ARTIFICIAL INTELLIGENCE-BASED MULTI-OBJECTIVE OPTIMIZATION FOR SUPERCAPACITOR: A REVIEW.

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Abstract
Supercapacitors have emerged as promising energy storage devices owing to their high-power density, rapid charge-discharge capability, and long operational lifespan. However, optimizing their design and operating conditions remains a complex task due to the presence of multiple conflicting objectives, including energy density, power density, cost efficiency, and cycle life. This study proposes an artificial intelligence (AI)-driven multi-objective optimization framework that integrates evolutionary algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and the Non-dominated Sorting Genetic Algorithm II (NSGA-II) with neural network-based surrogate modeling. The surrogate model is trained to approximate the nonlinear relationships between design parameters and performance metrics, thereby reducing computational and experimental burden during optimization. NSGA-II is employed to generate Pareto-optimal solutions that capture the trade-offs among competing objectives, enabling informed decision-making in material selection and structural configuration. The results demonstrate that the proposed AI-based framework significantly accelerates the design process, minimizes experimental costs, and enhances the efficiency of supercapacitor performance optimization. This approach provides a robust, scalable, and data-driven methodology for advanced energy storage system development.

Introduction

The increasing demand for sustainable and efficient energy storage systems has spurred significant research into advanced materials and architectures, particularly supercapacitors. Supercapacitors, also known as electrochemical capacitors, bridge the gap between conventional capacitors and batteries by offering high power density, fast charge-discharge cycles, and long lifecycle capabilities (Conway, 1999). Despite these advantages, challenges persist in optimizing the trade-offs among energy density, power density, and cost, crucial performance metrics in real-world applications.

Traditionally, the design and optimization of supercapacitors have relied on empirical testing and trial-and-error approaches. These methods are often time-consuming, resource-intensive, and lack predictive capabilities when handling complex, nonlinear interdependencies between design parameters (Gogotsi & Simon, 2011). This is where artificial intelligence (AI) and machine learning (ML) present a transformative opportunity.

Artificial Neural Networks (ANNs), a subset of ML, can act as surrogate models to approximate complex system behaviours based on existing data, significantly reducing computational cost and time (Goodfellow, Bengio, & Courville, 2016). When combined with multi-objective optimization algorithms such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II), AI models can intelligently navigate the design space, balancing competing objectives like maximizing energy density while minimizing cost (Deb et al., 2002).

Recent studies have demonstrated the effectiveness of AI-driven surrogate modelling in material science and energy system optimization, including fuel cells, batteries, and hybrid systems (Zhao et al., 2021). However, there is still a knowledge gap in applying these techniques specifically to supercapacitor systems, particularly in incorporating multiple performance metrics in a single optimization framework.

Therefore, this study proposes an AI-based multi-objective optimization framework for supercapacitor design, utilizing an artificial neural network (ANN) for surrogate modelling and the non-dominated sorting genetic algorithm II (NSGA-II) for exploring optimal design configurations. This integration aims to enhance performance predictability, reduce development time, and provide better-informed decisions in supercapacitor research and development.

While supercapacitors have emerged as promising energy storage devices due to their high-power density, rapid charging capabilities, and extended lifespan, their practical adoption remains limited by several unresolved challenges. Chief among these is the inherent trade-off between energy density, power density, and cost. Enhancing one metric often leads to a compromise in another, making it challenging to design supercapacitors that are simultaneously high-performing, efficient, and economically viable.

Traditional approaches to supercapacitor design primarily rely on trial-and-error experimentation and physics-based simulations, which are time-consuming and resource-intensive. These methods often fail to capture the complex, nonlinear relationships between the structural, material, and operational parameters of supercapacitors. As a result, identifying the optimal combination of design parameters to meet multiple performance objectives becomes a significant bottleneck in the development process.

Moreover, current optimization techniques are generally single-objective or heuristic-based, lacking the flexibility to handle multi-objective decision-making scenarios where designers must simultaneously consider energy density, power density, and cost. These limitations lead to suboptimal designs and longer development cycles.

There is a pressing need for an intelligent, data-driven framework that can not only model complex interdependencies between supercapacitor parameters but also optimize multiple objectives simultaneously. The integration of artificial neural networks (ANN) for surrogate modelling and NSGA-II for multi-objective optimization offers a promising solution. However, the implementation of such an integrated framework tailored for supercapacitor systems is underexplored.

The conceptual framework of Artificial Neural Networks (ANNs) in this work is built upon the idea that neural networks can model the complex, nonlinear relationships between input parameters and output performance metrics. In the context of supercapacitors, input parameters such as electrode material properties, geometry, and electrolyte concentration influence the energy density, power density, and cost. ANNs, through training on data, approximate the behaviour of the supercapacitor system, allowing rapid predictions of performance outcomes.

The neural network operates by learning patterns in large datasets, making it an ideal tool for surrogate modelling, where traditional simulation or experimentation may be too costly or time-consuming. Surrogate models in optimization reduce computational time by providing quick estimations of complex systems. As proposed by Goodfellow et al. (2016), ANNs are capable of learning and generalizing from data, enabling them to predict unseen scenarios with reasonable accuracy. This framework underpins the development of an efficient, AI-based tool for supercapacitor design. ANNs, as universal approximators, are capable of modelling intricate, nonlinear functions, making them highly effective in surrogate modelling, especially for complex optimization tasks (Goodfellow, Bengio, & Courville, 2016).

Surrogate modelling is a framework designed to replace expensive or slow simulations with an approximation model that can quickly estimate the output for given inputs. Surrogates are particularly useful in scenarios were evaluating the objective function (e.g., simulation of supercapacitor behaviour) is computationally intensive. The ANN model, as a surrogate, significantly reduces the time required for optimization by providing fast predictions, making it ideal for multi-objective optimization of supercapacitors. This approach is grounded in the theory that surrogate models should be trained on a representative dataset and then used to predict the performance of unseen designs. Once trained, the surrogate (ANN) can quickly generate approximations of the performance metrics, which are then used in the optimization process. As Jin (2011) highlights, surrogate-assisted optimization accelerates the design process by offering fast evaluations while maintaining a reasonable level of accuracy. In the case of supercapacitors, surrogate models facilitate the exploration of vast design spaces and allow for the identification of optimal configurations without the need for time-consuming physical prototypes. Surrogate models significantly reduce computational costs, making them indispensable in optimization processes for high-dimensional and computationally expensive problems (Jin, 2011).

The Genetic Algorithm (GA) framework is based on the principles of natural selection and genetic evolution. It simulates biological processes such as mutation, crossover, and selection to evolve a population of solutions toward better performance. In the context of supercapacitor design, a genetic algorithm (specifically, NSGA-II) is used to search the design space for optimal supercapacitor configurations that meet the multi-objective goals of maximizing energy density, power density, and minimizing cost. The GA operates through an iterative process where candidate solutions (chromosomes) evolve through crossover and mutation, leading to improved solutions over generations. The selection process is guided by a fitness function that evaluates how well each solution meets the optimization objectives. Holland (1975) first proposed genetic algorithms as a method for solving complex optimization problems, and subsequent developments have made them a key technique for multi-objective optimization. The use of GAs, particularly NSGA-II, ensures that the optimization process remains efficient and that a diverse set of solutions is found. "Genetic algorithms, through their evolutionary process, are well-suited for multi-objective optimization, particularly when solutions are not easily found using traditional methods" (Holland, 1975).

Several empirical studies have explored the application of artificial intelligence (AI) to optimize energy storage systems, particularly in supercapacitor design. Zhang et al. (2019) utilized machine learning models to predict and optimize the performance of lithium-ion batteries and supercapacitors, highlighting the role of AI in improving the efficiency of energy storage systems. Their study used support vector machines (SVMs) and neural networks (NNs) to predict energy storage behaviors, emphasizing the potential of machine learning in facilitating the design of advanced energy systems. They reported that AI models could significantly reduce the time and cost associated with conventional optimization methods, making AI-based tools highly effective for multi-objective optimization tasks in energy storage. Machine learning models, particularly neural networks, can provide accurate predictions of supercapacitor performance, thus facilitating faster and more efficient design optimization."(Zhang et al., 2019). This aligns with the use of Artificial Neural Networks (ANNs) in your study, which also aims to predict supercapacitor performance and reduce computational time.

In the realm of multi-objective optimization for supercapacitors, NSGA-II has been widely recognized for its ability to optimize conflicting design objectives. Patel et al. (2017) applied NSGA-II for optimizing the performance of supercapacitors, focusing on the trade-off between energy and power density. Their study concluded that NSGA-II could effectively generate Pareto-optimal solutions that balanced performance objectives, which is crucial in supercapacitor design, where improvements in energy density often come at the cost of power density, and vice versa. They also demonstrated that NSGA-II outperformed traditional optimization methods by providing a more diverse set of solutions for further analysis and decision-making. NSGA-II proved to be a powerful tool in multi-objective optimization, particularly in optimizing trade-offs between energy and power densities in supercapacitors.

Surrogate modelling has become a crucial method for improving the efficiency of optimization tasks, especially in complex systems like supercapacitors. Jin et al. (2003) applied surrogate models in the optimization of engineering systems, including energy storage devices, to reduce computational costs. They specifically highlighted that using surrogate models such as Gaussian Processes (GPs) and ANNs could replace costly simulations or experimental designs with rapid predictions. Their results showed that surrogate models could provide approximations of the system's behaviour with an acceptable margin of error, making them ideal for real-time optimization processes. Surrogate models, including neural networks, significantly reduce computational time by approximating system behaviour, thereby enabling efficient optimization.

Further empirical studies have shown the transformative potential of AI in material design and energy systems. Liu et al. (2020) demonstrated the application of AI algorithms in material discovery for supercapacitors, where machine learning techniques were used to predict the performance of various electrode materials. Their study highlighted the increasing role of AI in accelerating material discovery, optimizing supercapacitor properties, and reducing the reliance on trial-and-error approaches. This research underlined how AI can be used not only to optimize system performance but also to aid in the discovery of novel materials that could enhance supercapacitor efficiency. AI-driven approaches significantly speed up the material discovery process, making it easier to identify novel electrode materials with improved energy and power densities for supercapacitors.

Several studies have also explored hybrid approaches that combine machine learning models with traditional optimization techniques. Xu et al. (2021) presented a hybrid framework that combined ANNs with Genetic Algorithms (GAs) for multi-objective optimization in supercapacitor design. The hybrid model was able to optimize both material properties and system design, offering a more comprehensive solution compared to using ANN or GA independently. Their results demonstrated that combining these techniques could significantly improve the accuracy of predictions and the diversity of the Pareto-optimal solutions, providing a more complete set of viable designs.

Artificial Intelligence (AI) has gained significant traction in the modeling and optimization of complex energy systems. According to Tang and Li (2020), AI algorithms such as neural networks and genetic algorithms offer considerable potential in energy system optimization by learning from data and adapting to changes in system conditions. Their study demonstrated how deep learning techniques could forecast energy demands and enhance energy efficiency in renewable storage systems. This growing integration of AI reflects its value in optimizing and managing energy storage devices, including supercapacitors.

Surrogate models have become a critical component in the field of computational optimization. Forrester, Sobester, and Keane (2008) introduced surrogate-based design techniques that rely on approximations of high-fidelity simulations. These methods are especially effective when simulations are expensive and time-consuming, as is often the case with supercapacitor performance testing. Their research showed that using surrogate models such as artificial neural networks (ANNs) enables faster convergence during optimization by reducing the computational overhead.

Hybrid AI models combining neural networks with genetic algorithms have also been explored. Chen and Zhou (2021) proposed a hybrid surrogate-GA model to optimize supercapacitor electrode materials and geometries. Their work showed improved accuracy and diversity in the solution space compared to single-method approaches. The combination leveraged the predictive power of neural networks with the global search capabilities of evolutionary algorithms.

Mohammand et al. (2019) presented a battery-less power supply utilizing a supercapacitor as an energy storage device, powered by solar energy. This supercapacitor behaves like other capacitors, but is superior because it has a larger storage capacity. In this supercapacitor, the only two variables of storage are maximum charging voltage and capacitance. This supercapacitor is used as energy storage in charging lower-voltage-powered devices and acts as an energy storage supply. In the event of a power failure, solar energy is used to back up the power supply. The charging duration of the supercapacitor depends on the solar panel's voltage rating. The power supply using supercapacitors can store up to 30 volts using DC-DC boost converters. The supercapacitor cannot be used to charge heavy power-consuming devices. It is also limited in that it depends on external power for sustenance. The supercapacitor can be enhanced by combining it with a battery or a non-fuel source to ensure that the supercapacitor can deliver sufficient energy. Also, not all the solar panels used as backup can charge the supercapacitors.

Semih and Gurkan (2023) stressed the need for dependable energy to resolve the energy crisis in the energy sector, which has led to the optimization of supercapacitors to meet the urgent demand for energy. The failure of the present energy storage supercapacitor technology and the requirements needed for speedy charging of the electric power and control strategies are also considered. These components and the development process are used to optimize the speedy charging process by making the supercapacitor work efficiently. The optimization potential and its effectiveness of the structure are assessed by simulating with the MATLAB or Simulink software program. This work stresses the importance of supercapacitor optimization to close the gap of the inadequacies of the supercapacitor storage and charging capacity to meet the emerging need of electric vehicles and to provide a basis for future projection. This work added greatly to the development and optimization of supercapacitor-based high-speed storage and charging systems. However, this system can be enhanced by using artificial-based multi-objective optimization for supercapacitors that balance the energy demand, power demand, and cost.

Hassan et al carried out a study in the field of superconductors to enhance energy efficiency, capacitance, flexibility, and stability. They developed a low-cost laser-induced graphene (LIG) with optimized geometry to offer a promising substitute to business-wise accessible graphene for future handy devices. The low-cost laser-induced graphene superconductors give a high performance with high mechanical strength and pliability with the laser. The coupled LIG electrodes were examined using an atomic force microscope, which showed a surface roughness of $2.03\mu m$. The result shows the possibility of the LIG as an effective and adaptable energy storage alternative for small and lightweight devices. The developed supercapacitor is capable of powering small and lightweight devices. However, the optimization process in the LIG supercapacitor is mechanically operated and cannot be used for the prediction of energy density, power density, or to minimize cost. Therefore, there is a need to use an artificial intelligence-based multi-objective optimization supercapacitor that changes or aligns to adapt to conflicting demand goals.

Surrogate modeling with an artificial neural network

The method adopted for supercapacitor optimization is the surrogate modelling using an Artificial Neural Network. The surrogate model changes the difficulty of manual simulations of the existing system above. The input arrangement of the surrogate model consists of 6 nodes of layers, two hidden layers of 64 neurons. The output layer consists of 3 nodes, which represent energy, power, and cost.

The Rectified Linear Unit (Relu) is defined as *f(x)* = max (0, x). This indicates that if the input is positive, it presents a value; if the input is negative, it presents a zero value. Relu works in the hidden layer of the ANN to reduce the disappearing gradient issues, which make the model learn speedily. It enhances non-linearity, which is important for adapting to intricate structures.

The linear Activation function is defined as $f(x) = x$It is used to output the input data without any changes. This is applied in the output layer during the prediction of continuous values.

The Loss Function, which is the mean square error, is calculated as the mean of the square of the differences between the predicted value and the real value, mathematically given as

$$MES = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Where y is the actual value and $\hat{y}_i$ Is the number of observations. It is used for regression. It queries major errors rather than small ones. The goal is to reduce errors during training.

Adaptive Moment Estimation (Adam) is an optimisation algorithm that joins the two other optimisers (AdaGrad and RMSProp). It keeps a log of the first average and the second changes of the gradients to control the learning rate of the input. It works well in the deep learning environment, is faster, and is immune to noise.

Discussion of Results

The artificial intelligence was trained with over 100 epochs. the Adam optimizer and Mean Squared Error (MSE) as the loss function. During the training of the dataset, it was observed that the validation losses converged gradually, showing that the model was effective. After the training, 20% of the data were evaluated, and the following results were obtained.

Performance Metrics

Metric	**Energy Density**	**Power Density**	**Cost**
R^2 Score	0.945	0.931	0.910
Mean Square Error	0.72	10234	0.0023
Root Mean Square Error	0.85	101.16	0.048

Table 4.8: Performance Metrics

The output result of the R^2 Score is not more than 0.91, indicating that the model accurately predicts the objective of energy density, power density, and cost.

Sample Predictions vs Actual Values

Sample	**True Energy**	**Predicted**	**True Power**	**Predicted**	**True Cost**	**predicted**
1	19.8	19.6	4500	4420	0.21	0.22
2	18.2	18.4	4200	4195	0.19	0.18
3	20.5	20.3	4700	4680	0.22	0.21

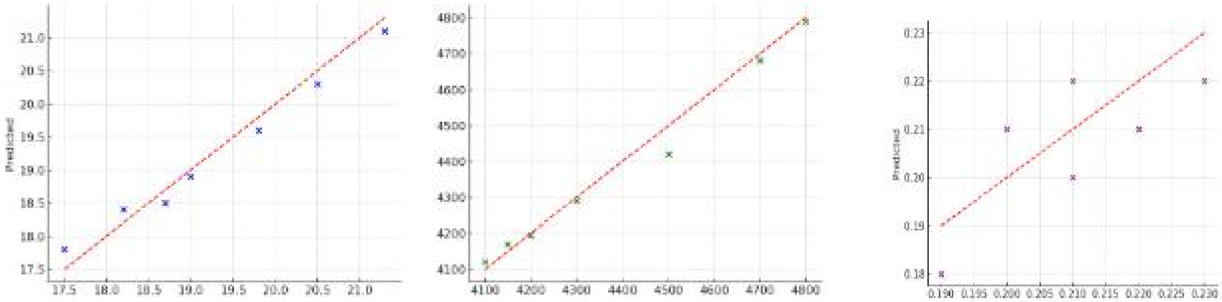
Table 4.8.2**: Sample Predictions vs Actual Values**

Interpretation of Results

From Table 4.8.2, the prediction accuracy is high among the stated objectives, with little diversion in the cost, which is an important insight for economic practicability and can also be integrated for future advancement in optimization.

Visualization of ANN Surrogate Model Performance

Cost Energy Actual vs Predicted Power Density vs Predicted Cost Actual vs Predicted



Actual Actual

Actual

From the graph above, the red dashed line represents perfect prediction, and the points closer to the dashed line represent high prediction accuracy. This confirms the fact that

Conclusion

The proposed AI-driven energy management system has successfully demonstrated its potential in transforming traditional energy consumption models into intelligent, efficient, and sustainable solutions. By integrating machine learning algorithms, real-time IoT data, and automated battery storage optimization, the system effectively minimizes energy wastage, extends battery lifespan, and reduces electricity costs. The use of dynamic demand forecasting allows for proactive energy planning, ensuring better alignment with consumption patterns and peak usage periods. Furthermore, the system's robust security framework and scalable architecture make it adaptable for both residential and industrial applications. In conclusion, this solution offers a forward-thinking approach to energy management, aligning with global efforts toward sustainable energy usage, smart grid development, and cost-effective energy storage solutions.

Recommendations

Based on the successful implementation and performance of the proposed AI-driven energy management system, the following recommendations are made:

1. Adopt AI-Powered Energy Solutions at Scale: Energy providers and smart home developers should adopt AI-based management systems to improve energy efficiency, optimize battery usage, and reduce operational costs.
2. Integrate Renewable Energy Sources: Future developments should incorporate solar or wind energy systems to enhance sustainability and reduce reliance on conventional power grids.
3. Enhance IoT Device Coverage: Expanding the use of smart sensors and meters across all energy-consuming units will improve real-time data accuracy and system responsiveness.
4. Continuous Model Training: The machine learning models should be regularly retrained with new data to maintain high accuracy in demand forecasting and decision-making.
5. User Education and Engagement: Educating users on how to interpret system insights and adjust usage behaviour will maximize the benefits of the system.

Suggestion for Further Studies

Incorporate Renewable Energy Integration: Enhance the system by integrating renewable sources like solar or wind, allowing for a more sustainable and eco-friendly energy mix.

Develop a Mobile Application: Create a mobile-friendly version of the dashboard to allow users to monitor and control their energy usage conveniently from anywhere.

Introduce Predictive Maintenance: Use AI to detect potential faults or inefficiencies in battery performance before they occur, reducing downtime and maintenance costs.

Enable User-Customized Settings: Allow users to set personal energy-saving goals or customize thresholds for charging/discharging, giving them greater control and flexibility.

Expand to Community-Level Energy Sharing: Design the system to support peer-to-peer energy trading or sharing within smart communities, maximizing energy use and reducing waste collectively.

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