration Number** | **Mean squared error** | **Notes** |
| 1 | 1.51% | Estimated bounds (see section BLANK.BLANK). . . |
| 2 | 1.34% | Widened bounds on thermoelastic and transformation strain properties. Maintained transformation temperature bounds. . . |
| 3 | 1.31% | Froze all properties besides transformation temperatures and smooth hardening coefficients. |

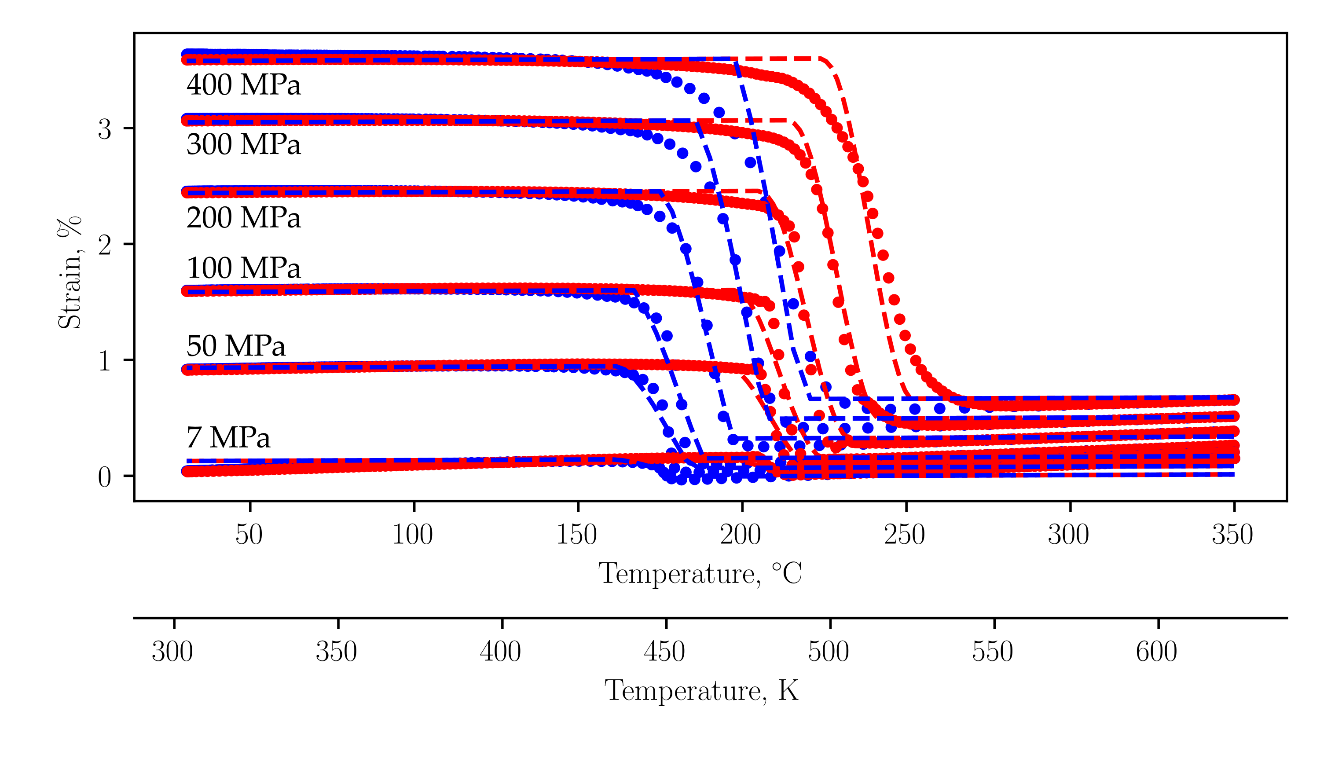


Figure : The final calibration agrees with the experimental data to within 1.31% mean squared error.

The final numerical calibration is depicted in Figure 5. The model predicts the elastic response in martensite accurately, which signifies that both the martensitic elastic modulus and transformation strain properties are well calibrated. Transformation temperatures show good agreement at low levels of applied stress. At higher levels of applied stress, the model-predicted transformation overshoots the experimental data and predicts a smaller hysteresis. This is because the transformation temperatures are not a linear function of stress (i.e., the stress-influence coefficients are not constant, see figure 3b in Bigelow [28]), and because the smoothness of transformation initiation is not constant with stress (compare the 100 MPa transformation into austenite with the analogous location at 300 MPa). This calibration is a great example of the utility of numerical optimization; the optimizer finds the best global fit of data, especially regarding the austenite transformation temperatures. For lower stresses, is too low, and is too high. At intermediate stresses, like 100 and 200 MPa, the transformation temperatures are almost perfect. Then, at 300 MPa, is too high and is too low. This could be better fit at the relevant stresses by biasing the solution to prioritize fitting certain stress levels (see [23]) or by simply calibrating the model at the stress levels that matter most.

However, this calibration is not perfect, mainly due to model deficiencies. In reality, the coefficient of thermal expansion varies with material phase. Clearly, the coefficient of thermal expansion in austenite is larger than that in martensite. This is a model deficiency because the current model uses a convex cutting plane assumption for numerical integration and could be improved in future work.

Regardless, these five optimizations improved calibration accuracy by over 50% compared to educated guesses , and were accomplished in less than an hour on a lightweight laptop with a low-performance processor (Intel Core m3-6Y30 CPU @ 0.90 GHz with 4 Gb RAM). This calibration routine can be performed by general analysts, designers, or material scientists, without the need for exotic hardware, python programming experience, or relatively clean datasets

**Conclusions and further refinements**

SMA-REACT is an open-source, easy-to-use tool for characterization data post-processing and shape memory alloy constitutive model calibration. While we have focused on the Lagoudas constitutive model and actuator (i.e., constant force thermal cycling) behavior, the tool is easily extensible to other constitutive models or loading modes. By framing the calibration routine as a numerical optimization problem, SMA-REACT can find robust calibrations that outperform conventional (i.e., by hand) calibrations by 50% or more, without requiring detailed knowledge of programming, optimization, or the Lagoudas constitutive model. This allows the tool to be approachable for a wide range of students and professionals working on shape memory alloys. The speed at which model calibrations can be fine-tuned allows for rapid iterations to converge to a satisfactory model calibration, which can then be used in commercial finite element suites like ABAQUS.

We distribute the SMA-REACT toolset and source code under the GNU General Public License, which allows anyone to run, study, share, and modify the code. We invite any modifications that users may find useful, including, but not limited to, alternative loading modes (i.e., superelasticity or combined superelasticity/shape memory [29]), alternative constitutive models [6], [30], [31], [32], or any usability enhancements for more robust data import or export. In particular, we believe integration with other open-source tools, such as the Shape Memory Materials Database and SMAnalytics would be very enabling to the greater SMA community [2]. SMA-REACT aims to reduce the barrier between materials scientists and engineers, and will hopefully enable more widespread adoption of shape memory alloys in engineering applications.

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**Appendix: Calibrating Martensite elastic modulus and transformation strain properties without global optimization**

Following the procedure described in Section BLANK.BLANK allows the analyst to derive bounds for transformation temperatures, stress-influence coefficients, and the Austenite elastic modulus. We will discuss one method to find the remaining properties without global optimization but requires many manual iterations.

The analyst has two choices when calculating the coefficient of thermal expansion . First, can be calculated separate from the transformation strain properties by extracting the total strain at another temperature :

Alternatively, it can be found concurrently with the other thermoelastic and transformation strain properties via a nonlinear system of equations. At a temperature , Hooke’s Law can be written as:

where

In this equation, there are six unknowns: and . Ideally, to calibrate these six unknowns, one will have performed six or more constant-force thermal cycle tests. However, for shape memory materials that do not exhibit two-way shape memory effect, both and can be set to zero, reducing the number of required tests to four. If the coefficient of thermal expansion was calibrated based on elastic response, the other five parameters are calibrated in the same way as described above.

Both of these approaches to calculate the remaining thermoelastic properties and transformation strain properties may introduce modeling errors. The nonlinearities associated with the current transformation strain make the transformation strain very sensitive to change in model parameters (in particular the rise time ). This sensitivity requires the analyst to try a range of starting values for before a nonlinear curve fitting routine converges to the global optimum. Typical values for range from and for materials with small and large changes in transformation strain as a function of stress, respectively. If , the strain due to thermal expansion will be incorrectly predicted across the tested temperature range. However, this is a limitation of the one-dimensional reduction of the Lagoudas constitutive model; assuming thermal expansion is invariant of material phase allows for the use of simpler nonlinear solution methods (i.e., Convex Cutting Plane).

At this point, all material properties are estimated; to fully capture the true strain-temperature response, iterative calibration of each smooth hardening coefficient is necessary until a satisfactory fit is accomplished. Due to the interdependencies highlighted earlier, each change of smooth hardening coefficient will need to be accompanied by a change in the associated transformation temperature and perhaps stress-influence coefficient (i.e., a change in will need to be accompanied by a change in and ). Without global numerical optimization, the best model calibration will be found via manual changes and the analyst’s intuition.

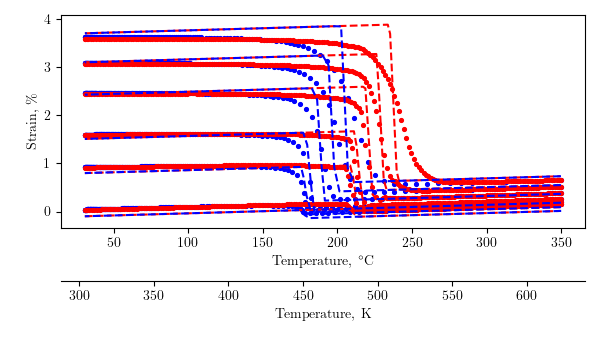


Figure 9: Calibration without global optimization produces a passable solution, but rely on user iterations to fine-tune model response.

The resulting conventional calibration, with , is shown in Figure 9. The mean squared error between model and experiment is 3.13%, which for many applications could suffice. Transformation temperatures and transformation strain properties are well-captured, as the model bisects the experimental curves as a function of stress (i.e., the martensite elastic response is under-predicted at low levels of applied stress but over-predicted at high levels of applied stress). However, there are several areas that could be improved. The coefficient of thermal expansion is too high, as shown by the large deviance between model and experiment in Martensite, especially immediately before forward transformation. This calibration routine still requires a nonlinear curve fitting procedure to find the transformation strain properties, as well as requiring more intuition about the relationship between model parameters and constitutive response.

1. The calibration stress is *a priori* defined by the designer. Common practice dictates selecting a value close to the design working stress of the material. [↑](#footnote-ref-3)