An Approach to Classify Engineering Materials Using Machine Learning Algorithm

P.J. Antony, Prajna Manujesh and N.A. Jnanesh

Abstract This review paper explores the attempts made by the numerous authors in the field of material selection. There are ample amounts of works carried out in the field of materials engineering with data mining approaches. From the literature it is revealed that not much of the work is explored on the classification of advanced composite materials using machine learning approaches.

Keywords Material selection · Data mining approach · Advanced composite materials · Machine learning

1 Introduction

Material science is an interdisciplinary field for applying the properties of materials in various fields of building. The extent of the materials in designing is boundless. Each new item is either in light of new material configuration or change in the current material properties. The quick improvements in the field of materials science with due significance to materials building is the present days need [1]. Therefore, the materials designer ought to have careful information for the material determination to the proposed applications in enhancing new items. The best item is the result of adjusted materials and ideal outline developments. Along these lines the determination of best materials spins around the material choice systems. Expectedly the material determination is trailed by examining the material information set and handling consecutively to channel, arrange lastly the learning removed from information set can be utilized for different configuration applications [2]. Along these lines the choice and characterization of materials are vital and basic in the active field of material designing.

P.J. Antony · P. Manujesh (✉) · N.A. Jnanesh
Department of Computer Science and Engineering,
KVG College of Engineering, Sullia 574327, India
e-mail: prajnamanu@gmail.com

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A. *Composite Materials*

Composite materials are an insignificant blend of two or more distinctive materials. One typically associates being the consistent stage (network) and the other being the broken stage (fortification). It is the flexibility of pattern consolidated with solidness of strengthening. The properties of these materials are unequivocally subject to the composite structure and these materials are broadly acknowledged materials in view of their versatility to various circumstances and the relative straightforwardness of mixing with different materials to show attractive properties [3]. The use of composites keeps on developing at amazing rates as these materials are utilized more as a part of their current markets and to end up built up in generally new markets, for example, biomedical and common structures [4]. The composites are customized to suit the particular applications making a more noteworthy favorable circumstances like; low warm conductivity and low coefficient of warm extension, high hub quality and solidness, and so forth. A key variable driving the expanded utilizations of composites over the late years is the improvement of new propelled types of cutting edge materials. This incorporates the improvement in elite sap framework and new styles of fortifications [5].

The utilization of composites has turned out to be progressively alluring distinct option for the ordinary materials for some building applications. The segments can be produced essentially because of their expanded quality, strength, consumption resistance, imperviousness to exhaustion and harm resilience attributes likewise they guarantee huge chances to assume an expanding part as interchange material to replace timber, steel, aluminum, and cement in structures even in high weight and forceful ecological circumstances [6]. Uses of composite are expanding colossally alongside the simultaneous requirement for information era. These are utilized as a part of practically every sort of designing structures, with their use going from airplanes, rocket through to water crafts, ships and seaward stages, autos, brandishing merchandise, compound preparing supplies, and common foundation, for example, spans and buildings [7, 8]. With the innovation advancements and improvements in procedures and items, the composites have ended up appealing contender for generally applications. The data to pick certain materials needs exhaustive comprehension and learning for choice parameters to fit into basic applications. Consequently determination of materials is the principal basic stages were accomplishment on materials decision is managed.

B. *Machine Learning*

Machine learning is a way to deal with configuration of a particular model that permits PCs to pick up information without being expressly modified. The material disclosure includes colossal measurable abnormality in the example of information dissemination. As needs be, various machine learning calculations will hardly take after how human might approach a learning assignment [9]. The regulated learning is the one class of machine realizing, where the class yield is refer to for all conceivable preparation and in addition test information. Further it is genuinely normal in order issues on the grounds that the goals are over and again guide the PC to take in an arrangement framework. For the most part, grouping learning is suitable for any issue in the connection where the class of obscure information will be anticipated utilizing the model from now on assembled. Sometimes, it would not be important to give set of groupings to each occurrence of the issues; rather the specialists can work out the arrangements for it and this would show as an unsupervised learning in any order connection [10, 11]. They guarantee huge advances within the materials science, and hold the broad surety for materials exploration and information revelation in defying with another material. Along these lines it would be helpful if its properties could be anticipated utilizing the past learning relating to other comparative known materials, as opposed to turning new trials or difficult computations expending time and cost [12].

2 Literature Survey

There are generous amount of work done using various algorithms of machine learning like genetic algorithms, neural network approach, support vector machines. Recently the materials scientists have begin the data mining ideas for discovering new materials for diverse applications of engineering.

A. *Genetic Algorithms Approach for the Design and Optimization*

Genetic algorithm (GA) is an inquiry heuristic that mirrors the procedure of natural selection. This heuristic is routinely used to produce valuable answers for optimization and inquiry issues. The subsequent section highlights the earlier work done by the various authors using genetic algorithm on material engineering.

Mc Crory et al. [13] observed the damage classifications in carbon fiber composites using acoustic emission method. The authors used ANN (Artificial Neural Network), UWC (Unsupervised Waveform Clustering), and MAR (Measured Amplitude Ratio) techniques, to distinguish different signal types arising in a carbon fiber panel subjected to buckling. And they lead to the characterization of the damage occurring within the panel. Further, Leo Marco et al. [14] have proposed a new and innovative data preprocessing technique that converts real-valued ultrasonic data into complex valued signals. However, Dharmadhikari sagar et al. [15] reviewed on the optimization of drive shaft using genetic algorithm and ANSYS. Composite materials along with conventional steel material for drive shaft can increase the advantages of design due to its high specific stiffness and strength. For identifying the elastic constants of composite laminates by using vibration test data, Maletta and Pagnotta [16] revealed a method which combines finite element analysis with genetic algorithm. Furthermore Badallo et al. [17] presented a comparative study on three common genetic algorithms namely; Archive-based Micro Genetic Algorithm (AMGA), Neighborhood Cultivation Genetic Algorithm (NCGA), and Non-dominate Sorting Genetic Algorithm II (NSGA-II) considering three different strategies for the initial population. The authors [17] studied with the objective of minimizing mass and maximizing the critical buckling load on a 'T' shaped stringers using CFRP stiffened panels.

In short, genetic algorithms are very easy to understand and virtually it does not demand any mathematical information. Especially the algorithms are better for optimization problems and also it solves the problems with multiple solutions.

B. *Machine Learning on Materials data*

During trade-off situations it would be worthwhile if its properties could be anticipated by utilizing past information relating to other comparable known materials, rather than falling back on new investigations on the other laboratory experiments. The biggest difficulty in creating such a prediction machine is the consistent definition of a material unique mark [12].

Authors Liu Ruoqian et al. [18] used machine learning approach to identify the complete space (or as much of it as possible) of microstructures that are theoretically predicted to yield the preferred mixture of properties demanded by a selected purpose. In addition Maree et al. [19] have investigated a generic machine-learning approach for the detection of known materials in using hyper spectral images. It was applied for the detection of simulated gaseous traces in thermal infrared hyperspectral images of real-world scenes. In spite of these findings, Garcia Angela et al. [20] have found the exact of scientific methods like CART and neural network. The work also focused with specimens 30% compressive anxiety strain with momentary velocity impacts to anticipate Young's modulus. Pilania Ghanshyam et al. [21] have showed that the materials discovery process can be significantly expedited and simplified if we can learn effectively from the available information or data. Similarly Liu et al. [22] have explored the multiple data mining experiments and strategies for establishing statistical models for capturing elastic localization relationships in high contrast composites. The efficacy of different approaches for feature selection and regression were studied systematically. In short the machine learning can be used for multidisciplinary areas for the sophisticated pattern recognitions. Thus the approach can be effectively used to perform intelligent decisions in building a model for predicting unknown data.

C. *Data Mining and Knowledge Discovery on Materials Data*

The usage of information mining systems out of sight of materials science and designing is seen as a fundamental development of materials informatics. This interdisciplinary study organizes data science, software engineering, and different spaces to give more current comprehension and empower learning disclosure. The materials informatics is a stage for material scientists to decipher exploratory data through the machine learning approaches. The work composed with new representations, arrangements, and more probable human consolidations driven by the space specialists. It can similarly accelerate the assessment process and guide the improvement of new materials with different engineering properties [23]. The Data mining and knowledge discovery techniques were employed to validate their usefulness in acquiring information about the viscoelastic properties of vapor-grown carbon nanofiber (VGCNF)/vinyl ester (VE) nano composites solely from the data derived from an investigational design studied by Abuomar Osama et al. [23]. To classify microstructures into groups automatically with high accuracy DeCost et al. [24] used support vector machines effectively. The authors claim the method best suits for finding the associations with large and dissimilar micro structural image data by comparing the histograms of the visual techniques.

In addition to the above paper the similarity based engineering materials selection model was proposed and implemented by Vanajakshi [25]. The work aims to select engineering materials based on the composite materials constraints. The result reviewed from this model was sustainable for the effective decision making in advanced engineering materials design and applications. However the authors Sharma and Krishna [26] have succeeded in developing a knowledge discovery system for the selection of cost effective polymer composites for a cylindrical pipe with longitudinal filament winding in the course of data mining approach. In addition Ashby et al. [27] found a novel material selection approach using software assisted tools. It contains a database of quantitative and subjective information for an extensive variety of engineering materials: metals, polymers, composites, and regular materials. Doan et al. [28] used an unsupervised pattern recognition approach for AE data originating from fatigue tests on polymer-composites. The work shows the different accessible challenges of AE analysis and damage detection in composites.

The Knowledge Discovery System through Data Mining procedures were being actualized by Doreswamy et al. [29] for finding the knowledge for practical polymer composites that meets the configuration necessities of a segment. The methodology utilizes the Decision Tree Classifier (DTC) with linear function. The work characterizes the fiber class into short, medium, and long fiber classes identified with the basic length of the fiber ‘l’c. A suitable test quality all things considered volume fractions, volumes, masses, expenses of long strands and of polymer network are examined through the composite principle of blend. The framework uncovered valuable information’s for the outline of designing materials. The work contains a group of modest bunch figurings for low cost polymer composite determination [26, 30].

Naïve Bayesian and C4.5 decision tree classifiers approaches used by Addina et al. [31], the work aims in classifying and selection of materials to suit some design specifications. The authors also highlight the predictive parameters and standard measures for the classification on the different class of materials. The data mining techniques were effectively implemented by Suh and Rajan [32] for the novel data integration among homogeneous materials databases. The Rajan also [33, 34] reports the task of selecting the right material for a given engineering design can appear to be overwhelming. The designers can fetch numerous materials for commercial applications. But the approach to sort the material with optimum selection requires a systematic approach based on understanding of the nature of materials science and engineering.

The above literature summarizes the data mining techniques are excellent means to predict future trends and helps in decision making in the field of materials informatics.

D. *Work Done on Materials Using Neural Network*

Artificial neural systems (ANNs) comprises set of exhibiting methodology, which can be used to endeavor issues that are troublesome for standard computers and human creatures. The ANNs has been associated with showcase troublesome strategies in various outline fields like, aviation, car, gadgets, assembling, mechanical technology, and information transfers, and so on. Over the late years the enthusiasm for the ANN exhibiting in the fields of physical metallurgy and materials science has been extended rapidly. Thus the neural systems assists critical focal points in taking care of issues that require constant encoding and translation of associations among the variables of high-dimensional space. The ANN's also offers very basic level distinctive way to deal with material demonstrating and material handling, control systems than the quantifiable systems [35].

Liu Ce et al. [36] have proposed Augmented Latent Dirichlet Allocation (ALDA) model to combine the rich set of low and mid level features captured through various aspects of material appearance under a Bayesian generative framework. The authors presented a model to identify the high level categories of materials like glass, metal, plastic, or wood, as a substitute of clearly estimating reflectance properties. Lee et al. [37] predicted the fatigue damage behavior using ANN approach. The authors report the possibility of accurate representations of the crack growth and cycle ratio out of very small experimental data. Thus the authors conclude ANN as a better approach for life estimation parameters. Dikbas et al. [38] succeeds in using ANN approach for the prediction of diffusion bonding behavior of SiCP reinforced aluminum alloy composites. Thereafter António et al. [39] proposed an artificial neural network (ANN) aims at modeling of machining circumstances in orthogonal cutting of PEEK composites. The design of experiments (DOE) approach for Polypropylene and waste ground rubber tire powder composites reported by Zhang Shu Ling et al. [40]. The approach predicts the effect of four polymer contents on the mechanical properties.

A novel way to deal with damage discovery in composite structures utilizing hyper spectral image index analysis algorithm with neural network modeling employing Weight Elimination Algorithm (WEA) was presented and discussed by Iskandarani and Mahmoud [41]. Likewise Kumar Sanjeev et al. [42] used ANN coupled with Taguchi approach for the optimization and prediction of surface roughness. The authors observed good agreement between experimental and predicted results. Meanwhile Altinkok and Necat [35] used back-propagation (BP) neural network for modeling of metal matrix composite and built a model for artificial neural network on the prediction of tensile strength, hardening behavior, and density properties of the Al_2O_3 particulate-reinforced Al–Si10 Mg composites. Incidentally Atuanya et al. [43] have predicted the mechanical properties of date palm wood fiber-recycled low density polyethylene composite using ANN technique.

In summary the neural network permits solutions to materials problems where multiple selection constraints must be satisfied simultaneously.

E. *SVM Related*

SVM finds a nonlinear decision function in the input space by mapping the data into a higher dimensional feature and separating it there by means of a maximum margin hyper plane. The reason why SVM insists on finding the maximum margin hyper plane is that it offers the best generalization ability and it allows not only the best classification performance on the training data, but also does the correct classification of the future data. Figure 1 shows how to map a data from higher dimension to lower dimension [44].

Ding et al. [45] have shown that the SVM network can make out the difference of AE sources more perfectly than using the BP neural network. Abu Omar et al. [46] used the support vector machines model to identify the desired mechanical property response resulted from a chosen untested combination. The model was also able to identify the desired mechanical property response (high storage modulus, high true ultimate strength, or high flexural modulus) resulted from a chosen untested combination of nine input factors mentioned in their study. Furthermore Sundararaghavan et al. [47] has worked on 3D microstructure grouping structure has been produced in view of support vector machines implementing a proficient measurable learning methods. Meanwhile Das et al. [48] have used some class SVM's to classify the damage signatures in composite plates. Subsequently Wang et al. [49] designed a measuring system using decision tree learning for insulating material hydrophobicity. Tang et al. [50] applied Support Vector Machine to set up a nonlinear mapping from influence factors of material performances to mechanical properties. Besides Fauvel Mathieu et al. [51] have proposed a method based on the data fusion of the morphological information and the original hyperspectral data.

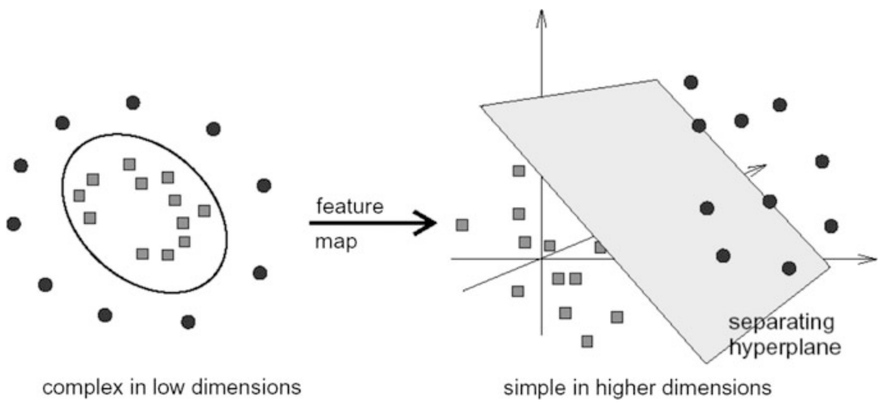

Fig. 1 Non-linear classifier

The authors claim the absolute classifications using a Support Vector Machines classifier. Finally it concludes that the support vector machine can be used effectively to yield the better results during selection of materials.

3 Objective

The main objective of the proposed research includes:

- To determine the association between data mining and machine learning systems to effectively discover the attributes that governs,specific properties of advanced composite materials from different corpora.
- To compare for associations and patterns, relating information among the different datasets of advanced composite materials, also to set up potential association between parameters that are not easily studied experimentally in a coupled manner.
- To get better material selection from the material classification process using any algorithm yields increased efficiency for optimizing materials processing techniques.

4 Methodology

Advanced composite material selection framework consists of three phases; foremost the Data acquisition in which pre processing of data will be done. The second phase continued with training of the filtered data that is known to specific classes and creating a classifier model based on the known data samples. Training is an iterative process where we need to build the best classifier model, in each iteration the built model is tested against the test data. Classification is the process of taking

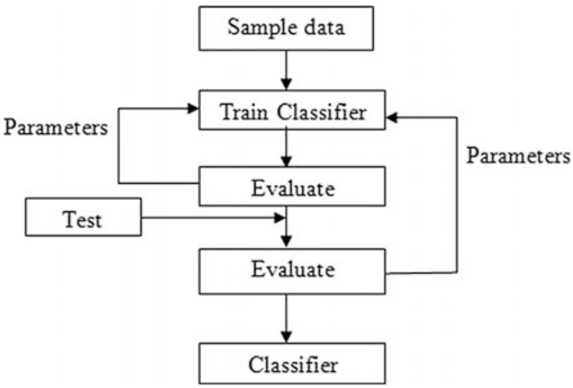

Fig. 2 Method of proposed approach

of classifier model built with a training data set and running it on the unknown test data to determine the class of data it belongs and finally to obtain the accurate classifier. Figure 2 shows the working model of the proposed approach.

5 Conclusion

The challenging task in materials science is the selection of materials from the material data set for a particular application in such a way that it should meet the design criterion. Through the published literature referred it is affirmative that no much work has been done on the composite materials extracting their properties. Earlier work explored does not contain feature classification based on complete properties like fiber type, effect of fiber orientation, fiber patters, fiber strength, mass density, specific strength, fire conflict, electrical properties, design flexibility and manufacturing economy, and degradation mechanisms, etc. Thus further work can be extended to obtain required classification of the advanced composite material systems taking wider array of physical properties into affect and also it reduces the repetitive manufacturing process for inventing new class of materials with enhanced physical attributes.

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