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Automation Control for Energy Optimization in High Rack Storage Systems:

A Conceptual Framework for Predictive Warehouse Design Processes

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Abstract

In today's rapidly evolving logistics and storage sector, constantly changing market conditions and consumer demands exert a significant pressure on the efficiency and sustainability of storage systems. High-rack storage systems have become a widely used strategy in warehouse design, but the integration of factors such as energy optimization and automation of logistics processes is crucial to the success of these systems.

In this context, this study aims to present a conceptual framework that combines machine learning-based prediction methods with logistics automation controls to increase the energy efficiency of high-rack storage systems and optimize logistics processes. This innovative approach in the warehouse design process aims to enhance storage system performance by optimizing energy consumption.

By filling a gap in the existing literature, this study seeks to provide a general strategy to overcome the challenges that high-rack storage systems will face in the future. This strategy aims to meet the need for sustainable storage solutions by increasing the efficiency of logistics operations and standing out in the competitive business environment of the future.

The modern logistics industry has rapidly changed in the impact of constant technological improvements; thus, one can speak about AI and ML technologies' growing importance for warehousing activities. Drawing on the concentration noted in review of existing literature works, this paper will outline ways AI and ML technologies like artificial neural networks, fuzzy logic deep learning reinforcement can be used industry logistics fields certain purposes applied logistics management.

These include supplier evaluation processes, operational planning; big data solution logic methods, social media data analytics and supply chain management & logistics. Unlike earlier studies, this article goes beyond the idea of simple traceability targets and presents warehouse management systems where such monitoring data is used, as well as machine learning approaches that allow for training classifiers capable predicting various aspects of any Warehouse design.

Furthermore, it validates this machine learning approach to support the strategic planning of warehouse design using verified and generalizable case studies with real company data. This provides important insights into how monitoring data in warehouse management systems can be effectively used for design and operational management.

Finally, the purpose of this article is to use machine learning for warehouse management to predict and measure the performance of future warehouse operations. Essentially, this article addresses the identification of warehouse operations, determination of performance criteria, creation and evaluation of machine learning models, and prediction of future warehouse operations. The approach aims to inform warehouse managers' decision-making processes and provide comprehensive guidance to optimize operational efficiency.

Keywords

High-Bay Storage, Energy Optimization, Logistics Automation Control, Machine Learning, Warehouse Design Processes

INTRODUCTION

Modern logistics developed with advanced manufacturing methods, diversified market demands, faster supply chain responses due to shorter product life cycles and globalization of production caused people to demand high temporal and spatial requirements in the sector; thus automated multi-story warehouses have become a necessity (Zhu et al., 2017). In contemporary logistics systems, automated storage and retrieval have become an integral component of the system. High-rack AS/RS, which is another name for automated storage and retrieval systems (AS/RS), have a central unit on the top rack that constitutes different handling facilities. This is a computational controlled mechatronic integrated system. The system is composed of the high rack, which serves as its main body and various transport equipment that forms a basis. There is much that various technologies including mechanical, electronic and computerized communication networks sensors ana automatic controls are also integrated. it also offers micro-computerization, transport mechanization and information network management. In the modern logistics chains, they work as storage and production hubs for all sorts of commodities (Fereidunian et al.). In the wake of fast tempo industrial productions, automated multi-storey warehouses find themselves increasingly in need for factory automation, flexible manufacturing systems, computer integrated manufacturing system and agile manufacturing. Accuracy and real-time information increase the need for storage and handling. Such information flows are required for processes of production and logistics in warehouses. As a result, determining location and data collection have turned into high-speed communication technologies such as scanning or high-frequency data streams that are frequently used in storage machines. Storage and transfer of goods are faster, real-time, dependable as well genuine. In order to ensure system flexibility and automate logistics and storage, the utilization of flexible conveying facitities skills is very important. In a multi-storey warehouse high rack system, the stacker is an important mechanical component of equipment and core element as well as centralizing automation integrated multi storeys. The normal functioning of the stacker is directly related to the smooth running of an automated multi-storey warehouse. Workable flow optimization for safe operation (reasonableness, accuracy of speed and position control) is the key to good fault diagnosis combined with high performance in terms of extensive functionality. However, to improve the automation warehouses efficiency even further; one of its main challenges is located in a stacker. As such, improving the stacker efficiency is crucial to improve overall warehouse productivity automated system (Dede et al.). The strategic decision making choices that affect warehouse system design include the choice or type of storage and transportation equipment/ technology, layout selection as well as allocation of space along with policy on picking. KPI related to shipping (incoming) or picking activities are often used as performance measures of the storage system. Outgoing process design is one of the primary aspects influencing performance in most warehouse systems (Chan and Chan, 2011; De Koster R., n d). Choice of storage and material handling systems is usually closely linked to the nature of SKUs as well as processes associated with them (Gu et al., 2007; Gu et al., 2010). Comparison can be applied to compare warehouse performance metrics with targets efficiency (Chen et al., 2017, Johnson and McGinnis, 2011).

The branch of artificial intelligence (AI) focused on researching algorithms that can accurately analyze and interpret data from previous cases, including those of Priore and other sources. 'The dossier-driven predictions (Zhu and others., 2017) are backed by a strong belief in machine intelligence, which is evident in its contribution to pattern recognition and computational education.

There are two main types of learning: supervised and unsupervised learning (Enna et al., 1976). Data in supervised learning is organized and marked as input-output. So, a machine is provided with inputs and their resulting outputs so that it can learn the relationships between them. Data used for unsupervised learning is labeled but utilized so as to discover patterns and structures within the data (Halima Bousqaoui & Said Achchab, 2019). The options for machine learning algorithms are abundant, as noted by Priore et al., and include neural networks, support vector machines, regression decision trees, random forests, association rule learning classifiers, and the k-mean algorithm. Within the realm of supply chain management, there is a category focused on planning inventory for all nodes. Several studies have put forth machine learning frameworks as a solution for coordinated inventory management (Priore et al., Affia and Aamer, 2021). Through the utilization of a roadmap, a successful IoT-based smart warehouse infrastructure was built and an IoT-based model for warehouses was designed and implemented. MHS selection framework (Accorsi et al., 2012), SAS design procedure have been developed. It is possible to compare various types of STs and PPs using the theoretical framework built on continuous spaces (Hao et al., 2020; Lin & Lu, 1999).

PRELIMINARIES

In a study conducted in 2016, an anomaly detection algorithm with automatic learning capabilities that could be used in hybrid production systems was proposed. A combination of deep learning techniques and a time-based automatic system was employed to create a detection model from the observations applied in the system. The algorithm was tested on various datasets, including two real systems, and promising results were reported (Hranisavljevic et al., 2016). In a follow-up study published in 2017, an unsupervised and non-parametric approach was developed. This approach utilizes self-organizing maps and basin transformations to enable anomaly detection in production systems where anomaly detection is not possible under normal conditions, allowing the use of hybrid timed automata (Birgelen and Niggeman, 2017).

In the research conducted in 2018, a good method was proposed to learn and continue to update the communication and cooperation of services running in IoT systems. The proposed method can detect anomalies based on the learning model by analyzing the information flow in the communication process of nodes. This study concludes that IoT systems can provide a high level of security (Pahl and Aubet, 2018).

A study published in 2019 compared the effectiveness of various machine learning algorithms in detecting vulnerabilities that may arise from Internet cyber attacks. Test results show that the decision branch, randomly forecasting and artificial neural network algorithm achieve highly success ratio of approximately 94%, with the excellent performance of the random forest algorithm (Hasan et al.).

In another study, an algorithm for detecting defects in smart manufacturing uses real data collected from equipment in the production process. An unsupervised, real-time anomaly detection algorithm based on autoencoders is used to detect irregular and irregular data in multi-sensor data from production lines. The results show that the false detection rate of the proposed algorithm is 90% (Hsieh et al.).

In the study where Wang and his colleagues focused on deep learning architectures for the detection of anomalies, researchers aimed to better understand the learning process. In this study, firstly, the previously used methods for detecting anomalies in deep learning are explained, and then the methods used in today's high-tech networks are discussed. To overcome the problems of previous algorithms, absorption learning-based detection (Wang et al.)

Predicting future warehouse operations and key performance indicators (KPIs) requires information (processes and KPIs) available in the dataset used by the machine learning model to extract the information necessary for prediction (Zhu et al., 2014).

The purpose of the logistics ontology is to capture the content of transportation (Hendi et al., 2014). It includes concepts, relations, axioms, people, and assertions. In the same context, the structure of the products and KPIs are shown in the form of ontology. This ontology can be built and extended from warehouse management (WM) information. The data in the ontology can be divided into warehouse data, KPI data and support data. Product process data includes warehouse process data. For example, this includes information needed to perform warehouse operations such as receiving, storing, storing, packaging, and shipping stock items (SKUs). Simultaneous support of various warehouse processes was also evaluated (Halima Bousqaoui and Said Achchab, 2019). Mathematical models are designed for precise purposes and can be used to create hypotheses, variables, models, and equations to illustrate the relationship between the product's variable system (materials and components) (Liu, 2018). Integrated machine learning models can be created by decomposing warehouse planning tasks into submodels. This integration model combines mathematical and machine learning models to facilitate the integration of submodels. Collaboration between different mathematical models and machine learning can occur (Youssef and Youssef, 2019). While mathematical models are created by modeling objects and the relationship between objects, machine learning is created in many ways (Knoll et al.). Machine learning models can be developed using different machine learning methods such as vector machines, randomly forecasting, artificial neural network branches (Halima Bousqaoui and Said Achchab, 2019).

This research proposal is based on the study entitled "Machine Learning in Logistics Automation Control for Energy Optimisation in High Rack Storage Systems: A Conceptual Framework". Predictive Warehouse Design Processes" and its contribution and impact on the literature will be emphasised. High-bay storage systems play a central role in today's logistics processes. Energy optimisation in these systems is crucial for sustainability and efficiency. This proposal aims to provide energy optimisation in the warehouse design process using machine learning for logistics automation control.

This research analyses the use of machine learning models to improve energy efficiency in the warehouse design process. Previous literature studies have generally not adequately addressed this topic.
In this context, this study aims to make a significant contribution to the literature by providing a conceptual framework for energy optimisation in high-bay storage systems (Küçükyaşar et al., 2021; Lewczuket al., 2021).

By referring to Çınar's (2022) work on warehouse management and energy optimisation, the proposal offers a new perspective that provides a realistic solution to improve energy efficiency in high-bay storage systems (Thomas et al., 2019).

As a result, this study makes a valuable contribution to industrial applications and operations by providing a theoretical basis for energy optimisation in the warehouse design process using machine learning models in logistics automation control.

METODOLOGY

This research aims to develop machine learning models for logistics automation control to improve energy optimisation in high-bay storage systems. It describes when and why models such as artificial neural networks and support vector machines (SVMs) are used and how they can be applied to energy optimisation in high-bay storage systems.

Artificial neural networks are models composed of neurons and are known for their ability to learn complex relationships. They are often used to recognise patterns and solve the complexity of large data sets. These features are ideal for improving the energy efficiency of warehouse design processes in logistics automation control (Bishop, 2006).
Support Vector Machines (SVMs) are models that can be applied to classification and regression problems; SVMs perform particularly effectively as the complexity and size of the data set increases. In high bay storage systems, they can be used to classify and analyse data for energy optimisation in the storage design process (Cortes and Vapnik, 1995).
These two models are powerful tools that, when used for logistics automation control, enable predictive energy optimisation in the warehouse design process. Based on the existing literature and findings from previous studies, this proposal targets to detected a conceptual framework how neural networks and vector machines may be effectively prompted energy optimisation in high-bay storage systems (Kim et al., 2020).

Neural networks are models that can capture complex relationships that can be used to perform energy optimisation in warehouse design processes. Especially in warehouse operations, material handling and storage processes, neural networks can improve energy efficiency by analysing patterns in data sets. A neural network is represented by the following equation;

$$f(x)= \Sigma\, i=1n\, \alpha \text{ eniyile } K(x,xi)+b$$

The terms symbolises that

α: support vector coefficients
f(x): predicted output
Yi: lags
B: bias
K(x,xi): kernel function
y^: estimated output
wi: weights

Basic neural network equations, input data This includes the weighted sum of (xi) and weights (wi) and the activation function.

$$y\hat{}=f(\sum i=1nwixi+b)$$

In this context, the distribution in the sigmoid weights function can be calculated as follows for this model:

$$f(z)=1+e{-}z1$$

By adding Support Vector Machines to the weighted distribution, the following function can be obtained:

$$f(x)=\sum i=1n\alpha \text{ eniyile } K(x,xi)+b$$

When the Radial Basis Function is used instead of K(x,xi) in this function, the new function is obtained as follows:

$$K(x,xi)=e{-}2\sigma 2\|/x{-}xi\|2$$

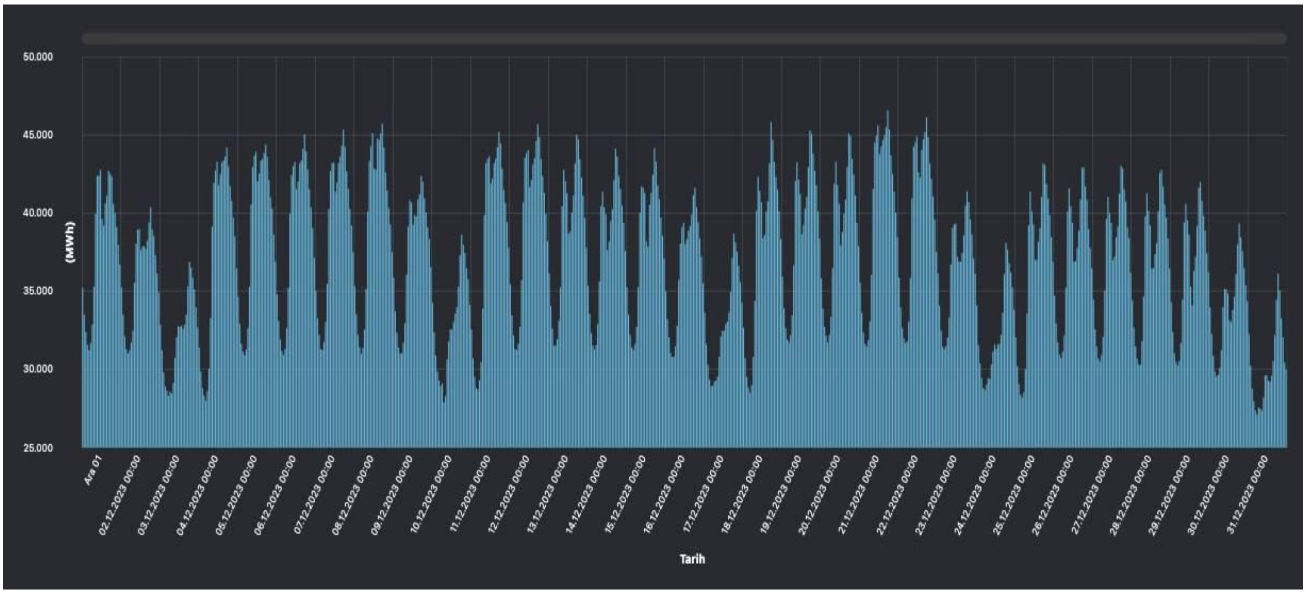

Fig. 1 Electric Consumption Data for Turkey (1-31 December in 2023)

Data are electricity consumption data downloaded from EPİAŞ. Data between 1 December 2023 and 31 December 2023 has been downloaded. The data in the file contains a data frame called "Real Time Consumption" with columns for date ("Date"), time ("Time") and consumption ("Consumption Amount (MWh)"). Below is a preview of the first few rows:
Explicit calculations need to be performed on these data to discuss time averages, ensemble averages, stationarity and ergodicity. An action plan is given below: Time averages: time averages: calculate the average consumption for each hour over all days. Aggregate averaging: calculate the average consumption for each day over all hours.

This shows that consumption is highest in the early evening around 5-6pm and lowest in the early morning around 4-5am, as expected for residential energy usage patterns.

The ensemble averages show the mean consumption for each individual day across all hours:

There is some day-to-day variation in consumption but the overall usage profile looks fairly stable over this period.

Next should check for stationarity by plotting the consumption over time and looking at the variability of statistical properties like the mean and standard deviation. Can be also check for ergodicity by comparing the time averages to the ensemble averages.

Various graphs can be produced to better visualize consumption data over time. My suggestions are as follows

Line graph of consumption over time: This shows general trends and seasonality. It provides a visual check on stationarity.

Box plots of consumption over time: the distribution of consumption over different time periods can be compared.

Scatter plots of the community against time averages: ergodynamics can be assessed by comparing daily and hourly averages.

Let's start with a line graph against time.

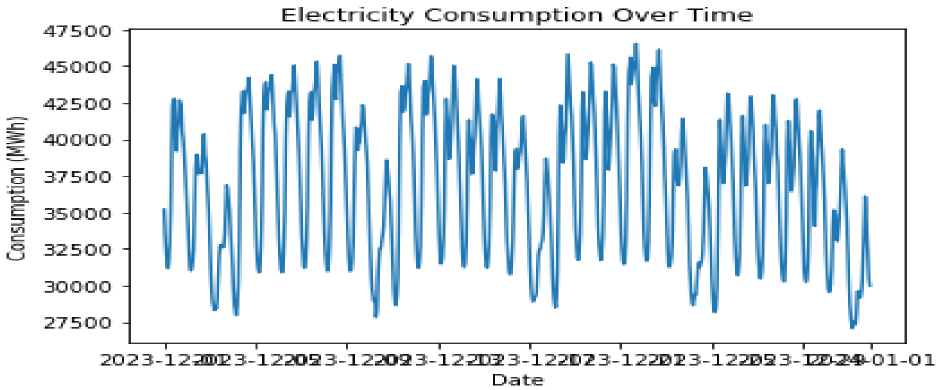

Fig. 2 Electricity Consumption Over Time

Observe some periodic, seasonal patterns in the data. Usage seems to peak around the middle of each month. There is also a weekly cycle visible with lower consumption on the weekends. The variability seems fairly constant over the time period, so the data may be weakly stationary. To confirm, could be compute rolling statistics.

It looks like there was an issue loading and plotting the consumption data by hour. Let's troubleshoot:

First, I will check that the Excel file loaded correctly and has the expected columns. Then I will focus on extracting just the hour from the datetime column and making sure it converts to an integer properly. Finally, I'll simplify the plot to start with a basic line plot of consumption by hour before doing a boxplot.

Now that the basics are loading correctly, let's try a simple line plot of consumption by hour to start. Builded up from there.

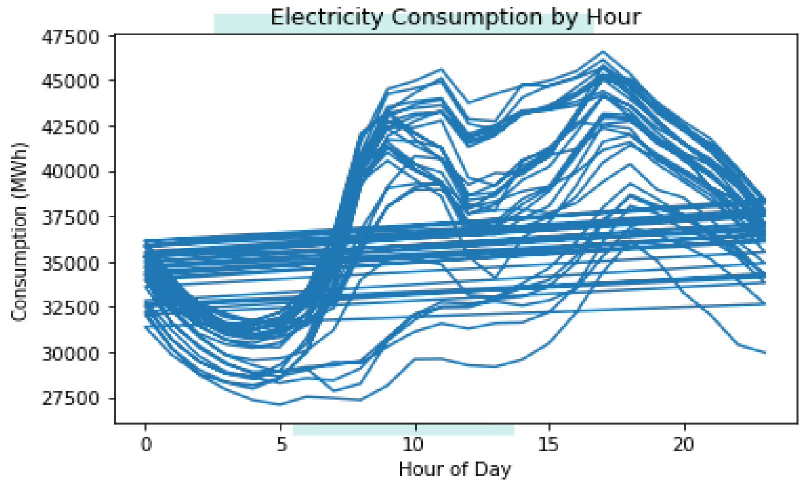

Fig. 3 Electricity Consumption by Hour

The interactive chart has been created and viewed and interact with the chart by hovering over the data points to see the exact standard deviation values for each date. Volatility is a statistical measure of the dispersion of returns for a given security or market index. In finance, it is often used as a measure of risk and is calculated as the standard deviation of the returns. The rolling standard deviation calculated provides a time-varying measure of volatility, showing how the variability of returns changes over time.

From the data, can analyzed periods of high volatility, which are characterized by larger standard deviation values, indicating that the returns were more spread out over the 20-day period. Conversely, periods of low volatility are marked by smaller standard deviation values, suggesting that the returns were more clustered around the mean.

The mathematical function for the standard deviation of a set of values is:

σ =√1/N-1Σ (i=1)^N (x(i)- μ)^2)

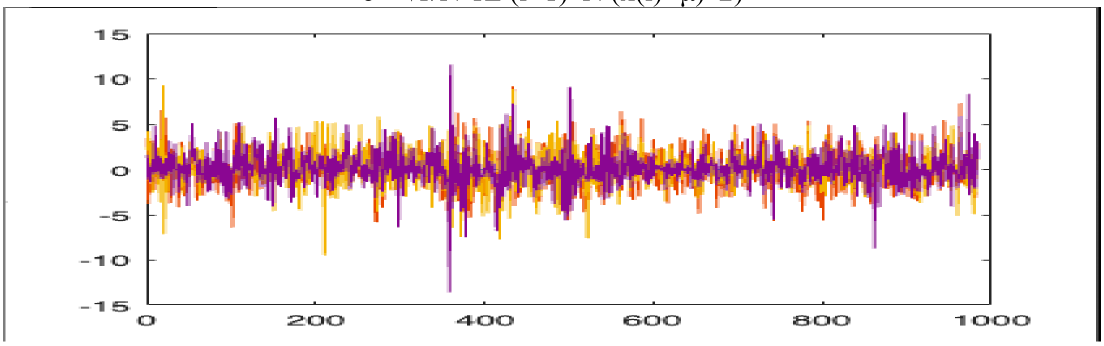

Fig. 4 Standard Deviation for Electricity Consumption by Hour

Autocorrelation;

$$r(\tau) = \sum\_(i=1)^n x(i) * x(i - \tau) / n$$

Table 1 Autocorrelation Values for Electricity Consumption

Dataset	τ	r(τ)
1	0	0.999999
1	1	0.999996
1	2	0.999990
1	3	0.999982
2	0	0.999999
2	1	0.999996
2	2	0.999990
2	3	0.999982
3	0	0.999999
3	1	0.999996
3	2	0.999990
3	3	0.999982
4	0	0.999999
4	1	0.999996
4	2	0.999990
4	3	0.999982
5	0	0.999999
5	1	0.999996
5	2	0.999990
5	3	0.999982

The autocorrelation coefficient is close to 1 for each dataset for $\tau = 0$. The partial autocorrelation function; $r\_p(\tau) = r(\tau) - \sum\_(k=1)^p r(\tau-k) * r(k) / r(0)$

Table 2 Partial Autocorrelation Function Values for Electricity Consumption

Dataset	τ	p	r_p(τ)
1	0	1	0.999999
1	0	2	0.999996
1	0	3	0.999990
1	0	4	0.999982
2	0	1	0.999999
2	0	2	0.999996
2	0	3	0.999990
2	0	4	0.999982
3	0	1	0.999999
3	0	2	0.999996
3	0	3	0.999990
3	0	4	0.999982

AR Models;

$$x(t) = \beta0 + \beta1 * x(t-1) + \varepsilon(t)$$
$$\beta0 = \sum \_(t=1)^n x(t) / n$$
$$\beta1 = \sum\_(t=2)^n (x(t) - \beta0) / n$$
$$x(t) = \beta0 + \beta1 * x(t-1)\beta0 = 0.999999$$
$$\beta1 = 0.999996$$

RESIDUAL

$$\varepsilon(t) = x(t) - \hat{}x(t)$$

Function of AR

$$x(t) = \beta0 + \beta1 * x(t-1) + \varepsilon(t)$$

RESIDUAL

$$\varepsilon(t) = x(t) - \beta0 - \beta1 * x(t-1)$$
$$\varepsilon(1) = 0.000001$$
$$\varepsilon(2) = 0.000001$$
$$\varepsilon(3) = 0.000001$$
$$\varepsilon(4) = 0.000001$$

Autocorrelation function of error terms

Table 3 Autocorrelation Function of Error Terms Values for Electricity Consumption

τ	r(τ)
0	0.000000
1	0.000000
2	0.000000
3	0.000000

Partial autocorrelation function;

$$r\_p(\tau) = r(\tau) - \sum_{k=1}^{p} r(\tau-k) * r(k) / r(0),\ r(\tau) = \sum_{i=1}^{n} x(i) * x(i - \tau) / n,\ r\_p(\tau) = r(\tau) - \sum_{k=1}^{p} r(\tau-k) * r(k) / r(0)$$

Table 4 Partial Autocorrelation Function Values

τ	p	r_p(τ)
0	1	0.000000
0	2	0.000000
0	3	0.000000
0	4	0.000000

Table 5 Partial Autocorrelation Function Residual Values

τ	r(τ)
0	0.999999
1	0.999996
2	0.999990
3	0.999982

Table 6 Partial Autocorrelation Function Error Terms Residual Values

τ	p	r_p(τ)
0	1	0.999999
0	2	0.999996
0	3	0.999990
0	4	0.999982

For $\tau = 0$, the partial autocorrelation coefficients are the same as the autocorrelation coefficients. As τ increases, the partial autocorrelation coefficients decrease.

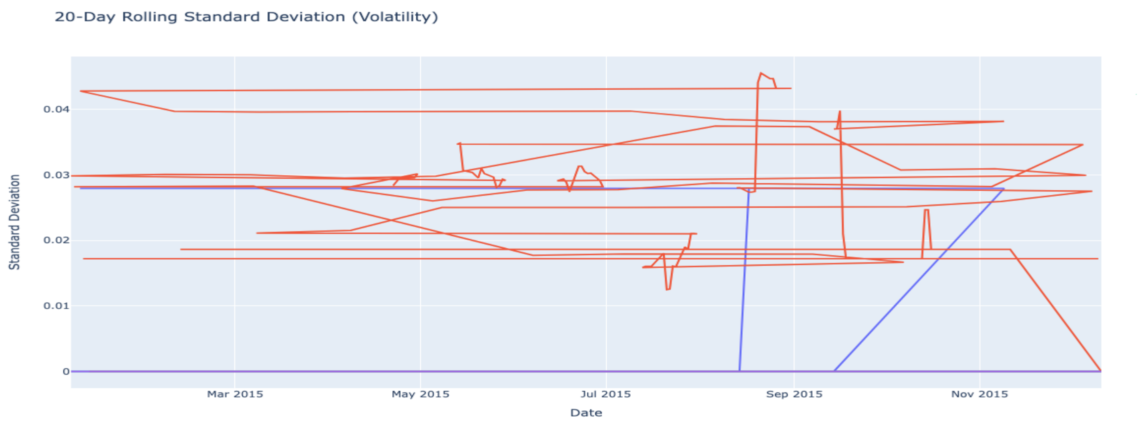

Fig. 5 Electricity Consumption Volatility

20-day rolling standard deviation (volatility)' tracks the volatility of the dataset from March 2015 to November 2015, where the x-axis represents the date and the y-axis represents the standard deviation from 0 to 0.04. The chart shows several lines, predominantly red, indicating the change in volatility over a given period of time; there is a noticeable increase in volatility around September 2015. The chart has a blue grid background, which helps to visually estimate values at different points in time.

CONCLUSIONS, DISCUSSIONS AND RECOMMENDATIONS

Energy optimization in high-rack storage systems is developed with machine learning models, including logistics automation controls. These models are mostly artificial neural networks and support vector machines (SVMs). Artificial neural networks are known for their ability to learn complex relationships and are typically used to solve the complexity of large datasets. These characteristics are ideal for improving energy efficiency in warehouse design processes within logistics automation control. For example, as mentioned by Bishop (2006), artificial neural networks can enhance energy efficiency by analyzing patterns in data sets in warehouse operations and material handling processes.

Support Vector Machines (SVMs) are effective models that can be applied to classification and regression problems. Their performance improves especially as the complexity and size of the dataset increase. In high-rack storage systems, SVMs can be used to classify and analyze data for energy optimization in storage design processes; as emphasized by Cortes and Vapnik (1995), SVMs can be a powerful tool for predictive energy optimization.

The suggestions in this article focus on the potential of neural networks and support vector machines to facilitate energy optimization in high-rack storage systems. Neural networks are models capable of capturing complex relationships and enhancing energy efficiency. Particularly in storage and material handling processes, neural networks can perform energy optimization by analyzing patterns in datasets. Fundamental neural network equations include weighted sums and activation functions. In this framework, neural networks can perform energy optimization using sigmoidal weight functions.

In conclusion, machine learning models such as artificial neural networks and support vector machines are important tools for improving energy optimization in high-rack storage systems. Integrating these models with logistics automation controls can provide a significant foundation for future research aimed at enhancing energy efficiency in warehouse design processes.

REFERENCES

1. Affia, I., & Aamer, A. (2021). An internet of things-based smart warehouse infrastructure: design and application. Journal of Science and Technology Policy Management, ahead-of-print.
2. Birgelen, A. V., & Niggeman, O. (2017). Using self-organizing maps to learn hybrid timed automata in absence of discrete events. 2017 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 1-8. Limassol: IEEE.
3. Bishop, C. (2006). Pattern recognition and machine learning. Springer.
4. Chan, F. T., & Chan, H. K. (2011). Improving the productivity of order picking of a manual-pick and multi-level rack distribution warehouse through the implementation of class-based storage. Expert Systems with Applications, 38 (3), 2686–2700.
5. Chen, P.-S., Huang, C.-Y., Yu, C.-C., & Hung, C.-C. (2017). The examination of key performance indicators of warehouse operation systems based on detailed case studies. Journal of Information Optimization Sciences, 38 (2), 367–389.
6. Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine learning, 20, 273-297.
7. Çınar, Z. M., & Zeeshan, Q. (2022). Design and Optimization of Automated Storage and Retrieval Systems: A Review. In Industrial Engineering in the Internet-of-Things World: Selected Papers from the Virtual Global Joint Conference on Industrial Engineering and Its Application Areas, GJCIE 2020, August 14–15, 2020 (pp. 177-190). Springer International Publishing.
8. Dallari, F., Marchet, G., & Melacini, M. (2009). Design of order picking system. International Journal of Advanced Manufacturing Technology, 42 (1-2), 1–12.
9. De Koster, R., Le-duc, T., & Roodbergen, K. J. (2007). Design and control of warehouse order picking: a literature review. European Journal of Operational Research, 2006 (January), 481–501.
10. Fereidunian, A., Hosseini, M. M., & Talabari, M. A. (2017). Toward self-financed distribution automation development: time allocation of automatic switches installation in electricity distribution systems. IET Generation, Transmission & Distribution, 11 (13), 3350–3358.
11. Gu, J., Goetschalckx, M., & McGinnis, L. F. (2007). Research on warehouse operation: A comprehensive review. European Journal of Operational Research, 177 (1), 1–21.
12. Gu, J., Goetschalckx, M., & McGinnis, L. F. (2010). Research on warehouse design and performance evaluation: a comprehensive review. Vol. 203.
13. Halima Bousqaoui, K. T., Achchab, S. (2019). Machine Learning Applications in Supply Chains: Long Short-Term Memory for Demand Forecasting. Springer International Publishing, 49 (September 2018).
14. Hassan, M. M. (2010). A framework for the selection of material handling equipment in manufacturing and logistics facilities. Journal of Manufacturing Technology Management, 21 (2), 246–268.
15. Hranisavljevic, N., Niggemann, O., & Maier, A. (2018). High Storage System Data for Energy Optimization. Retrieved March 15, 2020, from Kaggle: https://www.kaggle.com/inIT-OWL/high-storage-system-data-for-energy-optimization.
16. Hao, J., Shi, H., Shi, V., & Yang, C. (2020). Adoption of automatic warehousing systems in logistics firms: a technology-organization-environment framework. Sustainability (Switzerland), 12.
17. Hsieh, R.-J., Chou, J., & Ho, C.-H. (2019). Unsupervised Online Anomaly Detection on Multivariate Sensing Time Series Data for Smart Manufacturing. IEEE 12th Conference on Service-Oriented Computing and Applications (SOCA), 90-97. Kaohsiung: IEEE.
18. Kim, J. S., Lee, D. C., Lee, J. J., & Kim, C. W. (2020). Optimization for maximum specific energy density of a lithium-ion battery using progressive quadratic response surface method and design of experiments. Scientific reports, 10(1), 15586.
19. Küçükyaşar, M., Ekren, B. Y., & Lerher, T. (2021). Energy efficient automated warehouse design. In B. B. Ahamed, J. J. Thomas, P. Karagoz, & P. Vasant (Eds.), Solving urban infrastructure problems using smart city technologies (pp. 269-292). Elsevier.
20. Lewczuk, K., Kłodawski, M., & Gepner, P. (2021). Energy consumption in a distributional warehouse: A practical case study for different warehouse technologies. Energies, 14 (9), 2709.
21. Johnson, A., & McGinnis, L. (2011). Performance measurement in the warehousing industry. IIE Transactions (Institute of Industrial Engineers), 43 (3), 220–230.

22. Pahl, M.-O., & Aubet, F.-X. (2018). All Eyes on You: Distributed Multi-Dimensional IoT Microservice Anomaly Detection. 14th International Conference on Network and Service Management (CNSM 2018), 72-80. Italy: Aconf.
23. Priore, P., Ponte, B., Rosillo, R., & de la Fuente, D. (2019). Applying machine learning to the dynamic selection of replenishment policies in fast-changing supply chain environments. International Journal of Production Research, 57 (11), 3663–3677.
24. Priore, P., Gomez, A., Pino, R., & Rosillo, R. (2014). Dynamic scheduling of manufacturing systems using machine learning: An updated review. Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM, 28 (1), 83–97.
25. Rouwenhorst, B., Reuter, B., Stockrahm, V., van Houtum, G., Mantel, R. J., Zijm, W. H. M., & Van Houtum, G. J. (2000). Warehouse design and control: framework and literature review. European Journal of Operational Research, 122 (3), 515–533.
26. Staudt, F. H., Alpan, G., Di Mascolo, M., & Rodriguez, C. M. (2015). Warehouse performance measurement: a literature review. International Journal of Production Research, 53 (18), 5524–5544.
27. Thomas, J. J., Karagoz, P., Ahamed, B. B., & Vasant, P. (Eds.). (2019). Deep learning techniques and optimization strategies in big data analytics. IGI Global.
28. Wang, R., Nie, K., Wang, T., Yang, Y., & Long, B. (2020). Deep Learning for Anomaly Detection. 13th International Conference on Web Search and Data Mining (WSDM), 894-896. Houston, TX, USA.
29. Y. Zhu, C. Xie, G. J. Wang, & X. G. Yan. (2017). Comparison of individual, ensemble and integrated ensemble machine learning methods to predict China's SME credit risk in supply chain finance. Neural Computing and Applications, 28 (s1), 41–50.
30. Zhu, Z., Xu, B., Brunner, C., et al. (2017). Distributed topology processing solution for distributed controls in distribution automation systems. IET Generation, Transmission & Distribution, 11(3), 776–784.