Using Machine Learning to Optimize Resource Use in Batteries and Engines: A Review

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Abstract

Machine learning is the current hot topic in the technology industry with many seeing what potential uses it has across many different fields. One such potential application is in a specific subset of smart mobility, resource optimization. This paper analyzes the use of machine learning techniques to optimize the performance and design of batteries and engines. By analyzing other works a generalized overview of the topic is achieved alongside suggestions for future research.

Keywords
Machine Learning, Battery Efficiency, Engine Efficiency, Smart Mobility

1. Introduction
Machine learning and artificial intelligence are the current hot topic in the field of technology. Be it identifying medical maladies, driving vehicles, predicting bird migration, or generating words or images. One such potential application is in the subset of smart mobility, the optimization of engines and batteries. There are many potential ways to use this technology to increase the efficiency of these devices while decreasing the resource cost used to create and operate them. By simulating physics one can theoretically generate designs that through rapid iteration have become more efficient than the original design. This is optimization through design, another method of optimization that machine learning has the potential for is the optimization of operations. This is using machine learning to predict scenarios and find the best way to use the current resources in a way that reduces the long-term costs.

These two applications of machine learning are important due to the potential benefits when it comes to resource management. By using the advanced simulations of the first method, new styles of machinery can be predicted which can help save on development and testing costs occurred from the testing of multiple different iterations of design. The second method is also useful as it can help optimize the day-to-day resource costs and predict a path forward that costs less resources to achieve similar goals. These technologies offer potential to reduce the needless waste of resources which can help lower the number of wasted resources. Therefore, the goal of this research is to analyze other research relating to these topics to assist in the development of future research.

1.2 Objectives of Research
To help propagate the spread of such techniques this paper's job is simple, the analysis of recent research about optimizing engines and batteries through machine learning. Alongside this an analysis of the strengths and weaknesses of such processes and suggestions for future research.

2. A Primer on Machine Learning
Machine Learning is specifically the use of classification algorithms to predict the outcome of any given event want given enough data. To accurately predict the outcome of a given event, the factors that go into any decision must be understood. For a person, this is accumulated through studied knowledge and wisdom from experience which allows for the accurate prediction of events. A computer achieves a similar goal by assigning mathematical values to the factors that affect the outcome. This is done by describing features inside a dataset that denotes information relating to the real-life factor and giving enough information to the machine learning model to predict the outcomes. The

formula used to achieve these predictions is known as a classifier. By choosing the right classifier, the accuracy of the prediction can be more accurate, while an ill-fitting classifier will be less accurate.

Furthermore, there is the question of authenticity of the prediction can be gathered by processing the information contained within the decision matrix. The decision matrix is a breakdown of the results obtained from testing the machine learning model, which has four potential results of true positive, false positive, true negative and false negative. By analyzing these numbers one can find the rates of occurrence, which will return the true positive rate, the false positive rate, the true negative rate, the false negative rate, and the accuracy. The true positive rate, which is the rate at which a prediction is determined true. The false positive rate is the rate at which a prediction is true, but the actual outcome is false. The true negative rate is the rate at which false predictions correctly align with results. False negative is the rate at which predictions of false match the result observed. By using these values, the correlation between prediction and actuality can be calculated, which is often labeled as the accuracy of a model. The results of this inform the model, which is the saved results which are used to predict outcomes.

By using this technology, the results of occurrences can be predicted with enough data. To achieve the optimization of resources using these technologies the method changes a little, but the end results are similar. By using machine learning tools in combination with a robust physics simulation, rapid iteration of designs can occur from the machine learning model. By rapidly iterating it can come up with a theoretical model that works within the simulation and offers benefits within a shorter timeframe than people doing the same. These simulated designs can then be tested in real lab conditions to either prove the model correct, or the failure used to fine-tune the model. The same is true when it comes to process optimizations, which is where the model predicts the most efficient use of current resources and uses that to optimize their use. In an engine this would be optimizing the cycles of the engines, or in a house optimizing the amount of energy being used by predicting where the energy is needed instead of constantly providing energy everywhere.

3. Methods

The research analyzed is all collected from papers explicitly using machine learning techniques to reduce the number of resources used in batteries and engines. Be this from optimizing processes such as electricity allocation, or optimization of designs. Each research is then divided by the target of optimization, and the classifiers tested in that study. By gathering this information and aggregating it into easy to digest tables and graphs a quick to reference visual can be generated that other research can reference for their own studies.

4. Data Collection

To gather the research reviewed in this writing, papers that contained any combination of these keywords: “machine learning”, “optimization”, “battery”, “engine” were searched for in multiple research search engines. The research gathered was then reviewed to ensure the contents of the research matched the criteria of the review. Using this method 16 papers were gathered and reviewed.

5. Review of Collected Materials

The studies found were specifically searched for as per the criteria listed above. Some of the studies focused specifically on using machine learning techniques to optimize battery designs via repeated testing of simulated battery designs. By doing this they reduced the workload required to create said designs in the simulation, instead of spending the time tweaking values to find the best fit. Dave et al (2022) did something similar using a machine learning model to predict potential non-aqueous electrolytes for a lithium-ion battery, by went a step further and developed “Cilo” a mechanical system that would test the predictions and attempt to generate the electrolyte mixture returned by the model. This allowed for quick testing of the machine learning predictions and allowed for rapid development. Duquesnoy et al. (2023) followed something similar however they focused on optimizing the machine learning methods. Houchins and Viswanathan (2020) had also done something similar however focused on the creation of optimized cathodes. Fini et al.(2023) did something tangentially related, focusing on using machine learning to create a more optimal liquid cooling system for batteries.

In the realm of engines, a similar application of these technologies has occurred as well. Owoyele and Pal (2021) achieved this by using a novel ensemble method that had a simple classifier create a baseline, and then had a more complex classifier tweak the prior model in a way that increased the fitness of the model without overfitting which predicted a model of engine that reduced fuel consumption by a rate of 1.9 percent. Posch et al.(2021) did something similar using an artificial neural network to predict the output of large engine prechambers to help in the design process of engines. Sharma et al.(2023) did something similar however focused on designing a biogas and biodiesel engine. Using these tests, they were able to replicate the design in a lab that operated as intended. Bai et al.(2023) did something similar, however they used wheat germ oil and hydrogen and were testing the most optimal combination of the two.

While these studies focused on using machine learning to rapidly iterate on designs, others focused on using the predictive qualities of the technology to predict resource usage. Ge et al.(2022) used a genetic algorithm, specifically Bat Optimization, alongside an extreme learning machine classifier to predict the state of health of a lithium-ion battery. Something that Zhou et al. (2023) and Jia et al.(2022) did as well with different genetic algorithms, the grey wolf optimization and improved sparrow search algorithm respectively. These models all found success in predicting the estimated health of the lithium-ion batteries and could be used as an early warning system in mechanical devices reliant on such batteries. A more unique approach was taken by Rehman et al. (2020) who used machine learning to analyze the energy expenditure of households that had solar panels and optimized the expenditure of the gathered solar energy to reduce the amount of energy taken from the local power grid.

Something similar was also analyzed in the case of engines, seeing if machine learning techniques could assist engines and how they ran. Mishra and Subbarao(2021) used an ensemble classifier mixing a double-Wiebe function and random forest and assist a reactivity controlled compression ignition device. Another method using machine learning is using the predictive nature of the technology to optimize the calibration of said engines. Wang et al. (2022) and Wong et al. (2018) used Gaussian process regression and extreme learning machine classifiers to predict the most optimal calibration of the engines. Finally, Zhao et al. (2019) used a custom c-loss based extreme learning machine to estimate the power usage of a small-scale turbojet engine for energy consumption prediction.

6. Results and Discussion

6.1 Classifying the Results

In the papers analyzed for this review, two key groups exist when it comes to optimizing a technology. Optimization through iteration of design, and optimization through modification of working processes. Or more succinctly, design and efficiency. For the first group this is achieved by running simulations on a robust physics system generating and testing new designs at a rapid pace until the classifier can find the most optimal design within the simulation based on data ingested. This method focuses on making the designs being optimized more effective. The other method is through process management, this is where a classifier uses the data to predict what should occur next to achieve optimal performance. The result of both being to increase efficiency while decreasing cost by reducing the numbers of iteration or reducing the waste of energy in inefficient ways.

Past this, the research can be further divided by the specific target of the optimization. Many of the studies surveyed focused on batteries specifically, while the other group focused on engines and their operations. This creates four major combinations that were noted: the battery design group, the battery efficiency group, the engine design group, and the engine efficiency group.

The battery design group was mostly focused exclusively on using machine learning techniques to create more efficient batteries. By having it use high level physics simulations, the machine learning models tested multiple configurations until it found what it determined to be the most efficient. The battery efficiency group, unlike their design counterparts, focused on optimizing the use of the available resources of said batteries. There were two schools of thought in this group, the first group focused on using machine learning techniques to calculate the state of health and charge times of lithium-ion batteries. Using this information more efficient travel routes and mechanical information can be achieved. The other group focused on optimizing the energy stored within the battery. They did this by using machine learning techniques to predict the amount of energy needed and the most efficient way to allocate it using the smallest amount of energy possible (Rehman, 2020).

Then, there is the engine efficiency group which used machine learning techniques to analyze the engine processes and manage the process increasing the efficiency of the engines. This was often done by managing the engines through electronics and predicting what the most efficient course of action would be. Then there is the engine design group, which instead focused on using machine learning techniques to rapidly iterate and design said engines in an advanced physics simulation. The goal being to test the theoretically more efficient engines designed in the simulations much like the battery design group.

Each of these groups used machine learning techniques to achieve their goals, however they often used different types of classifiers for their research. Common methods were ensemble (a combination of classifiers) classifiers, Extreme learning machine classifiers which are special neural networks that are feed-forward only, and gradient boosted classifiers which are classifiers that use a separate formula to calculate the best feature weights for a given dataset then apply them to the model in question.

6.2 Numerical Results

The first division of the papers reviewed for this is into groups of battery and engine. From here the groups can be broken down further into groups focusing on improving the design, and those focusing on improving the operating efficiency. Thus, four clean groups are classified below: battery design, battery efficiency, engine design, and engine efficiency.

Following this the papers surveyed were then divided by type of machine learning classifier used in their predictions in each group. When it came to battery design, the most popular classifier used was ensemble methods including Dragonfly's Bayesian solution with two(Dave et al. 2022)(Houchins 2020). One of which used a neural network inside their ensemble while the other focused on linear algorithms. Then, there was an ensemble classifier in this group that instead combined Gauss Process Regression and Bayesian Optimization(Duquesnoy 2023). The last classifier used in battery design is a genetic algorithm boosted artificial neural network(Fini et al 2023). In the battery efficiency group, there were three different versions of Extreme Learning Machine with different variations of genetic algorithm(Ge et al. 2022)(Jia et al. 2022)(Zhou et al. 2023). This group was dominated by this classifier, with a single outlier in the form of a Gradient Boosted Tree ensemble classifier from Rehman et al. (2020). When it came to engine efficiency, there were two Extreme Learning Machine variations in this group(Wong 2022)(Zhao 2019). Alongside them was a Gaussian Random Forest ensemble (Mishra 2021) classifier and a Gaussian Process Regression classifier(Wang 2022). Finally in engine design there was a novel ensemble method named ActivO(Owoyele, 2021), two artificial neural networks(Posch, 2023)(Sharma, 2023), and a Multiple Linear Regression classifier(Bai, 2023). All this information can be found below in a thorough breakdown of the key elements and classification of each work.

Table 1. Breakdown of Type of Optimization and Classifiers used by Article Referenced

Article Referenced	**Target of Optimization**	**Tested Classifiers (Italics for suggested method)**
Dave et al. (2022)	Battery Design	*Dragonfly-Bayesian and Gauss Process Regression ensemble*
Duquesnoy et al. (2023)	Battery Design	*Gauss Process Regression and Bayesian Optimization Ensemble*
Houchins and Viswanathan (2020)	Battery Design	*Dragonfly-Bayesian, Gaussian Regression and Feedforward Neural Network Ensemble*
Fini et al. (2023)	Battery Design*	*Artificial neural network and multi-objective genetic algorithm*
Ge et al. (2022)	Battery Efficiency	*Bat Algorithm-Extreme Learning Machine*
Jia et al. (2022)	Battery Efficiency	*Improved Sparrow Search Algorithm and Deep Extreme Learning Machine*
Rehman et al. (2020)	Battery Efficiency**	*Gradient Boosted Tree Ensemble*
Zhou et al. (2023)	Battery Efficiency	*Grey Wolf Optimization and Deep Extreme Learning Machine*
Mishra and Subbarao (2021)	Engine Efficiency	*Gaussian/Random Forest Ensemble*

Wang et al. (2022)	Engine Efficiency	*Gaussian process regression*, support vector machine, artificial neural network
Wong et al. (2018)	Engine Efficiency	*Extreme Learning Machine*
Zhao et al. (2019)	Engine Efficiency	*C-Loss Extreme Learning Machine*
Bai et al. (2023)	Engine Design	*Multiple Linear Regression,* Random Forest, Decision Tree, Support Vector Machine
Owoyele and Pal (2021)	Engine Design	*ActivO*, μGA
Posch et al. (2021)	Engine Design	*Artificial Neural Network*, Random Forest, Support Vector Machine
Sharma et al. (2023)	Engine Design	*Artificial Neural Network*

* This work focused specifically on designing liquid cooling for batteries specifically, but has been counted for simplicity
** This work focused on optimizing household energy efficiency by managing a solar powered battery, so it has been counted for simplicity

6.3 Graphical Results

To further illustrate the types of classifiers being used, below are figures 1-4 which show the breakdown of what classifiers are used for each of the categories.

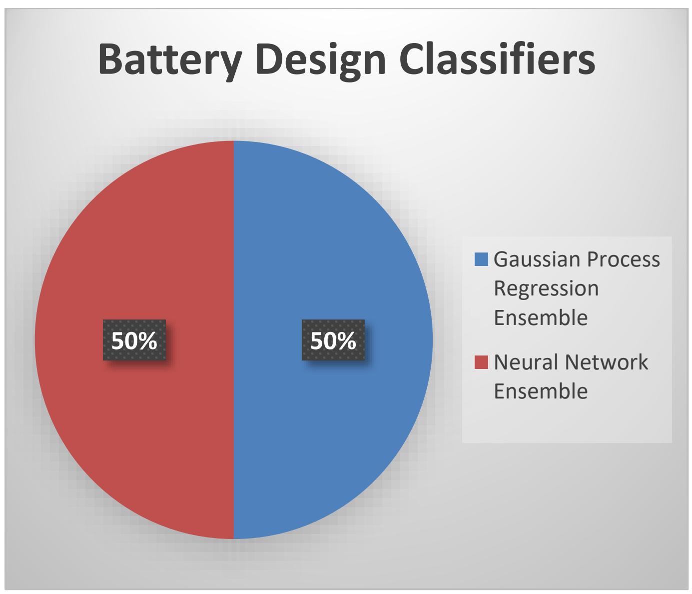

Figure 1. Battery Design Classifier Breakdown

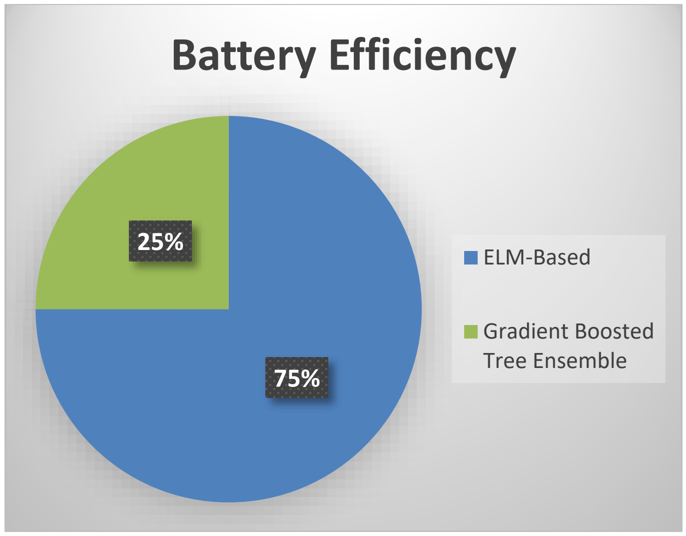

Figure 2. Battery Efficiency Classifier Breakdown

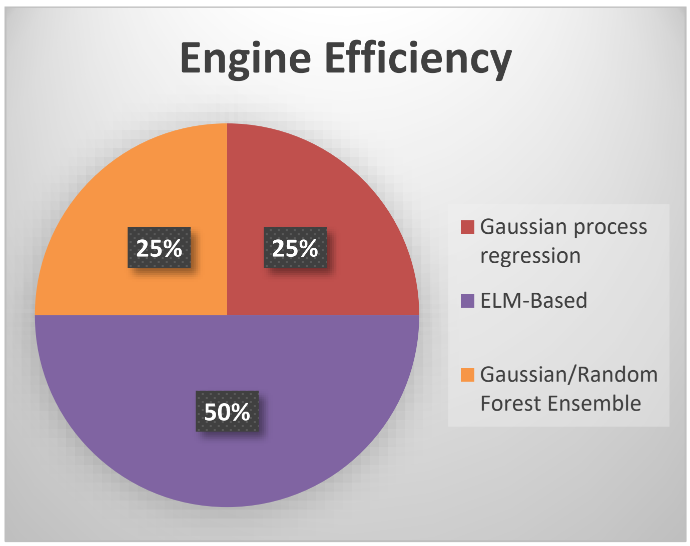

Figure 3. Engine Efficiency Classifier Breakdown

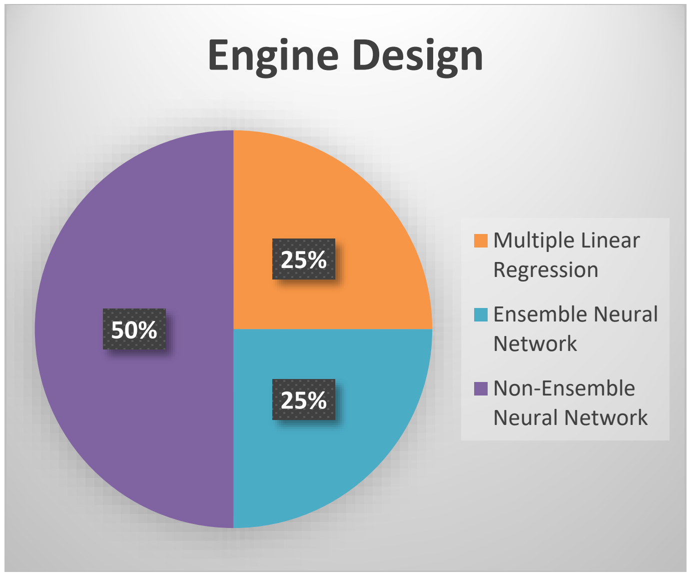

Figure 4. Engine Design Classifier Breakdown

6.4 Analysis of Results

The first thing that becomes apparent when analyzing the works researched is that many of them find a single classifier, one that another study referenced in the work used before, and solely focused on obtaining results from that classification method. This means that there is room for more experimentation with other types of classifiers. Of the sixteen studies surveyed only 4 of the works(Wang 2022)(Bai 2023)(Owoyele 2021)(Posch 2021) even checked other classification methods against the ones used. Three of the studies that tested multiple classifiers belonged to the Engine Design group, with one being a part of the Engine efficiency group.

Ensemble methods made up the bulk of the classifiers used, which makes sense as ensemble classifiers combine to get a more stable accuracy. Extreme Learning Machine was a very popular choice making up five of the classifiers, with a feedforward cousin appearing in another ensemble method. Multiple regression-based methods also find their way in, finding themselves four suggestions across three groups. The papers surveyed for the engine design group stands out as it had two non-ensemble neural networks being used, both ANN classifiers. Genetic algorithms were popular in many of the ensemble methods six explicitly mentioning the use of them. This makes sense as it allows the classifiers to find the best weights through trial and error preventing it from interfering in the rapid decision-making process in the efficiency groups, whereas the design groups were more likely to set their own factor weights.

7. Future Work

The use of machine learning to optimize efficiency and reduce resource costs holds a lot of potential. The tool offers a way to rapidly iterate upon designs, it allows for small optimization tweaks to engines that design themselves around gathering the important data needed for predictions, and this potential has been noticed by several researchers. A lot of the research gathered in this review is currently theoretical, as the models and designs produced have not yet been replicated in a physical capacity. Thus, creating these designs and testing them would be a good first step if the resources and environment necessary are available. Beyond that, further work can be done in testing different machine learning techniques to see if there are more efficient methods when it comes to designing engines and batteries. The use of genetic algorithms in rapid design iteration may prove itself useful during the rapid testing phase the models do. Furthermore, there are many other potential applications of these machine learning techniques in related fields. For example, using predictive techniques to optimize the charging of batteries against the other power usage in homes which was lightly covered in Rehman et al.(2020).

8. Conclusion

Machine learning is a useful tool for the prediction of events that can be quantified mathematically. Using it can help monitor and predict occurrences, or rapidly iterate upon designs once given a clear ruleset. By using this tool, the runtime processes of batteries and engine can be made more efficient by having a management system optimizing the tasks performed. Alongside this the technology shows potential when used to rapidly iterate on designs given proper rules and access to a physics simulation detailed enough. It is for these reasons that further research should be done to implement these potential improvements and document the outcomes.

More research should also go into other process optimizations, such as the optimization of household energy expenditure. By using machine learning techniques to optimize processes and designs in ways that reduce the cost or negative effects a key portion of the smart mobility agenda can be achieved. Beyond this, technology also has the potential to make the general consumers' life a little easier. It may be in a slight way, such as saving a bit of money on one's energy bill, but every little thing counts. A handful of currency saved will eventually build up overtime. The application of these techniques can make a handful of small resource-saving changes in theory, and if proven true can potentially reduce the stress on the average person.

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Biographies

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