Energy Efficiency Modeling Using Whale Optimization Algorithm and Ensemble Model

Adel Oubelaid[1], M. Y. Shams[2], Mostafa Abotaleb[3]

[1] Laboratoire de Technologie Industrielle et de l'Information, Faculté de Technologie, Université de Bejaia, 06000 Bejaia, Algeria
[2]Faculty of Artificial Intelligence, Kafrelsheikh University, Kafrelsheikh, Egypt
[3]Department of System Programming, South Ural State University, 454080 Chelyabinsk, Russia
Emails: adel.oubelaid@univ-bejaia.dz; mahmoud.yasin@ai.kfs.edu.eg; abotalebmostafa@bk.ru

Abstract

machinery enterprises can benefit greatly from including energy efficiency models into their energy management and conservation efforts. Due to a lack of theoretical formulations, this paper integrates machining parameters and configuration parameters into energy efficiency models, with ML methods applied to increase generality. A three-year data set from a manufacturing facility serves as the basis for a comparison examination of two scenarios, with an emphasis on evaluating forecast precision, stability, and computing efficiency. To estimate future energy efficiency in Scenario 1, only cross-sectional data is utilized, completely discounting the wear and tear on spindle motors and cutting tools. In this study, we use five error measures to compare and contrast three classic ML algorithms: artificial neural networks, support vector regression, and Gaussian process regression. In Case 2, we build the a voting ensemble model in a more realistic setting, taking into account the dynamic characteristics of the aging spindle motor and tool wear. It is clear from the comparison that all of the Case 1 models experience performance erosion, but the proposed voting ensemble model is able to produce a sustainable increase in accuracy.

Keywords: Machining system; energy efficiency modeling; deep learning; machine-learning

1. Introduction

Over the next 15 years, population expansion and industrialisation are expected to increase energy consumption considerably, to the tune of 47 percent [1]. More over 30 percent of the world's total electrical energy consumption is accounted for by the industrial manufacturing sector [2]. Machine tool-related methods, such as the introduction of EU guidelines for eco-design and the establishment of ISO 14995 for energy monitoring, are among the most famous of the many efforts currently under way throughout the world to reduce manufacturing's energy consumption [3]. The term "energy efficiency" refers to a metric for conserving energy. Modelling the energy (efficiency) of machine tools is a valuable technique for examining the energy mechanism [5]. This is because the model can be used to assess the energy efficiency under varying machining circumstances or after adjusting the machining settings. Energy (efficiency) modelling has been studied extensively over the past two decades [6] as a prerequisite for energy-aware design and optimization.

Physical approaches and experimental statistical methods are the two broad buckets into which current modelling techniques may be placed. Energy efficiency models are developed using physical modelling, a form of white-box approach, by applying the laws of energy transfer from electrical to mechanical systems. While physical models are preferable in theory, they are rarely used in practice because mechanical machining is inherently unpredictable and process-dependent [7]. When there is no physical foundation, experimental statistical approaches are the favoured method in this field [8].

Doi: https://doi.org/10.54216/JAIM.020103
Received: April 23, 2022 Accepted: October 11, 2022

For these procedures, machining parameter combinations are first tested in a variety of machine-tool-workpiece settings. Using statistical techniques like polynomial regression [9] and ridge regression [10], the mapping connections are investigated based on the experimental energy data.

Despite their prevalence in the field, physical and experimental approaches to machining are often tailored to a narrow range of machining configurations with fixed parameter spaces, machine tool requirements, and tool-workpiece pairings. Energy efficiency models are inadequate for predicting energy efficiency for these interactive and integrated machining systems [5] because they do not take into account the configuration factors (such as machine tools, cutting tools, and workpieces). However, a fresh round of modeling should be carried out if there is any change to the setups. More frequent changes in machining setups are often seen with flexible machining, which means that computational efficiency must be sacrificed more often [11], [12]. Taking into account factors such as complicated chip creation, material property requirements, tool wear, machine degradation, and so on presents additional difficulties in building generalized models of energy efficiency.

However, the computational complexity of modeling tends to rise as the number of configuration factors grows. However, multi-colinearity and numerical instability may hinder the accuracy of predictions using traditional statistical approaches when fitting high-nonlinear and high-dimensional functions [8]. Even in the face of complex behaviors, machine-learning (ML) approaches make it feasible to transform the massive amounts of data produced by equipment into useful knowledge [13]. Science has looked at ML tools extensively, and the results have provided fresh options for the modeling of machining systems. Artificial neural networks [14], support vector regression [15], Gaussian process regression [16], and regression trees [17] are all examples of methods that may be found in the literature. There are now just three categories that may be used to classify the ML algorithms that have been used to energy modeling. The vast majority of these research focused on ANN models that were sensitive to input parameters. You may find examples in [18] and [19]. The second study type involved the development of energy models that only took into account some of the factors involved in the machining setup. For instance, Quintana et al. [20] used machining parameters, tool radius, and lubrication to create an ANN predictor for modeling power consumption in high-speed ball-end milling operations. Energy consumption during high-speed hard-turning may be predicted with an ANN model developed by Al-Hazza et al. [21]. This model includes the tool rake. Thirdly, studies were conducted to see if different methods, including GPR [22] and its variant [23], might be used to make ANN models more precise. When it comes to audio identification [24], computer vision [25], and natural language processing [26], deep learning (DL) has recently seen unprecedented success as a key branch of ML. It's become commonplace for DL technologies to set new benchmarks for precision across a wide range of use cases. To improve the prediction performance of machining systems, it is then common practice to employ DL models. However, DL approaches have been tried and proven with high success in other relevant domains, such as equipment defect detection [27], tool wear [28], and machine remaining life prediction [29].

2. Literature Review

Energy efficiency in buildings is the provision of the required amenity with the minimum amount of energy input. Smart cities are more likely to endure for the long haul if they are highly efficient since doing so lowers their energy bills and helps them produce fewer harmful pollutants. A high level of energy efficiency is the product of a number of elements working together. These factors include the building's materials, orientation, heating and cooling systems, the climate, and other environmental factors. When these criteria are thought upon throughout the planning stage, success is almost guaranteed [30]. Efforts to improve energy efficiency will increase after that. Some ways to boost efficiency include informing occupants about the building's impact on the environment and urging them to stop wasting energy, conducting an audit to identify opportunities, switching to more energy-efficient appliances or equipment, minimizing air circulation, and so on. There is an ongoing endeavour to design and produce better energy efficiency to minimize the total maintenance costs of buildings because they account for 40 percent of worldwide energy usage across all building types. The heating, cooling, and lighting systems in your home will run more efficiently with these presents. As an example, the sensors might regulate the temperature and lighting so that less energy is used for heating and lighting when there are less people present. They're also great for preventing fires and floods by sounding the alarm before they happen. Energy efficiency is now widely recognized as an important quality indicator that provides a competitive edge in many fields, including government and public services, commerce, sports and entertainment, industry, and private pursuits. For energy efficiency to be maximized, it is necessary to have entry to and interact with a wide range of equipment, elements, devices, energy sources, meters, etc., as well as the inhabitants of the facilities

Doi: https://doi.org/10.54216/JAIM.020103
Received: April 23, 2022 Accepted: October 11, 2022

being evaluated, in order to collect relevant data about the surrounding environment. The use of AI in tandem with precise building thermal modelling techniques and technologies will allow the smart building to make decisions in real-time based on past performance and environmental parameters (which may be highlighted by new analytics techniques) in order to maximize energy efficiency .

3. Proposed Methodology

A. Data preprocessing

Any modeling technique based on machine learning requires data preparation, which might include things like cleaning, converting, and decreasing data. When talking about data, "cleaning" refers to the process of eliminating any mistakes, gaps, or noise from the initial collection. Pre-made software solutions like Data Wrangler and FineBI allow IT workers to efficiently cleanse data. Data transformation includes operations like normalizing, smoothing, and aggregating the raw data. The data shown here may be categorized in several different ways, such as a time series, an image, or as a continuous variable[31-33].

B. Training and Testing Sets

We were separated into files that were used to help train our classifiers (using our remaining reserves of self-control) and files that were used to test those classifiers (using our remaining reserves of self-control). As can be seen in Figure 1, we partitioned our data set such that the most thorough section could be used immediately away to make critical and challenging preparations.

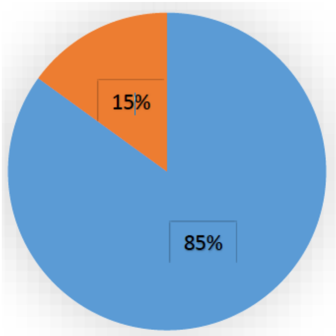

Figure 1: Dataset Split

C. The Proposed Ensemble Model

First, files utilized to boat-train our classifiers once we relaxed our grip, second, the suggested procedure, and third, our final results. The three primary classifiers utilized to construct this image: These classifiers include decision trees (DT), multilayer perceptrons (MLP), and support vector machines (SVM). The guided whale optimization approach is applied to maximize the number of votes cast by these classifiers inside a voting ensemble model (WOA).

D. Support Vector Machines (SVM)

Support vector machines (SVMs) are a popular form of classification software that belongs to the supervised learning subfield. Simply said, it can classify unknown samples based on a set of training data that has already been sorted into two groups. The SVM training technique builds a model for making predictions from a dataset that contains examples labeled in a variety of ways. To aid in the task of categorization, support vector machines (SVMs) generate a hyperplane or a set of hyperplanes in a high-dimensional space. Figure 2 provides a high-level overview of the SVM procedure.

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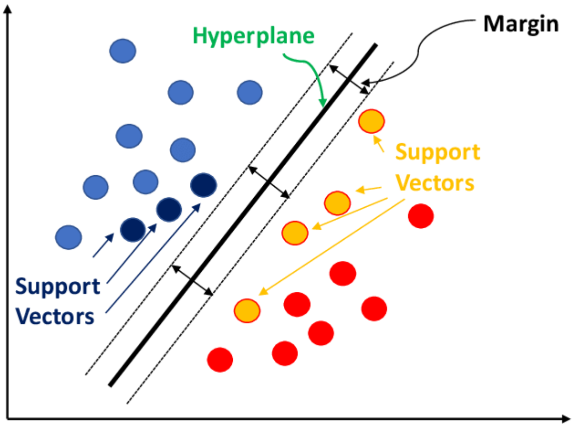

Figure 2: Structure of support vector machines.

E. Multilayer Perceptron (MLP)

One definition of a neural network is a set of linked nodes (neurons) that exchange information with one another (synapses). Artificial neural networks, which take their cues from the human nervous system, are widely used to reproduce estimations because of how well they resemble the real thing. An input layer, a hidden layer, and an output layer are the three basic components of any artificial neural network. To generate an activation function, this method feeds information into a group of input layer nodes. The invisible weighting layer is placed between the input and output layers, giving the former more sway over the latter. The output layer is the last to contribute to the final product. The numerous linked nodes of a multilayer neural network are seen in Figure 3.

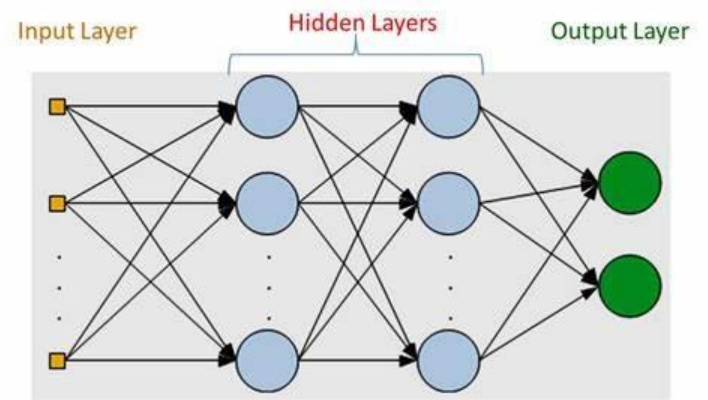

Figure 3: Structure of a multilayer neural network.

F. Decision Trees (DT)

This approach to problem-solving makes use of a greedy search to identify the most promising nodes in a decision tree. Partitioning is repeated from most to least specific until all data can be neatly placed into its assigned containers. There is a strong correlation between the complexity of the decision tree and the probability that all data points are grouped together. A concise tree makes it simpler to identify the leaves, or data points, that belong to a specific category. While this level of purity may have been attained with relative ease at the outset, it becomes progressively challenging to preserve it as a tree grows, and as a result, there is frequently insufficient data contained inside a given subtree. Overfitting happens frequently because to the scattered nature of the data. Parsimony, as expressed by Occam's Razor, which advises against "entities being multiplied beyond necessity," is consistent with the preference for small trees in decision trees. A decision tree shouldn't grow more complicated than it has to be since the simplest explanation isn't always the most compelling. Both aims can be achieved by pruning, which involves the elimination of branches that result in progeny with few redeeming qualities (reducing complexity and preventing overfitting). After this is done, the accuracy of the model may be evaluated through cross-validation. The random forest method is one strategy for keeping decision trees trustworthy; it does this by guaranteeing that each tree in the ensemble is unique, which in turn improves the classifier's predictive power. Here, we see a simplified version of a decision tree depicted in Figure 4.

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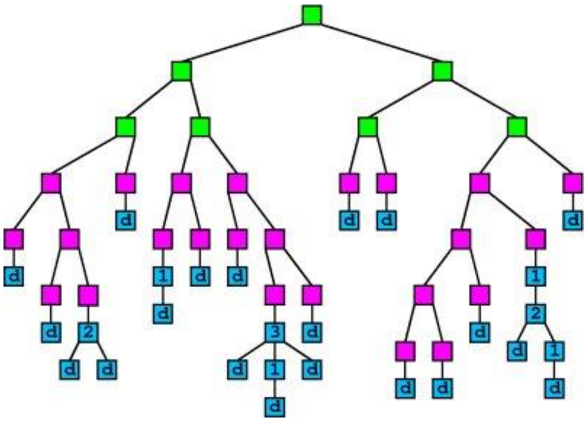

Figure 4: Structure of a decision tree.

G. Whale Optimization Algorithm (WOA)

Metaheuristics are used to find, design, or choose a heuristic (partial search algorithm) that may offer a good enough solution to an optimization problem in computer science and mathematical optimization, despite inadequate information or limited processing capability. Metaheuristics allow us to sample a manageable subset of the vast possible solutions, which would be impossible to do with a purely systematic approach. In many cases, metaheuristics are more adaptable than other approaches to optimization because they may be applied in a wide range of contexts without the need for considerable planning or a thorough grasp of the optimization issue at hand. Using metaheuristics, as opposed to optimization algorithms and iterative methods, does not ensure the discovery of a globally optimum solution for a class of problems. Depending on the values of the produced random variables, the solution that is finally found might change as a result of the stochastic optimization utilized by various metaheuristics. In combinatorial optimization, metaheuristics are a type of solution-exploration tool that might potentially find high-quality solutions with less computing effort than optimization algorithms, iterative approaches, or basic heuristics. Thus, they might be regarded as options for fixing optimization issues. There is a mountain of writings on the topic. Most metaheuristics articles focus on the author's experiences in trying out the algorithm in practice, making them largely exploratory in character. Some formal theoretical results are also available, though, and these shed light on questions like convergence and the feasibility of achieving the global optimum. Recently, there has been an explosion of publications suggesting various metaheuristic strategies, all of which have the potential of bringing something new and useful to the field. Most studies on this topic have been subpar owing to difficulties including imprecise wording, weak presentation of crucial topics, questionable research methods, and inadequate reference of past work.

4. Results

We employ a variety of Python3 libraries to implement machine learning (ML) models for tagging. NumPy, SciPy, scikit-learn, Keras, pandas, and Matplotlib are just a few of the many helpful Python tools available. Scikit-learn has been demonstrated to be the most reliable and approachable machine learning library. This collection relies heavily on the Python programs NumPy, SciPy, and Matplotlib. The confusion matrix is a useful tool for gauging a classifier's accuracy since it highlights the number of times that the data set was used to make a wrong prediction. True positives have an observed value that agrees with the model's prediction (TP). A true negative has unreliable outcomes regardless of what might be predicted (TN). Table 1 displays comparisons between the suggested strategy and some of the most well-known machine learning techniques. See below for a breakdown of how employing the optimum voting ensemble classifier improved accuracy, sensitivity, specificity, p-value, n-value, and F-score.

Table 1: Classification results using the proposed method compared to other methods

	Accuracy	Sensitivity	Specificity	Pvalue	Nvalue	F-score
NN	0.9172	0.8649	0.9804	0.9816	0.8571	0.9195
SVM	0.9091	0.8649	0.9756	0.9816	0.8276	0.9195
DT	0.9207	0.8649	0.9821	0.9816	0.8684	0.9195

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Guided WOA	0.9685	0.9412	0.9877	0.9816	0.9600	0.9610

Table 2 presents statistical analysis demonstrating the voting ensemble classifier's superiority. When using the proposed optimal voting ensemble, the outcomes improve.

Table 2: Statistical analysis of the results recorded by the proposed method

	NN	SVM	DT	Guided WOA
Number of values	10	10	10	10
Minimum	0.9172	0.9091	0.9207	0.9685
25% Percentile	0.9172	0.9091	0.9207	0.9685
Median	0.9172	0.9091	0.9207	0.9685
75% Percentile	0.9197	0.9116	0.9232	0.9685
Maximum	0.9272	0.9291	0.9407	0.9685
Range	0.01	0.02	0.02	0
10% Percentile	0.9172	0.9091	0.9207	0.9685
90% Percentile	0.9272	0.9281	0.9397	0.9685
95% CI of median				
Actual confidence level	97.85%	97.85%	97.85%	97.85%
Lower confidence limit	0.9172	0.9091	0.9207	0.9685
Upper confidence limit	0.9272	0.9191	0.9307	0.9685
Mean	0.9192	0.9121	0.9237	0.9685
Std. Deviation	0.004216	0.006749	0.006749	0
Std. Error of Mean	0.001333	0.002134	0.002134	0
Lower 95% CI of mean	0.9161	0.9073	0.9189	0.9685
Upper 95% CI of mean	0.9222	0.9169	0.9285	0.9685
Coefficient of variation	0.4587%	0.7400%	0.7307%	0.000%
Geometric mean	0.9192	0.9121	0.9237	0.9685
Geometric SD factor	1.005	1.007	1.007	1
Lower 95% CI of geo. mean	0.9161	0.9073	0.9189	0.9685
Upper 95% CI of geo. mean	0.9222	0.9169	0.9285	0.9685
Harmonic mean	0.9191	0.912	0.9236	0.9685
Lower 95% CI of harm. mean	0.9162	0.9073	0.9189	0.9685
Upper 95% CI of harm. mean	0.9221	0.9168	0.9284	0.9685
Quadratic mean	0.9192	0.9121	0.9237	0.9685
Lower 95% CI of quad. mean	0.9161	0.9072	0.9188	0.9685
Upper 95% CI of quad. mean	0.9222	0.917	0.9285	0.9685
Skewness	1.779	2.277	2.277	
Kurtosis	1.406	4.765	4.765	
Sum	9.192	9.121	9.237	9.685

The Wilcoxon signed-rank test is used to compare the proposed strategy with the alternatives. The results of this investigation are displayed in Table 3. The p-value in the table provides proof of this.

Table 3: Wilcoxon signed rank test of the recorded results of the proposed method

	NN	SVM	DT	Guided WOA
Theoretical median	0	0	0	0

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Actual median	0.9172	0.9091	0.9207	0.9685
Number of values	10	10	10	10
Wilcoxon Signed Rank Test				
Sum of signed ranks (W)	55	55	55	55
Sum of positive ranks	55	55	55	55
Sum of negative ranks	0	0	0	0
P value (two tailed)	0.002	0.002	0.002	0.002
Exact or estimate?	Exact	Exact	Exact	Exact
P value summary	**	**	**	**
Significant (alpha=0.05)?	Yes	Yes	Yes	Yes
How big is the discrepancy?				
Discrepancy	0.9172	0.9091	0.9207	0.9685

In Figure 5, we see a graph depicting how much better the optimum voting ensemble classifier is than the baseline models. This schematic depicts the proposed solution's enhanced efficacy.

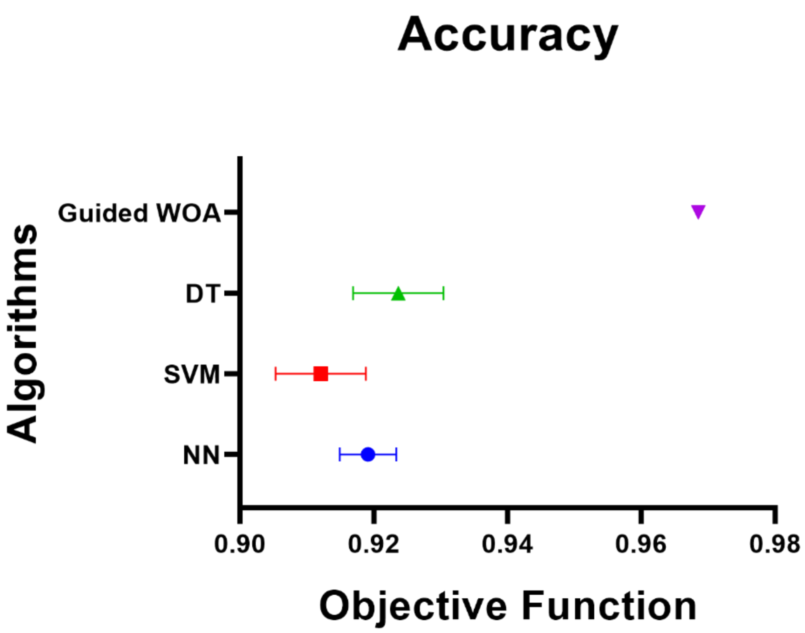

Figure 5: The accuracy of the proposed method compared to other methods

5. Conclusion

Both steady-state modelling and simple modelling that accounts for the impacts of spindle motor aging and tool wear on energy efficiency in mechanical machining are included in our search for the optimal algorithms. Prediction accuracy is simply one aspect of the scope of a set of models; other factors include the data and feature kinds employed, as well as the data and computational volumes. The steps involved in selecting features and preparing the necessary data are first discussed. The evaluation of performance is done using five standard statistical measures. Learning curve analysis is used to examine how sensitive ML models are to changes in the amount and duration of their training data. The analysis of differences between the two types of modelling algorithms reveals both their advantages and disadvantages. The performance of the proposed voting ensemble model is superior when it comes to feature learning on pictures and time series. In addition, its performance is better when dealing with small sample circumstances. The best results in terms of precision, consistency, and speed may be obtained when factors like spindle motor age and tool wear are disregarded.

Doi: https://doi.org/10.54216/JAIM.020103
Received: April 23, 2022 Accepted: October 11, 2022

Funding: "This research received no external funding"

Conflicts of Interest: "The authors declare no conflict of interest."

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Received: April 23, 2022 Accepted: October 11, 2022