Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol.13, (2024)
https://www.jneonatalsurg.com

Taguchi-Based Multi-Objective Optimization of Energy Management Systems for Reduced Electricity Consumption

Mohan T Patel[1], Dr. Nikhil J. Rathod[2]

[1]Research Scholar, Department of Electrical Engineering, Vikrant University, Gwalior

[2]Associate Professor, Department of Mechanical Engineering, Vikrant University, Gwalior

Cite this paper as: Mohan T Patel, Dr. Nikhil J. Rathod, (2024) Taguchi-Based Multi-Objective Optimization of Energy Management Systems for Reduced Electricity Consumption .Journal of Neonatal Surgery, 13, 2031-2041

ABSTRACT

Modern energy management systems (EMS) must effectively manage electricity demand in order to increase system performance, save operating costs, and improve dependability. The Taguchi design of experiments strategy is used in this study to optimize electricity demand in a methodical manner. In order to maximize system efficiency while minimizing electricity consumption and mean squared deviation (MSD), three control parameters, each at three levels, were examined. The most important parameters and their ideal settings were determined using response tables, analysis of variance (ANOVA), and signal-to-noise (S/N) ratio analysis.

The findings show that whereas factor C is primarily responsible for increasing system efficiency, factor B has the greatest influence on electricity demand and MSD, accounting for over 90% of the total variation. While maximum efficiency was attained at A_3B_2C, the ideal parameter combination for reducing electricity demand and MSD was determined to be $A_1B_1C_{2.3}$. With R2 values above 96%, the generated models demonstrate great predictive accuracy..

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

1. INTRODUCTION

The necessity for effective energy management systems (EMS) has increased due to the quick rise in electricity consumption caused by urbanization, industrial growth, and the incorporation of cutting-edge electrical technologies. In addition to lowering electricity consumption, modern EMS seeks to maximize system efficiency and maintain operational stability under a range of operating circumstances. Ineffective demand management creates serious economic and environmental problems by raising energy bills, increasing peak loads, and decreasing system reliability.

Optimization strategies are essential for enhancing EMS performance. Large datasets, intricate mathematical formulas, and substantial computer work are frequently needed for conventional optimization techniques, which restricts their use in real-world energy systems. Furthermore, a variety of interacting control parameters affect EMS performance, therefore a strong optimization strategy that can find ideal operating conditions with few experiments is crucial.

An efficient tool for robust design and system optimization is the statistically based design of experiments (DOE) technique known as the Taguchi method. The Taguchi approach allows for the systematic assessment of several factors while taking unpredictable parameter fluctuation into account by using orthogonal arrays and signal-to-noise (S/N) ratios. In engineering systems, this strategy has been frequently used to reduce performance variation and enhance quality while lowering experimental costs.

The Taguchi approach has important benefits for optimizing electricity demand in the context of energy management.

It offers important insights into the relative significance of system factors by concurrently examining several performance objectives, such as lowering power demand and mean squared deviation (MSD) while maximizing efficiency. Additionally, the identification of statistically significant factors influencing EMS performance is made easier by analysis of variance (ANOVA).

The Taguchi method for optimizing power demand in an EMS is the main topic of this work. An L9 orthogonal array was used to examine three control parameters at three levels in order to assess their impact on system stability, efficiency, and power demand. ANOVA and signal-to-noise ratio analysis were used to identify the best parameter.

2. LITERATURE REVIEW

Involved in multi-objective EMS optimization and show how certain control parameters dominate demand and efficiency. This work makes three major contributions: (i) it applies the Taguchi approach to systematically optimize electricity demand in an EMS; (ii) it identifies important factors influencing demand, variability, and efficiency; and (iii) it establishes ideal operating conditions that improve system performance and robustness. The results of this study serve as a basis for future multi-objective and real-time energy optimization research and offer useful recommendations for the development and operation of energy-efficient EMS.

The effective operation of contemporary power systems depends on Energy Management Systems (EMS), which provide real-time monitoring, optimum control, and intelligent decision-making to lower energy consumption, increase dependability, and promote sustainability objectives. Modern EMS research covers a broad range of applications, from microgrids and renewable energy integration to building automation and industrial operations.

2.1 Foundations of EMS Research

Over the past few decades, EMS has changed dramatically, moving from basic monitoring tools to sophisticated control systems that incorporate optimization and decision-support algorithms. Early EMS research demonstrated the potential for large energy savings and cost reductions through efficient energy usage analysis and targeting tactics. It concentrated on energy conservation and basic load monitoring in commercial and industrial settings.

Jiayi Zhang highlights that EMS is a strategic framework for combining conventional and renewable energy sources to achieve sustainability and lower costs and emissions, rather than just a technical tool.

2.2 Optimization in EMS

One of the main purposes of contemporary EMS is optimization. For cost and demand minimization, traditional model-based approaches like mixed-integer linear programming (MILP), predictive control, and stochastic programming have been extensively studied, especially in microgrid settings where the addition of distributed energy resources (DERs) adds complexity.

The trend toward multi-objective and adaptive EMS that may balance economic, environmental, and reliability criteria is further demonstrated by cognitive and hybrid EMS strategies that combine fuzzy logic with sophisticated optimization algorithms (such as PSO, GA, and Firefly Algorithm).

2.3 Data-Driven and AI-Based EMS

Research on data-driven EMS has been accelerated by the growing availability of real-time data and developments in artificial intelligence (AI). To enhance decision-making in dynamic environments, machine learning, reinforcement learning, and meta-learning frameworks are being combined. For example, deep learning has been used in distribution management systems (DMS) and EMS to enable quicker, almost real-time optimization in intricate power systems. By addressing issues related to dynamic load and renewable penetration, a meta reinforcement learning-based EMS framework (MetaEMS) shows improved adaptability and performance in building energy management.

2.4 Microgrid and Networked EMS

Microgrids and networked systems have received more attention in EMS research as distributed generation and DERs have grown in popularity. Optimal power distribution, frequency and voltage control, and smooth transitions between grid-connected and islanded modes are among the goals of microgrid EMS. As EMS must manage numerous DERs, storage systems, and loads while preserving stability and resilience, recent assessments have focused on architectural classifications and control mechanisms for networked microgrids, reflecting the increasing complexity.

2.5 Demand Side Management and EMS

Demand side management (DSM), which focuses on load scheduling, peak shaving, and load shifting, is a crucial part of EMS research. Effective demand side optimization can dramatically lower peak demand and total operating costs in hybrid renewable energy systems and smart grids, according to research.

More intelligent load shaping tactics are made possible by integrating demand response systems with EMS, especially when interacting with time-varying tariffs and fluctuating renewable energy.

2.6 Gaps and Emerging Trends

Despite advancements, the EMS literature still has a number of study gaps:

Integration Challenges: While many EMS solutions concentrate on specific optimization issues (such as demand or cost), multi-objective frameworks that strike a balance between sustainability, stability, and efficiency are still in the early stages of development.

Data and Forecasting: Real-time optimization efficiency is impacted by accurate load and renewable generation forecasting, which is still crucial yet difficult.

Scalability: Scalability and complexity problems arise when EMS techniques from small-scale or residential systems are applied to big industrial or utility contexts.

Standardization: Wider adoption is hampered by the absence of consistent standards for EMS interfaces and performance assessment.

In comparison to residential applications, systematic evaluations also emphasize the need for additional research on industrial EMS, especially with regard to decision-making processes and data analytics integration.

3. MATERIALS AND METHODS

3.1 Energy Management System Description

Under various operational situations, the Energy Management System (EMS) under consideration in this study is intended to monitor, regulate, and optimize electricity use. The system incorporates a number of configurable factors that affect efficiency, operational stability, and electricity usage. Three major responses were used to assess the EMS performance: system efficiency, mean squared deviation (MSD), and electricity demand. The system's energy consumption, resilience to fluctuations, and operational efficacy are all represented by these performance indicators.

3.2 Selection of Control Factors and Levels

Three control factors (designated as A, B, and C) were chosen for optimization based on initial system analysis and operational considerations. To capture nonlinear effects while preserving experimental viability, each factor was investigated at three distinct levels. Table 1 lists the components along with the levels that correspond to them.

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

The impacts of the chosen control parameters on EMS performance were methodically examined using the Taguchi design of experiments (DOE) approach. With just nine experimental runs, three factors at three levels may be evaluated thanks to the selection of a L9 orthogonal array (3^3). Compared to a full factorial design, this greatly decreased the experimental effort.

The EMS was used to record the response values throughout each experimental run, which corresponds to a distinct combination of factor levels. Table 2 displays the experimental layout.

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

Taguchi quality characteristics were used to calculate signal-to-noise (S/N) ratios for each response in order to assess system robustness and performance consistency:

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):

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

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

3.6 Statistical Analysis

To measure each control factor's contribution and ascertain its statistical significance on the EMS performance responses, Analysis of Variance (ANOVA) was used. At a 95% confidence level, factors with p-values less than 0.05 were deemed statistically significant.

To explain the connection between control factors and S/N ratios, regression models were created using estimated model coefficients. The coefficient of determination (R2), modified R2, and standard error (S) were used to evaluate the model's adequacy.

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

Minitab statistical software was used for all statistical studies, including Taguchi design, S/N ratio computation, regression modeling, and ANOVA. Integrated analytical tools facilitated data visualization and result understanding.

4. Experimental Setup and Procedure

4.1 Experimental Setup

An Energy Management System (EMS) intended to assess electricity demand, system stability, and operational efficiency under various operating situations was the subject of the trials. Key operational settings that affect power consumption and energy utilization are represented by adjustable parameters in the EMS. To evaluate their individual and combined effects on system performance, these parameters were modified in accordance with the Taguchi experimental design.

To guarantee accuracy and repeatability, the experimental investigation was conducted under carefully monitored circumstances. Before collecting data, the system was allowed to reach steady-state functioning and the EMS was setup with predetermined parameter settings for each experimental run. To reduce measurement uncertainty, similar sample intervals were used for all measurements.

4.2 Experimental Design

The tests were designed using a Taguchi L9 orthogonal array (3^3). Three control factors (A, B, and C) can be evaluated at three levels each with fewer experimental runs thanks to this approach. Table 3 displays the experimental matrix.

Table 3
Taguchi L9 Experimental Matrix

Experiment No.	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2

Experiment No.	A	B	C
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

Each experimental run's measured electrical demand, MSD, and efficiency values were methodically documented. The calculation of signal-to-noise (S/N) ratios and ensuing statistical analysis were based on these experimental findings. To prevent bias in the data gathered, care was made to guarantee consistent experimental conditions throughout all runs.

4.6 Reliability and Repeatability

The experiments were carried out with calibrated measurement equipment and consistent working circumstances to guarantee experimental dependability. By keeping the same factor settings and seeing little variance in the recorded answers, repeatability was confirmed. By taking into consideration the heterogeneity in the experimental data, the Taguchi signal-to-noise ratio analysis further improved robustness.

5. Results and Discussion

The experimental findings from the Taguchi-based optimization of the Energy Management System (EMS) are presented and discussed in this section. Utilizing signal-to-noise (S/N) ratios, regression modeling, and analysis of variance (ANOVA), the investigation focuses on electricity demand, mean squared deviation (MSD), and system efficiency.

5.1 Experimental Results

The L9 orthogonal array's experimental results show a discernible difference in EMS performance between various control factor combinations. System efficiency ranged from 14.30% to 20.20%, MSD values varied from 28.04 to 112.28, and electricity demand values ranged from 5.30 to 10.68. These differences support the necessity for systematic optimization by demonstrating that the chosen control settings have a major impact on EMS performance.

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

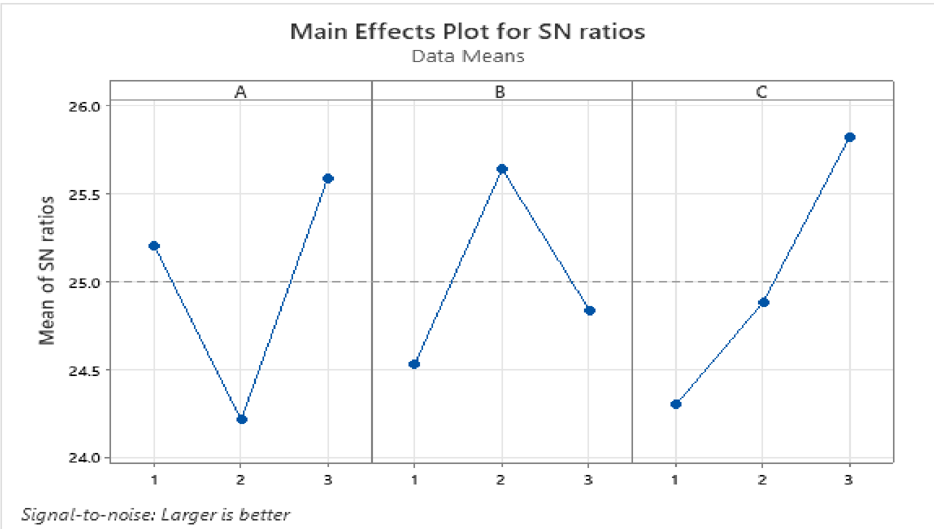
5.2.1 Electricity Demand

The "smaller-is-better" S/N ratio was used for electricity demand. According to the answer table for S/N ratios, factor B ranks first in influence and has the largest Delta value (5.14), followed by factors C and A. At A_1, B_1, and C_2, the highest S/N ratios were found, indicating reduced electricity use and enhanced robustness under these conditions.

5.2.2 Mean Squared Deviation (MSD)

The "smaller-is-better" criterion was also used to examine MSD. With a Delta value of 10.85, which is significantly larger than those of factors A and C, the S/N ratio response demonstrates a strong effect of factor B. Once more, $A_1B_1C_2$ was found to be the best combination for reducing MSD, demonstrating the EMS's stability and consistency under these conditions.

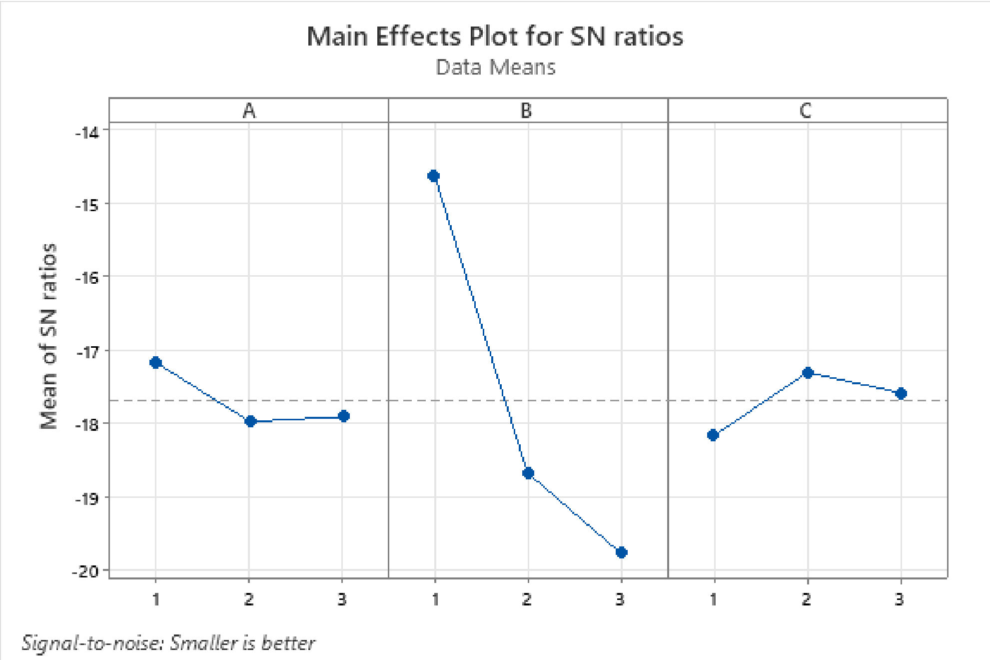
Level	A	B	C
1	60.98	28.84	74.86
2	70.13	70.84	62.33
3	69.41	100.84	63.34
Delta	9.15	72.01	12.53
Rank	3	1	2



5.2.3 Efficiency

The "larger-is-better" S/N ratio was used to assess efficiency. Factor C was shown to be the most significant parameter, followed by factors A and B, in contrast to demand and MSD. Maximum EMS efficiency was achieved at A_3, B_2, and C_3, where the highest S/N ratios were found.

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.

The majority of the variation in electricity demand was attributed to factor B, which was shown to be highly significant ($p = 0.001$). At the 95% confidence level, factors A and C were also significant.

Factor B once more dominated the system response in the MSD analysis, with an F-value greater than 1000, underscoring its crucial function in reducing variability.

At the 95% confidence level, none of the factors were significantly significant for efficiency; nevertheless, factor C had the greatest impact, demonstrating its significance in improving EMS performance.

The outstanding model adequacy and reliable representation of the experimental data by the constructed regression models are confirmed by the high R2 values (better than 96% in all cases).

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	2	0.0606	0.0606	0.0303		

Error						
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 EMS can simultaneously cut energy usage and increase stability, as evidenced by the identical ideal settings for MSD and electricity demand. The best design for efficiency, however, varies, emphasizing a trade-off between maximizing efficiency and minimizing demand.

5.5 Discussion

The findings show that factor B is the most important parameter for EMS optimization since it is crucial in regulating power demand and system variability. This implies that factor B-focused operational solutions can greatly increase robustness and energy savings. On the other hand, system efficiency is mostly controlled by factor C, suggesting that operating conditions for efficiency gains might differ from those for demand minimization.

The observed trade-off between efficiency and demand minimization highlights the necessity of multi-objective optimization techniques in EMS design. Although the Taguchi approach successfully finds reliable parameter values for specific goals.

6. Conclusion

In this work, the Taguchi approach was used to optimize electricity demand in an Energy Management System (EMS). The impacts of three important control factors—A, B, and C—on power demand, mean squared deviation (MSD), and system efficiency were assessed at three levels using a L9 orthogonal array. Regression modeling, ANOVA, and signal-to-noise (S/N) ratio analysis were used to determine ideal parameters and measure factor importance.

The following are the primary conclusions:

Dominant Factors: While factor C mainly controlled system efficiency, factor B was shown to be the most important element affecting power demand and MSD. All responses showed moderate impacts from factor A.

Optimal Settings: A trade-off between efficiency optimization and demand reduction was highlighted by the EMS's achievement of maximum efficiency at $A_3B_2C_3$ and low electricity demand and MSD at $A_1B_1C_2$.

Method Effectiveness: The Taguchi method produced reliable and statistically significant insights into factor effects while effectively reducing experimental runs. The trustworthiness of the experimental data was confirmed using regression models, which showed great prediction accuracy ($R^2 > 96\%$).

Practical Implications: To reduce energy consumption and enhance system stability, the study offers precise recommendations for EMS parameter tweaking. In order to balance competing objectives like efficiency and demand reduction, the results further highlight the necessity of multi-objective optimization.

To sum up, our study shows that Taguchi-based optimization is a useful and efficient method for improving EMS performance. In order to obtain comprehensive and sustainable energy management solutions, future research may expand on this study by incorporating renewable energy sources, real-time adaptive control, or multi-objective optimization techniques.

REFERENCES

[1] Al Zubaidi, S., & Tomsovic, K. (2021). Energy Management System Architectures and Functionalities: A Comprehensive Review. Electric Power Systems Research, 198, 107329.

[2] Amin, S., Khan, M. J., & Qu, Q. (2019). Optimization Techniques for Demand Side Management in Smart Grid Systems: A Review. Renewable and Sustainable Energy Reviews, 112, 97–128.

[3] Azadeh, A., Ghaderi, S. F., & Sohrabkhani, S. (2018). Application of Taguchi and Response Surface Methodology for Optimization of Energy Consumption. Journal of Cleaner Production, 180, 720–732.

[4] Goyal, R., Singh, M., & Gupta, A. (2022). Taguchi–Grey Relational Analysis for Multi Objective Optimization of Distribution Networks. International Journal of Electrical Power & Energy Systems, 135, 107469.

[5] Han, Y., Zeng, P., & Wang, X. (2023). A Review of Energy Management System (EMS) Design and Implementation for Smart Grids. IEEE Access, 11, 14521–14542.

[6] Hocaoglu, F. O., & Karabiber, A. (2019). Pareto Based Multi Objective Optimization Techniques in Microgrid Energy Management. Applied Energy, 250, 710–725.

[7] Lee, J., & Park, Y. (2021). Taguchi Optimization of Control Parameters in Power Electronics for Improved Efficiency and Power Quality. IEEE Transactions on Industrial Electronics, 68(4), 3221–3230.

[8] Liu, H., & Wang, S. (2019). Particle Swarm Optimization Based Residential Load Scheduling for Smart Grids Under Time of Use Pricing. Energy, 188, 116040.

[9] Minitab, LLC. (2024). Minitab Statistical Software: Release 21. Minitab, LLC.

[10] Singh, R. K., & Sharma, P. (2021). Performance Optimization of Wind Turbines Using Taguchi DOE Under Variable Wind Conditions. Renewable Energy, 163, 1466–1478.

[11] Zhang, S., Li, Y., & Wu, L. (2018). Hybrid Genetic Algorithm for Demand Side Management in Smart Grids. Energy, 165, 757–768.

[12] Zheng, X., & Li, J. (2020). Energy Management Systems: Structure, Models and Optimization Framework. Energy Reports, 6, 239–252.

[13] Nur E Alam, M., Abedin, T., Samsudin, N. A., et al. (2025). Optimization of energy management in Malaysian microgrids using fuzzy logic based EMS scheduling controller. Scientific Reports, 15, 995. doi:10.1038/s41598 024 82360 4 — A fuzzy logic EMS improves microgrid scheduling and performance.

[14] Khan, A. M., Hekmati, A., & Bagheri, M. (2025). Enhancing cost effectiveness in residential microgrids: optimization for EMS with proactive EV charging. Frontiers in Energy Research.

[15] Qamar, H. M., Guo, X., Seif Ghith, E., et al. (2025). Assessment of energy management and power quality improvement of hydrogen based microgrid system through PSO MWWO technique. Scientific Reports, 15, 863. doi:10.1038/s41598 024 78153 4 — Investigates EMS optimization for power quality in hydrogen microgrids.

[16] Optimal energy management system for grid connected hybrid power plant and battery integrated into multilevel configuration. (2024). Energy, 294, 130765 — Presents an EMS for hybrid renewable power systems with experimental HIL results.

[17] Zhang, H., Shi, X., Lu, H., et al. (2025). Energy management method of integrated energy system based on energy and carbon pricing strategy and reinforcement learning. Frontiers in Energy Research.

[18] Etghani, M. M., & Boodaghi, H. (2025). Artificial Neural Networks and Taguchi Methods for Energy Systems Optimization: A Comprehensive Review. Energy Engineering, 122(11), 4385–4474 — Reviews ANN and Taguchi applications in energy system optimization.

[19] Energy management system in networked microgrids: an overview. (2024). Energy Systems. Springer — A recent survey on EMS architectures and optimization in connected microgrids.

[20] Zarma, T. A., Ali, E. A., Galadima, A. A., et al. (2025). Energy demand forecasting for hybrid microgrid systems using machine learning models. Proceedings of Engineering and Technology Innovation, 29, 68–83 — Focuses on ML based demand forecasting in EMS.

[21] Rathod, N.J., Chopra, M.K., Chaurasiya, P.K. et al. Optimization on the Turning Process Parameters of SS 304 Using Taguchi and TOPSIS. Ann. Data. Sci. 10, 1405–1419 (2023). https://doi.org/10.1007/s40745-021-00369-2 22.

[22] Rathod, N.J., Chopra, M.K., Shelke, S.N. et al. Investigations on hard turning using SS304 sheet metal component grey based Taguchi and regression methodology. Int J Interact Des Manuf 18, 2653–2664 (2024). https://doi.org/10.1007/s12008-023-01244-5 23.

[23] N.J. Rathod, M.K. Chopra, U.S. Vidhate, N.B. Gurule, U.V. Saindane, Investigation on the turning process parameters for tool life and production time using Taguchi analysis, Materials Today: Proceedings, Volume 47, Part 17, 2021, Pages 5830-5835, https://doi.org/10.1016/j.matpr.2021.04.199. 24.

[24] Rathod, N.J., Chopra, M.K., Chaurasiya, P.K. et al. Design and optimization of process parameters for hard turning of AISI 304 stainless steel using Taguchi-GRA-PCA. Int J Interact Des Manuf 17, 2403– 2414 (2023).

https://doi.org/10.1007/s12008-022-01021-w 25.

[25] Rathod, N.J., Chopra, M.K., Chaurasiya, P.K. et al. Optimization of Tool Life, Surface Roughness and Production Time in CNC Turning Process Using Taguchi Method and ANOVA. Ann. Data. Sci. 10, 1179–1197 (2023). https://doi.org/10.1007/s40745-022-00423-7 26.

[26] N.J. Rathod, M.K. Chopra, U.S. Vidhate, U.V. Saindane, Multi objective optimization in turning operation of SS304 sheet metal component, Materials Today: Proceedings, Volume 47, Part 17, 2021, Pages 5806-5811, https://doi.org/10.1016/j.matpr.2021.04.143 27.

[27] P. K. Chaurasiya, N. J. Rathod, P. K. Jain, V. Pandey, Shashikant and K. Lala, "Material Selection for Optimal Design Using Multi-Criteria Decision Making," 2023 3rd International Conference on Advancement in Electronics & Communication Engineering (AECE), GHAZIABAD, India, 2023, pp. 206-210, doi: 10.1109/AECE59614.2023.10428303. 28.

[28] Mahesh T. Dhande, et al. 2023. HMCMA: Design of an Efficient Model with Hybrid Machine Learning in Cyber security for Enhanced Detection of Malicious Activities. International Journal on Recent and Innovation Trends in Computing and Communication. 11, 11s (Oct. 2023), 721–734. DOI:https://doi.org/10.17762/ijritcc.v11i11s.9729.

[29] T. Dhande M, Tiwari S, Rathod N. Design of an efficient Malware Prediction Model using Auto Encoded & Attention-based Recurrent Graph Relationship Analysis. Int. Res. J. multidiscip. Technovation [Internet]. 2025 Jan. 22 [cited 2025 Dec. 13];7(1):71-87. Available from: https://asianrepo.org/index.php/irjmt/article/view/103 30.

[30] Kalangi, C., Rathod, N.J., Madhuri, K.S. et al. Performance optimization of ethanol blends in diesel model using Taguchi and grey relational approach. Sci Rep 15, 36048 (2025). 31.

[31] Rathod, N.J., Bonde, P. & Nehete, H.R. Parametric optimization of WEDM of SS 304 stainless steel for material removal rate and surface roughness using Taguchi and Response Surface Methodology. Interactions 246, 60 (2025). https://doi.org/10.1007/s10751-025-02273-0 32.

[32] Nikhil Janardan Rathod , Praveen B. M. , Mayur Gitay, Sidhhant N. Patil, Mohan T. Patel, (2025) Optimization Of Multiple Objectives in The Machining Process of SS304 Sheet Metal Components.. Journal of Neonatal Surgery, 14 (14s), 801-809 33.

[33] Rathod, N.J. et al. (2026). Wire Electrical Discharge Machining Process Parameter Optimization via the Taguchi Method. In: Al-Ramahi, N., Musleh Al-Sartawi, A.M.A., Kanan, M. (eds) Artificial Intelligence in the Digital Era. Studies in Systems, Decision and Control, vol 594. Springer, Cham. 34.

[34] Rathod, N.J. et al. (2026). Aluminum Machining Process Parameter Optimization in WEDM with the GRA Approach. In: Al-Ramahi, N., Musleh Al-Sartawi, A.M.A., Kanan, M. (eds) Artificial Intelligence in the Digital Era. Studies in Systems, Decision and Control, vol 594. Springer, Cham. 35.

[35] Rathod, N.J. et al. (2026). Optimizing Wire Electric Discharge Machining Process Parameters for AISI 304 Stainless Steel via Taguchi Design of Experiments. In: Al-Ramahi, N., Musleh Al-Sartawi, A.M.A., Kanan, M. (eds) Artificial Intelligence in the Digital Era. Studies in Systems, Decision and Control, vol 594. Springer, Cham. https://doi.org/10.1007/978-3-031-89771-9_8 36.

[36] Rathod, N.J. et al. (2026). SS304 CNC Turning Process Mathematical Modeling and Machining Parameter Optimization Utilizing the Taguchi Technique. In: Al-Ramahi, N., Musleh Al-Sartawi, A.M.A., Kanan, M. (eds) Artificial Intelligence in the Digital Era. Studies in Systems, Decision and Control, vol 594. Springer, Cham. https://doi.org/10.1007/978-3-031-89771-9_2 37.

[37] Nikhil Janardan Rathod, Praveen B. M., Mayur Gitay, Sidhhant N. Patil, Mohan T. Patel, (2025) Implementation of Machine Learning Approaches for the Modeling and Predictive Turning Maintenance Operations Incorporating Lubrication and Cooling in Systems of Manufacturing. Journal of Neonatal Surgery, 14 (15s), 1741-1748 38.

[38] Nikhil J. Rathod, Nilesh Ingale, Mahesh T. Dhande, Santhosh H Pawar, A REVIEW ON AI ENABLED MULTI MODEL CARDIOVASCULAR MONITORING SYSTEM FOR PREDICTION OF PHYSIOLOGICAL STRESS, Department of Computer Science and Technology, 2025, 180724/IJORAR-1019, 39.

[39] Mayur Jayant Gitay, Dr. Nilesh Diwakar, Dr. M. K. Chopra, Dr. Nikhil J. Rathod, Analysis of the performance of a CI engine operating in dual fuel mode with biogas and biodiesel, Eur. Chem. Bull. 2023,12(3) 4462-4472 40.

[40] Prashant S. Raut, Dr. Nilesh Diwakar, Sumit Raut, Dr. Nikhil J. Rathod, Performance Evaluation and Emission Characteristic of Biodiesel (Methyl Ester) CI Engine, Eur. Chem. Bull. 2023, 12 (S3), 2240 – 2245 41. Sumit R. Raut, Dr. Nilesh Diwaka, Prashant S. Raut,

[41] Dr. N. J. Rathod, Additives Characterization for Enhanced Biodiesel Performance in a CI Engine, Eur. Chem. Bull. 2023, 12 (S3), 2234 – 2239 42.

[42] Sumit R. Raut, Dr. Nilesh Diwakar, Prashant S. Raut, Dr. N. J. Rathod, The Technique Performance Evaluation and Emission Characteristics of diesel, cerium oxide, and ethanol, Eur. Chem. Bull. 2023, 12 (S3), 3172 – 3184. 43.

[43] Prashant S. Raut, Dr. Nilesh Diwakar, Sumit Raut, Dr. Nikhil J. Rathod, The Technique Performance Evaluation and Emission Characteristics of Biodiesel, Eur. Chem. Bull. 2023, 12 (S3), 3147 – 3155

[44] Dr. Mayur Jayant Gitay, Dr. Nikhil J. Rathod , Mr. Rohit K. Dhende, Mr. Sagar S. Sasan. "PERFORMANCE ANALYSIS OF NATURAL FIBER REINFORCED COMPOSITES FOR SUSTAINABLE ENGINEERING

APPLICATIONS", Multidisciplinary Journal of Academic Publications ISSN (Online): 3107-538X Vol. 02, Issue 01, January – February 2026, MJAP/05/0402.

[45] Dr. Mayur Jayant Gitay, Dr. Nikhil J. Rathod , Mr. Rohit K. Dhende, Mr. Sagar S. Sasan, "IMPACT AND CRASHWORTHINESS PERFORMANCE OF COMPOSITE STRUCTURES IN AUTOMOTIVE APPLICATIONS", Multidisciplinary Journal of Academic Publications ISSN (Online): 3107-538X Vol. 02, Issue 01, January – February 2026, 2026/MJAP/09/0403.

[46] Dr. Mayur Jayant Gitay, Dr. Nikhil J. Rathod , Mr. Rohit K. Dhende, Mr. Sagar S. Sasan, "IMPACT AND CRASHWORTHINESS PERFORMANCE OF COMPOSITE STRUCTURES IN AUTOMOTIVE APPLICATIONS", Multidisciplinary Journal of Academic Publications ISSN (Online): 3107-538X Vol. 02, Issue 01, January – February 2026, 2026/MJAP/09/0403.

[47] Dr. Mayur Jayant Gitay, Dr. Nikhil J. Rathod , Mr. Rohit K. Dhende, Mr. Sagar S. Sasan, "THERMO-MECHANICAL PERFORMANCE OF POLYMER MATRIX COMPOSITES: A CRITICAL REVIEW", Multidisciplinary Journal of Academic Publications ISSN (Online): 3107-538X Vol. 02, Issue 01, January – February 2026, 2026/MJAP/09/0405.