

Machine Learning Assisted Empirical Formula Augmentation

Bin Xiong*

Department of Advanced Materials and Technology, University of Science and Technology Beijing, Beijing, China

Introduction

Increasing the temperature range at which shape memory alloys (SMAs) are usable has made it increasingly important to modify the martensite transformation temperature through composition design. For composition design, the empirical formula based on conventional statistics is essential. Because of the absence of exploratory information, an enormous deviation might exist among the forecast results from the exact equations got by various information sources. In present work, we proposed an expansion technique of experimental equation in light of an AI strategy to construct the connection between martensite change start temperature (Ms) and pieces in Cu-Al-based SMA framework. A progression of ML models were laid out by physical and compound elements and a Gaussian spiral premise bit capability support vector machine (SVR.rbf) model was screened out in light of numerical and space information standards. The abundant augmented dataset, which incorporated both experimental and predicted data from the SVR.rbf model, served as the basis for the fitting of an enhanced empirical formula for Ms as a function of compositions. The accuracy and robustness of the augmented empirical formula were significantly improved without incurring additional experimental costs in comparison to the previous empirical formula that was fitted using a limited experimental dataset. Based on a small experimental dataset, this strategy provides a recipe for developing an empirical formula.

Description

One important method of scientific research is concluding empirical law from experimental or calculational data. The exactness and pertinence of the observational regulation is firmly subject to the amount and nature of the information test. Because we collect data from a variety of experiments using a variety of processing parameters, we frequently encounter low-quality datasets, such as insufficient data, a severely skewed distribution, and low mergeable data, in practical research. The low-quality data will result in a formula with low accuracy. It is possible to solve the problem by increasing the quantity or quality of data samples under consistent experimental conditions; however, this comes with high experimental costs. Machine learning (ML) is becoming a potent approach to material data issues as a result of the growth of materials information. ML has been successful in solving problems involving small amounts of data in addition to dealing with big data. Data augmentation is a useful ML technique that enhances the quantity and quality of data by adding information gathered from a variety of sources to the base dataset [1].

One of the most crucial steps in making the data more useful is data augmentation. Shape memory composites (SMAs) is a sort of significant utilitarian material that has been generally utilized in sensors, actuators, ecological security refrigeration and energy transformation hardware because

of its extraordinary shape memory impact and superelasticity. One of the most crucial material parameters in material design is the martensitic transformation temperature, which determines the temperature window of SMAs in their applications. Temperatures of martensitic transformation are highly influenced by composition. Consequently, it is a helpful method for controlling the martensitic change temperatures by piece plan, which likewise turns into a significant method for widening the application temperature scope of SMAs and to create ultralow-temperature or high-temperature SMAs. As a result, accurate composition design relies on establishing a connection between the temperatures of martensitic transformation and SMA compositions [2-5].

Conclusion

In general, sufficient experimental data are required to fit an accurate empirical formula. However, researchers typically use only a few to a dozen experimental data for formula fitting because experimental costs are limited. A straightforward and attainable solution might be to acquire additional experimental data from additional researchers to increase the total quantity of data. However, it is frequently challenging to easily determine the mergeability of data from various researchers. The ML model is becoming an important and powerful tool for material discovery and design, even building emerging materials intelligence ecosystems, as it is able to not only perform statistical fitting but also build physically meaningful relationships by mining hidden information beneath the data. This is in contrast to the traditional data fitting method

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*Address for Correspondence: Bin Xiong, Department of Advanced Materials and Technology, University of Science and Technology Beijing, Beijing, China, E-mail: Binxiong44@eduhk.hk

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