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Optimising Multi-Objective Taguchi-Based Energy Management Systems for Reduced Power Consumption

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ABSTRACT

To boost system efficiency, reduce operating costs, and enhance reliability, modern energy management systems (EMS) must efficiently control power demand. This work use the Taguchi design of experiments approach to systematically optimize electricity demand. Three control parameters, each at three levels, were investigated in order to optimize system efficiency while reducing power consumption and mean squared deviation (MSD). Response tables, analysis of variance (ANOVA), and signal-to-noise (S/N) ratio analysis were used to identify the most critical parameters and their optimal values.

The results demonstrate that factor B has the most impact on power demand and MSD, accounting for more than 90% of the total fluctuation, whereas factor C is mainly in charge of boosting system efficiency. The optimal parameter combination for lowering power consumption and MSD was found to be $A_1B_1C_{2.3}$, even though maximum efficiency was reached at A_3B_2C. The produced models show excellent prediction accuracy with R2 values exceeding 96%....

Keywords: *Energy Management System; Electricity Demand Optimization; Taguchi Method; Signal-to-Noise Ratio; Analysis of Variance (ANOVA); Mean Squared Deviation; Energy Efficiency; Experiment Design; Robust Optimization*

1. INTRODUCTION

The rapid increase in power consumption brought on by urbanization, industrial expansion, and the adoption of cutting-edge electrical technology has raised the need for efficient energy management systems (EMS). Modern EMS aims to maximize system efficiency and preserve operational stability under a variety of operating conditions in addition to reducing power usage. Inadequate demand management raises energy costs, increases peak loads, and reduces system dependability, all of which lead to major economic and environmental issues. Improving EMS performance requires optimization measures. Conventional optimization strategies sometimes need large datasets, complex mathematical formulae, and significant computer effort, which limits their application in real-world energy systems. EMS performance is also impacted by a number of interacting control factors, therefore a robust optimization technique that can identify optimal operating conditions with few tests is essential. The Taguchi method, a statistically based design of experiments (DOE) methodology, is an effective tool for robust design and system optimization. Using orthogonal arrays and signal-to-noise (S/N) ratios, the Taguchi methodology enables the methodical evaluation of several aspects while accounting for unanticipated parameter variation. This approach has been widely employed in engineering systems to cut experimental costs while improving quality and reducing performance variance. In the context of energy management, the Taguchi technique offers significant advantages for optimizing power usage. By simultaneously analyzing many performance goals, such as reducing power demand and mean squared deviation (MSD) while optimizing efficiency, it provides valuable insights into the relative importance of system elements. Additionally, analysis of variance (ANOVA) facilitates the discovery of statistically important factors impacting EMS performance.

This paper focuses on the Taguchi approach for optimizing power demand in an EMS. Three control factors were examined at three levels using a L9 orthogonal array to evaluate their effects on power demand, efficiency, and system stability. The optimal parameter was determined using ANOVA and signal-to-noise ratio analysis.

2. LITERATURE REVIEW

Participate in multi-objective EMS optimization and demonstrate how demand and efficiency are dominated by certain control factors. Three main contributions are made by this work: (i) it systematically optimizes electricity demand in an EMS using the Taguchi approach; (ii) it identifies key factors influencing demand, variability, and efficiency; and (iii) it establishes optimal operating conditions that enhance system robustness and performance. The findings of this study provide valuable suggestions for the creation and management of energy-efficient EMS and serve as a foundation for future multi-objective .

and real-time energy optimization research.

Energy Management Systems (EMS), which offer real-time monitoring, optimal management, and intelligent decision-making to reduce energy consumption, boost dependability, and support sustainability goals, are essential to the efficient running of modern power systems. Microgrids, renewable energy integration, building automation, and industrial processes are just a few of the many applications covered by current EMS research.

2.1 Foundations of EMS Research

EMS has evolved significantly over the last few decades, going from simple monitoring tools to complex control systems with optimization and decision-support algorithms. Early EMS research showed that effective energy usage analysis and targeting strategies might result in significant cost and energy savings. It focused on basic load monitoring and energy conservation in commercial and industrial environments.

Jiayi Zhang emphasizes that EMS is more than simply a technical instrument; it is a strategic framework for integrating conventional and renewable energy sources to achieve sustainability and reduce costs and emissions.

2.2 Optimization in EMS

Optimization is one of the primary goals of modern EMS. Traditional model-based techniques including mixed-integer linear programming (MILP), predictive control, and stochastic programming have been thoroughly researched for cost and demand minimization, particularly in microgrid situations where the presence of distributed energy resources (DERs) adds complexity.
Cognitive and hybrid EMS solutions that integrate fuzzy logic with complex optimization algorithms (such PSO, GA, and Firefly Algorithm) further illustrate the trend toward multi-objective and adaptive EMS that may balance economic, environmental, and reliability objectives.

2.3 Data-Driven and AI-Based EMS

The increasing availability of real-time data and advancements in artificial intelligence (AI) have sped up research on data-driven EMS. Frameworks for machine learning, reinforcement learning, and meta-learning are being merged to improve decision-making in dynamic situations. Deep learning, for instance, has been utilized in EMS and distribution management systems (DMS) to enable faster, nearly real-time optimization in complex power systems. A meta reinforcement learning-based EMS framework (MetaEMS) demonstrates enhanced adaptability and performance in building energy management by solving problems with dynamic load and renewable penetration.

2.4 Microgrid and Networked EMS

As distributed generation and distributed energy resources (DERs) have gained prominence, EMS research has focused more on microgrids and networked systems. Among the objectives of microgrid EMS are optimal power distribution, frequency and voltage regulation, and seamless transitions between grid-connected and islanded modes. Recent evaluations have concentrated on architectural classifications and control mechanisms for networked microgrids, reflecting the growing complexity as EMS must manage many DERs, storage systems, and loads while maintaining stability and resilience.

2.5 Demand Side Management and EMS

An essential component of EMS research is demand side management (DSM), which focuses on load scheduling, peak shaving, and load shifting. According to studies, demand side optimization can significantly reduce peak demand and overall operating costs in smart grids and hybrid renewable energy systems. Integrating demand response systems with EMS enables more intelligent load shaping strategies, particularly when dealing with time-varying tariffs and fluctuating renewable energy.

2.6 Gaps and Emerging Trends

Despite improvements, there are still several research gaps in the EMS literature:

Integration Challenges: Multi-objective frameworks that balance sustainability, stability, and efficiency are still in the early phases of development, whereas many EMS solutions focus on particular optimization challenges (such demand or cost).

Data and Forecasting: Accurate load and renewable generation forecasting, which is still important but challenging, affects real-time optimization efficiency.

Scalability: When EMS approaches from small-scale or residential systems are applied to large industrial or utility contexts, scalability and complexity issues occur.

Standardization: The lack of uniform guidelines for EMS interfaces and performance evaluation hinders broader implementation.

Systematic reviews also highlight the need for more study on industrial EMS, particularly in relation to data analytics integration and decision-making processes, when compared to residential applications.

3. MATERIALS AND METHODS

3.1 Energy Management System Description

The Energy Management System (EMS) considered in this paper is designed to monitor, control, and optimize power usage under diverse operational conditions. Efficiency, operating stability, and power consumption are all impacted by the system's many adjustable components. The EMS performance was evaluated using three primary responses: power demand, mean squared deviation (MSD), and system efficiency. These performance indicators show how much energy the system uses, how resilient it is to changes, and how well it operates.

3.2 Selection of Control Factors and Levels

Based on preliminary system analysis and operational considerations, three control parameters (identified as A, B, and C) were selected for optimization. Each factor was examined at three different levels in order to capture nonlinear effects while maintaining experimental viability. The components and the corresponding levels are listed in Table 1.

Table 1
Control Factors and Levels

Factor	Level 1	Level 2	Level 3
A	A_1	A_2	A_3
B	B_1	B_2	B_3
C	C_1	C_2	C_3

3.3 Experimental Design Using Taguchi Method

Using the Taguchi design of experiments (DOE) technique, the effects of the selected control parameters on EMS performance were carefully investigated. The use of a L9 orthogonal array (3^3) allows for the evaluation of three parameters at three levels with just nine experimental runs. This significantly reduced the experimental effort as compared to a complete factorial design.
Each experimental run's response values, which correspond to a unique combination of factor levels, were recorded using the EMS. The experimental arrangement is shown in Table 2.

3.4 Performance Metrics

Three response characteristics were analyzed:

Electricity Demand (Y): Shows how much power the EMS uses. Reducing the demand for electricity is the goal.

Mean Squared Deviation (MSD): Indicates how variable system performance is. Improved robustness and stability are indicated by a lower MSD.

Efficiency (Effi): Shows how well the EMS uses energy. It is good to have higher efficiency values.

3.5 Signal-to-Noise (S/N) Ratio Analysis

To evaluate system robustness and performance consistency, signal-to-noise (S/N) ratios were computed for each response using Taguchi quality characteristics:

Smaller-is-Better (Electricity Demand, MSD):

$$\mathrm{S/N} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right)$$

Larger-is-Better (Efficiency):

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right)$$

where $y_i$is the observed response and $n$is the number of observations.

3.6 Statistical Analysis

Analysis of Variance (ANOVA) was performed to quantify the contribution of each control element and determine its statistical significance on the EMS performance responses. Factors with p-values less than 0.05 were considered statistically significant at a 95% confidence level.
Regression models were developed using estimated model coefficients to explain the relationship between control factors and S/N ratios. The model's suitability was assessed using the coefficient of determination (R2), modified R2, and standard error (S).

3.7 Optimization Procedure

The optimization process consisted of the following steps:

Conduct experiments according to the Taguchi L9 orthogonal array.

Calculate S/N ratios for each response.

Develop response tables and main effect plots.

Identify optimal factor levels based on S/N ratio maximization or minimization criteria.

Validate the results through ANOVA and regression analysis.

3.8 Software Tools

All statistical analyses, including Taguchi design, S/N ratio computation, regression modeling, and ANOVA, were conducted using Minitab statistical software. Data visualization and result comprehension were made easier by integrated analytical tools.

4. EXPERIMENTAL SETUP AND PROCEDURE

4.1 Experimental Setup

The trials focused on an Energy Management System (EMS) designed to evaluate electricity demand, system stability, and operational efficiency under different operating conditions. Adjustable parameters in the EMS reflect important operational settings that impact power consumption and energy utilization. These parameters were adjusted in compliance with the Taguchi experimental methodology in order to assess their individual and combined effects on system performance.

The experimental examination was carried out under closely controlled conditions to ensure accuracy and repeatability. The system was permitted to achieve steady-state operation prior to data collection, and the EMS was configured with preset parameter settings for every experimental run. All measurements were made using comparable sample intervals to minimize measurement uncertainty.

4.2 Experimental Design

A Taguchi L9 orthogonal array (3^3) was used in the design of the tests. This method allows for the evaluation of three control factors (A, B, and C) at three levels each with fewer experimental runs. The experimental matrix is shown in Table 3.

Table 3
Taguchi L9 Experimental Matrix

Experiment No.	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3

Experiment No.	A	B	C
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

4.3 Experimental Procedure

The experimental procedure followed the steps outlined below:

The EMS control factors were set according to the L9 orthogonal array for each experimental run.

The system was operated until steady-state conditions were achieved.

Electricity demand, mean squared deviation (MSD), and efficiency were measured for each run.

Measurements were repeated where necessary to reduce random errors.

The collected data were tabulated for further statistical analysis.

4.4 Measurement of Performance Parameters

Electricity Demand (Y): Measured as the average power consumption of the EMS during steady-state operation.

Mean Squared Deviation (MSD): Calculated to quantify performance variability and robustness of the EMS under different operating conditions.

Efficiency (Effi): Defined as the ratio of useful energy output to total energy input, expressed as a percentage.

4.5 Experimental Data Collection

The measured electrical demand, MSD, and efficiency values for each experimental run were meticulously recorded. These experimental results served as the basis for the computation of signal-to-noise (S/N) ratios and subsequent statistical analysis. Care was taken to provide uniform experimental conditions throughout all runs in order to prevent bias in the results collected.

4.6 Reliability and Repeatability

To ensure experimental reliability, the studies were conducted under consistent working conditions and with calibrated measuring equipment. Repeatability was verified by maintaining the same factor values and observing minimal variation in the recorded responses. The Taguchi signal-to-noise ratio analysis further enhanced resilience by accounting for the variability in the experimental data.

5. RESULTS AND DISCUSSION

This section presents and discusses the experimental results from the Taguchi-based optimization of the Energy Management System (EMS). The study focuses on electricity demand, mean squared deviation (MSD), and system efficiency using signal-to-noise (S/N) ratios, regression modeling, and analysis of variance (ANOVA).

5.1 Experimental Results

The experimental results for the L9 orthogonal array demonstrate a noticeable variation in EMS performance across different combinations of control factors. MSD values ranged from 28.04 to 112.28, electricity demand ranged from 5.30 to 10.68, and system efficiency ranged from 14.30% to 20.20%. These variations show that the selected control parameters have a significant impact on EMS performance, supporting the need for systematic tuning.

A	B	C	Y
1	1	1	5.30

1	2	2	7.78
1	3	3	9.16
2	1	2	5.38
2	2	3	8.66
2	3	1	10.68
3	1	3	5.48
3	2	1	9.40
3	3	2	9.44

A	B	C	MSD
1	2	2	60.600
1	3	3	92.212
2	1	2	28.346
2	2	3	69.768
2	3	1	112.283
3	1	3	28.040
3	2	1	82.162
3	3	2	98.030

5.2 Signal-to-Noise Ratio Analysis

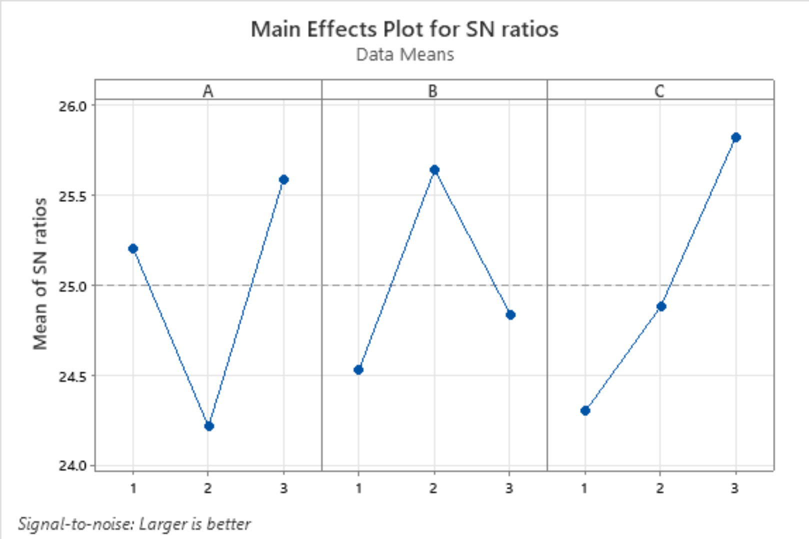
5.2.1 Electricity Demand

For electricity demand, the "smaller-is-better" S/N ratio was applied. The S/N ratio answer table shows that factor B has the highest Delta value (5.14) and the highest influence, followed by factors C and A. The highest S/N ratios were seen at A_1, B_1, and C_2, indicating lower electricity use and improved robustness in these circumstances.

5.2.2 Mean Squared Deviation (MSD)

MSD was also examined using the "smaller-is-better" criterion. The S/N ratio response shows a considerable effect of factor B with a Delta value of 10.85, which is much higher than that of factors A and C. Again, the most effective combination for lowering MSD was discovered to be $A_1B_1C_2$, indicating the stability and consistency of the EMS under these circumstances.

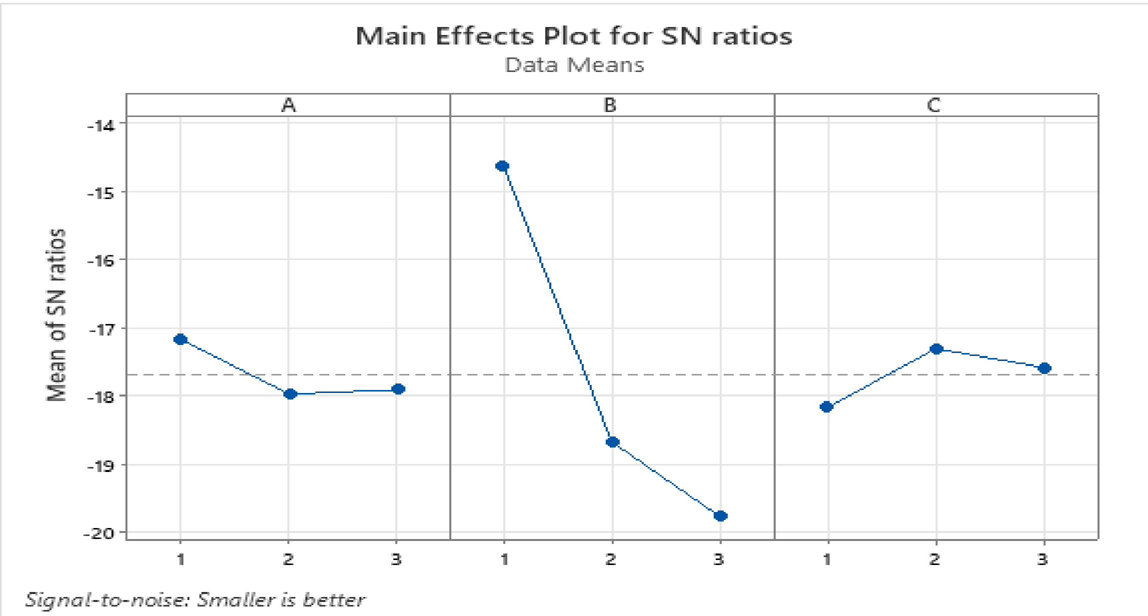
Level	**A**	**B**	**C**
1	60.98	28.84	74.86
2	70.13	70.84	62.33
3	69.41	100.84	63.34
Delta	9.15	72.01	12.53
Rank	3	1	2



5.2.3 Efficiency

Efficiency was evaluated using the "larger-is-better" S/N ratio. In contrast to demand and MSD, factor C was shown to be the most significant characteristic, followed by factors A and B. The highest S/N ratios were recorded at A_3, B_2, and C_3, when maximum EMS efficiency was attained.

Level	**A**	**B**	**C**
1	7.413	5.387	8.460
2	8.240	8.613	7.533
3	8.107	9.760	7.767
Delta	0.827	4.373	0.927
Rank	3	1	2



5.3 Analysis of Variance (ANOVA)

To ascertain each control factor's statistical significance and contribution, an ANOVA was used.

Factor B was found to be extremely significant ($p = 0.001$), accounting for the majority of the variation in electricity demand. Factors A and C were also significant at the 95% confidence level.

With an F-value more than 1000, Factor B once again dominated the system response in the MSD analysis, highlighting its critical role in lowering variability.

None of the factors were significantly significant for efficiency at the 95% confidence level; nevertheless, factor C had the biggest influence, indicating its importance in enhancing EMS performance.

The high R2 values (greater than 96% in all cases) attest to the exceptional model adequacy and trustworthy representation of the experimental data by the built regression models.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	1.1766	1.1766	0.5883	19.41	0.049
B	2	44.0714	44.0714	22.0357	726.85	0.001
C	2	1.1612	1.1612	0.5806	19.15	0.050
Residual Error	2	0.0606	0.0606	0.0303		
Total	8	46.4698				

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	1.371	1.371	0.6854	7.57	0.117
B	2	187.313	187.313	93.6567	1033.83	0.001
C	2	3.707	3.707	1.8535	20.46	0.047
Residual Error	2	0.181	0.181	0.0906		
Total	8	192.572				

5.4 **Optimal Parameter Settings**

Based on the S/N ratio and ANOVA analyses:

Minimum electricity demand: $A_1B_1C_2$

Minimum MSD: $A_1B_1C_2$

Maximum efficiency: $A_3B_2C_3$

The same optimal settings for MSD and electricity demand show that the EMS may simultaneously reduce energy consumption and improve stability. However, the optimal design for efficiency varies, highlighting a trade-off between demand minimization and efficiency maximization.

5.5 **Discussion**

The results demonstrate that, due to its critical role in controlling power demand and system variability, factor B is the most significant parameter for EMS optimization. This suggests that robustness and energy savings can be significantly increased by factor B-focused operational solutions. However, factor C primarily controls system efficiency, indicating that operating conditions for efficiency increases may be different from those for demand minimization. The need for multi-objective optimization techniques in EMS design is highlighted by the apparent trade-off between efficiency and demand minimization. Even so, the Taguchi method effectively determines trustworthy parameter values for particular objectives.

6. Conclusion

In this paper, an Energy Management System (EMS) was optimized for electricity demand using the Taguchi technique. Using a L9 orthogonal array, the effects of three significant control factors—A, B, and C—on power demand, mean squared deviation (MSD), and system efficiency were evaluated at three levels. To identify optimal parameters and gauge factor relevance, regression modeling, ANOVA, and signal-to-noise (S/N) ratio analysis were employed.

The following are the primary conclusions:

1. Dominant Factors: It was found that factor B was the most significant factor influencing power demand and MSD, while factor C primarily influenced system efficiency. Factor A had moderate effects on every response.

2. Optimal Settings: The EMS's attainment of maximum efficiency at $A_3B_2C_3$ and low electricity demand and MSD at $A_1B_1C_2$ demonstrated a trade-off between efficiency optimization and demand reduction.

3. Method Effectiveness: The Taguchi method successfully reduced the number of experimental runs while yielding trustworthy and statistically meaningful insights into factor effects. Regression models demonstrated excellent prediction accuracy ($R^2 > 96\%$), confirming the reliability of the experimental data.

4. Practical Implications: The study provides specific suggestions for adjusting EMS parameters in order to lower energy usage and improve system stability. The results further emphasize the need for multi-objective optimization to reconcile conflicting goals such as efficiency and demand reduction.

In conclusion, our research demonstrates that Taguchi-based optimization is a practical and effective way to enhance EMS performance. Future research may build on this work by utilizing multi-objective optimization approaches, real-time adaptive control, or renewable energy sources to achieve comprehensive and sustainable energy management systems.

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