Vol. 6, No. 3, 2024

Andriy Andrushko[1], Vasyl Tomiuk[2]

[1]Computer Design Systems Department, Lviv Polytechnic National University,
12, St. Bandera str., Lviv, Ukraine, E-mail: andrii.m.andrushko@lpnu.ua, ORCID 0000-0003-4229-7589
[2]Computer Design Systems Department, Lviv Polytechnic National University,
12, St. Bandera str., Lviv, Ukraine, E-mail: vasyl.v.tomiuk@lpnu.ua, ORCID 0000-0003-4999-7019

LEVERAGING IOT DATA FOR ACCURATE TEMPERATURE FORECASTING IN THE FOOD AND BEVERAGE INDUSTRY

Received: November 20, 2024 / Revised: November 25, 2024 / Accepted: November 30, 2024

https://doi.org/

Abstract. In the food and beverage industry, maintaining optimal temperature conditions is crucial for ensuring product quality and safety. The advent of the Internet of Things (IoT) has enabled real-time temperature monitoring through sensor networks, providing a wealth of data that can be harnessed for predictive analytics. This study presents a robust method for analyzing and forecasting IoT temperature data, specifically tailored to the operational dynamics of the food and beverage sector. By leveraging exponential smoothing techniques and a learning approach, we aim to present an algorithm capable of delivering accurate temperature forecasts to support proactive decision-making.

Keywords: IoT, data, temperature forecasting, food and beverage industry, exponential smoothing, time series analysis, seasonality.

Introduction and Problem Statement

The IoT is an emerging paradigm that aims to unify physical objects through the deployment of various network architectures, including ad-hoc networks and the Internet [1]. However, the mere application of IoT systems is not enough. To deliver meaningful information to managers, IoT data must be properly processed. Enterprises can use data analytics tools to transform a huge volume of sensor-collected data into valuable insights [2]. Data analytics can help optimize operational processes, forecast demand, and enable predictive maintenance of equipment, ensuring minimal downtime and reducing maintenance costs [3].

The utilization of IoT data to support managers is particularly important in the food and beverage industry, as IoT implementation in this industry is a relatively new phenomenon. The future of the hospitality management industry is being shaped by the current boom in IoT technology [4]. Moreover, the integration of new technologies, particularly those based on IoT, is expected to bring safer, more efficient, and sustainable food chains in the near future [5].

This article aims to present a robust algorithm for analyzing IoT data and forecasting future events in the food and beverage industry to support managerial decisions. By leveraging the unique characteristics of IoT data and addressing the specific operational dynamics of the industry, the proposed algorithm can be implemented in software systems to provide managers with actionable insights that can enhance monitoring, improve efficiency, and ensure better quality control.

Main Material Presentation

IoT Data in the Food and Beverage Sector. The hospitality industry encompasses a broad range of services, including accommodation, food and beverage, and other services. Within this expansive industry, the food and beverage sector represents a substantial component, focused on preparing, presenting, and serving food and beverages to customers either on-premise (at restaurants and hotels) or off-premise (through takeaway, restaurant catering services, and food delivery) [6].

Within the food and beverage industry, IoT data is extremely vital for monitoring and maintaining optimal operational conditions. The main variables measured by IoT systems include temperature, pressure, humidity, and flow rates [3]. Among these, temperature is especially critical, as it directly relates to food safety standards and regulations. Monitoring temperature ensures that perishable goods are stored correctly, reducing the risk of spoilage and contamination. Other variables, such as pressure and humidity, also play crucial roles in maintaining the quality of food and beverages, as well as contributing to overall operational efficiency.

IoT systems collect and store data as time series, necessitating the use of appropriate forecasting approaches to analyze and predict future conditions. The specific system considered in this study involves refrigerators used in restaurants, cafes, hotels, and similar establishments where food and beverages are stored. These refrigeration systems are designed to maintain temperatures within predefined limits, meaning we can assume no long-term trend in the data. Instead, the focus is on detecting and managing short-term fluctuations and patterns.

One significant pattern in the data is daily seasonality, influenced by the operational specifics of the food and beverage industry. There are certain day periods when customer demand peaks, such as during breakfast, lunch, and dinner times. During these periods, refrigerators are accessed and utilized more frequently, which can impact the temperature they maintain. Understanding these daily operational patterns is crucial for accurate forecasting and effective management of refrigeration systems. So, the ability to forecast temperature fluctuations accurately can help managers in the food and beverage industry make informed decisions, optimize their operations, and maintain high standards of quality and safety.

Metodology – the forecast algorithm. The existence of efficient algorithms for analyzing IoT data is an important aspect of IoT big data [7]. Therefore, in the pursuit of a more accurate temperature forecasting model for the hospitality sector, we propose a refined algorithm that integrates deseasonalization techniques, exponential smoothing and continuous learning approach.

Exponential smoothing is chosen for this algorithm because it is a more generalized technique that is used with discrete time series and does not explicitly account for a trend [8, 9], unlike methods such as the decomposition method or regression equations. Given that our data is assumed to have no trend, exponential smoothing is particularly suitable for short-term forecasting where the primary focus is on capturing recent trends. Accounting for seasonality aligns well with the operational characteristics of refrigerators in the industry. Furthermore, testing different time spans allows the algorithm to identify the most accurate data segments by considering varying lengths of historical data, enhancing its robustness and flexibility.

The algorithm leverages deep learning techniques, which in this context refers to its ability to adapt and learn from data dynamically. This includes testing different smoothing constants to determine the optimal balance between recent and older data -- in order to select the right constants for forecasting, different values are tried out on past time series, and the ones that minimize an error function like Mean Absolute Deviation (MAD) or Mean Squared Error (MSE) are the ones used for forecasting [10]. Also, the algorithm uses different time spans of 7-day, 15-day, and 30-day periods, and utilizes a moving window of recent data to ensure it remains focused on current trends and behaviors.

The following steps outline our comprehensive approach:

1. Preliminary Configuration.

• Always start with the most recent data available.

• Choose three different time spans as the base for the forecast: 7-day, 15-day, and 30-day periods. The latest day in the dataset should be the end for all these periods.

• For each time span, perform steps 2-4.

2. Data Aggregation and Initial Analysis.

• Aggregate the temperature data into the defined daytime periods: night (12:00 a.m. – 6:00 a.m.), morning (6:00 a.m. – 12:00 p.m.), afternoon (12:00 p.m. – 6:00 p.m.), and evening (6:00 p.m. – 12:00 a.m.). Calculate the average temperature for each of these periods daily.

• Analyze the aggregated data for seasonality within each day to identify patterns of fluctuation between periods (e.g., night to morning, morning to afternoon, etc.). Plot the data to visualize these patterns.

• Calculate the overall average temperature and seasonal indices for each period (night, morning, afternoon, evening) based on the selected time span.

3. Deseasonalization.

• If seasonality exists, deseasonalize the data by dividing each record by its appropriate seasonal index. If there is no seasonality, simply move to step 4.

• Use the deseasonalized data for further analysis.

4. Simultaneous Testing of Time Spans and Smoothing Constants.

• For each time span (and its respective averages and seasonal indices), apply exponential smoothing with four different smoothing constants (α): 0.1, 0.5, 0.7, and 0.9.

• For each combination of time span and smoothing constant, calculate the mean absolute deviation (MAD) and the mean absolute percent error (MAPE).

• Select the time span and smoothing constant combination that yields the lowest MAD and MAPE.

5. Develop the Forecast.

• Base the forecast on the aggregate data from the selected time span. This will provide a general point of reference for the next period of six hours.

• If the forecast was developed with the deseasonalized data, reseasonalize the forecasted values by multiplying them by their respective seasonal indices to arrive at the final forecast.

6. Continuous Updating.

• Repeat the entire algorithm daily as new data is collected. For example, when data for July 8 is available, update the analysis and repeat the testing for the 7-day, 15-day, and 30-day periods ending on July 8. This ensures that the method uses the most recent data, and any changes in temperature behavior are captured and accounted for in the forecasts.

Algorithm testing and validation. To verify the validity of the proposed algorithm, we used a real dataset of temperature measurements collected via an IoT sensor system. Sensors were installed in refrigerators, and the data was collected over three months, from December 11, 2023, to March 15, 2024. The complete dataset consisted of 3,737 records. After cleaning the data, the final dataset included 3,267 records. This final dataset was used to test and validate the forecast algorithm described previously. We follow the algorithm and describe each step.

Results and Discussion

Preliminary configuration. We tested the algorithm with three moving time windows. This method ensures that the analysis or forecast remains relevant by consistently incorporating the most recent data, thereby capturing the latest trends and patterns.

February 15 was chosen as the end date for the first window, February 16 and February 17 for the second and third windows, respectively. The real measurements from February 16, 17, and 18 were supposed to be used to test tracking signals after the optimal forecast approach is chosen according to the algorithm. For each time window, three different forecast bases of 7-day, 15-day, and 30-day time spans were identified. The details of each forecast base are shown in Table 1.

For each time span within every moving window, the data was aggregated based on the assumed daily seasonality in the food and beverage industry operations. The temperature measurements within each day were aggregated as follows:

• *Night*: Measurements from 12:00 a.m. up to (but not including) 6:00 a.m.

• *Morning*: Measurements from 6:00 a.m. up to (but not including) 12:00 p.m.

• *Afternoon*: Measurements from 12:00 p.m. up to (but not including) 6:00 p.m.

• *Evening*: Measurements from 6:00 p.m. up to (but not including) 12:00 a.m.

Table 1

Time spans (forecast bases) for three moving windows.

Moving Windows	7-Day Time Span		15-Day Time Span		30-Day Time Span	
	Start Date	**End Date**	**Start Date**	**End Date**	**Start Date**	**End Date**
#1 -- Ending Feb 15	Feb 9	Feb 15	Feb 1	Feb 15	Jan 17	Feb 15
#2 -- Ending Feb 16	Feb 10	Feb 16	Feb 2	Feb 16	Jan 18	Feb 16
#3 -- Ending Feb 17	Feb 11	Feb 17	Feb 3	Feb 17	Jan 19	Feb 17

Data Aggregation and Initial Analysis. For each of these periods (night, morning, afternoon, and evening), average temperature values were calculated. After these calculations, a new dataset with four temperature values for each day was formed. Next, the overall average temperature and seasonal indices for each time span within each moving window were calculated (Table 2).

Table 2 (a)

Average temperature and seasonal indices for the Moving Window #1

	7-Day Time Span		15-Day Time Span		30-Day Time Span	
Season	**Average**	**S. Index**	**Average**	**S. Index**	**Average**	**S. Index**
night	2.65	0.99	2.12	0.88	2.05	0.89
morning	2.86	1.07	2.61	1.08	2.46	1.07
afternoon	2.82	1.06	2.62	1.08	2.54	1.10
evening	2.35	0.88	2.34	0.96	2.15	0.94
Overall average	2.67		2.42		2.30	

Table 2 (b)

Average temperature and seasonal indices for the Moving Window #2

	7-Day Time Span		15-Day Time Span		30-Day Time Span	
Period	**Average**	**S. Index**	**Average**	**S. Index**	**Average**	**S. Index**
night	2.48	0.89	2.06	0.82	2.00	0.87
morning	2.92	1.05	2.75	1.09	2.47	1.07
afternoon	2.98	1.07	2.79	1.11	2.55	1.11
evening	2.73	0.98	2.50	0.99	2.19	0.95
Overall average	2.78		2.53		2.30	

Table 2 (c)

Average temperature and seasonal indices for the Moving Window #3

	7-Day Time Span		15-Day Time Span		30-Day Time Span	
Period	**Average**	**S. Index**	**Average**	**S. Index**	**Average**	**S. Index**
night	2.65	0.94	2.21	0.86	2.06	0.88
morning	2.95	1.04	2.76	1.08	2.51	1.07
afternoon	3.03	1.07	2.81	1.09	2.58	1.10
evening	2.70	0.95	2.49	0.97	2.20	0.94
Overall average	2.83		2.57		2.34	

The analysis of Table 2 reveals consistent seasonality in the temperature data across all moving windows and time spans. The morning and afternoon periods typically show higher temperatures, while the night and evening periods show lower temperatures. These findings validate the presence of daily seasonality, indicating that the next steps should involve data deseasonalization to remove these patterns. This process will allow the forecast algorithm to focus on other underlying trends and provide more accurate predictions.

Testing time spans and smoothing constants. After the data was deseasonalized, we applied exponential smoothing to identify the time span that yields the lowest mean absolute deviation (MAD) and mean absolute percent error (MAPE). Exponential smoothing was applied to each time span using four different smoothing constants (α): 0.1, 0.5, 0.7, and 0.9. These constants were chosen to observe the impact of different weights on the previous time periods.

For each combination of time span and smoothing constant, MADs and MAPEs were calculated. The results are shown in Table 3.

Table 3

MADs and MAPEs for all time spans and moving windows

Moving Window	Accuracy Measures	TIME SPANS											
		7-Day				**15-Day**				**30-Day**			
Smoothing constants		***α = 0.1***	***α = 0.5***	***α = 0.7***	***α = 0.9***	***α = 0.1***	***α = 0.5***	***α = 0.7***	***α = 0.9***	***α = 0.1***	***α = 0.5***	***α = 0.7***	***α = 0.9***
#1 -- Ending Feb 15	MAD	0.7622	0.5961	**0.5708**	0.5795	0.7848	0.7531	0.7358	**0.6902**	0.663	**0.6023**	0.6428	0.6133
	MAPE	45.72 %	40.60 %	38.52 %	**37.52%**	96.80%	95.00%	85.98%	**75.67%**	99.27 %	**80.27 %**	89.02 %	82.00%
#2 -- Ending Feb 16	MAD	0.6787	0.6755	0.6273	**0.5663**	0.8156	0.8103	0.7836	**0.7272**	0.6914	0.6853	0.6702	**0.6322**
	MAPE	55.79 %	47.33 %	41.26 %	**35.06%**	94.74%	92.35%	82.27%	**70.32%**	102.80 %	97.57 %	91.02 %	**83.18%**
#3 -- Ending Feb 17	MAD	0.6941	0.6451	0.5947	**0.5407**	0.7758	0.7478	0.7241	**0.6705**	0.7197	0.6825	0.6645	**0.6284**
	MAPE	59.83 %	46.28 %	40.12 %	**34.23%**	92.52%	89.28%	79.30%	**67.37%**	105.45 %	97.05 %	90.38 %	**82.68%**

For Moving Window #1, the combination of a 7-day time span and a smoothing constant of 0.7 produced the lowest MAD, indicating the best accuracy. This suggests that a shorter, recent data-focused approach with a moderate weight on the most recent data is effective in this context.

For Moving Window #2, a similar trend is observed with the 7-day time span and a smoothing constant of 0.9 yielding the lowest MAD and MAPE. This consistency across different windows further supports the reliability of these combinations for accurate forecasting.

For Moving Window #3, once again, the 7-day time span with a smoothing constant of 0.9 resulted in the lowest MAD and MAPE. This recurring pattern across all windows suggests that the 7-day time span with a high weighting on recent data is the optimal choice for the given dataset.

Forecast development and signals tracking. Tracking signals are critical in validating forecasts by measuring the cumulative forecast error over time and comparing it to acceptable limits. This helps to identify if the forecast remains within a tolerable range or if adjustments are needed. The tracking signal is calculated by dividing the running sum of forecast errors (RSFE) by the mean absolute deviation (MAD). Typically, tracking signals are set to be within ±3 MADs, as this is a common threshold used to detect significant deviations in forecasting.

The results of the forecast development and validation using tracking signals are summarized in Table 4.

The tracking signals indicate that the forecast for Moving Window #1 exceeds the acceptable range of ±3 MADs, suggesting possible issues with the forecast for this period. However, this discrepancy can be attributed to the abnormal temperature values observed on February 15 ("0.48" is far below the temperature ranges the system should maintain). Since the moving window #1 embraces the first four periods in our forecast, the rest of the periods also exhibit tracking signals that are out of the acceptable range. To further analyze the robustness of the forecast algorithm, we exclude the first window and focus on forecasts for February 17 and February 18, as shown in Table 5.

Table 4

Forecasts and Tracking Signals for February 16, February 17, and February 18

Moving Window	**Season**	**Time period**	**Forecast value**	**Actual value**	**Error**	***RSFE***	**Absolute error**	**Cum. error**	***MAD***	**Tracking signal**
#1 -- Ending Feb 15	night	1	1.01	0.48	-0.53	-0.53	0.53	0.53	0.53	-1.0
	morning	2	0.68	2.57	1.88	1.35	1.88	2.41	1.21	+1.1
	afternoon	3	1.98	3.31	1.33	2.68	1.33	3.74	1.25	+2.1
	evening	4	2.43	3.44	1.02	3.70	1.02	4.76	1.19	+3.1
#2 -- Ending Feb 16	night	5	3.08	3.42	0.34	4.03	0.34	5.10	1.02	+4.0
	morning	6	3.98	3.04	-0.94	3.09	0.94	6.04	1.01	+3.1
	afternoon	7	3.20	3.52	0.33	3.42	0.33	6.36	0.91	+3.8
	evening	8	3.20	3.21	0.01	3.42	0.01	6.37	0.80	+4.3
#3 -- Ending Feb 17	night	9	3.14	2.53	-0.61	2.81	0.61	6.98	0.78	+3.6
	morning	10	2.59	3.36	0.77	3.58	0.77	7.75	0.78	+4.6
	afternoon	11	2.98	3.47	0.49	4.07	0.49	8.24	0.75	+5.4
	evening	12	3.03	3.41	0.38	4.45	0.38	8.62	0.72	+6.2

Table 5

Forecasts and Tracking Signals for February 17 and February 18

Moving Window	**Season**	**Time period**	**Forecast value**	**Actual value**	**Error**	***RSFE***	**Absolute error**	**Cum. error**	***MAD***	**Tracking signal**
#2 -- Ending Feb 16	night	1	3.08	3.42	0.34	0.34	0.34	0.34	0.34	+1.0
	morning	2	3.98	3.04	-0.94	-0.60	0.94	1.28	0.64	-0.9
	afternoon	3	3.20	3.52	0.33	-0.28	0.33	1.60	0.53	-0.5
	evening	4	3.20	3.21	0.01	-0.27	0.01	1.61	0.40	-0.7
#3 -- Ending Feb 17	night	5	3.14	2.53	-0.61	-0.89	0.61	2.22	0.44	-2.0
	morning	6	2.59	3.36	0.77	-0.12	0.77	2.99	0.50	-0.2
	afternoon	7	2.98	3.47	0.49	0.37	0.49	3.48	0.50	+0.7
	evening	8	3.03	3.41	0.38	0.75	0.38	3.86	0.48	+1.6

By excluding the first window and focusing on the forecasts for February 17 and February 18, it can be seen that the tracking signals stay within the acceptable range of ±3 MADs. This indicates that the algorithm performs well when accounting for typical temperature variations, and deviations observed in Moving Window #1 are likely due to specific anomalies on February 15.

Overall, the results affirm that the forecasting algorithm, with the chosen time spans and smoothing constants, provides reliable forecasts. However, the presence of anomalies must be considered, and continuous monitoring with tracking signals is essential to maintain forecast accuracy.

Conclusions

In the food and beverage sector, IoT systems have become increasingly vital, providing real-time monitoring and management capabilities that enhance operational efficiency, ensure quality control, and support compliance with stringent food safety regulations. Today, many restaurant businesses invest in smart technologies to differentiate from competitors, deliver better service, and provide a good customer experience [11], therefore the role of sophisticated forecasting tools becomes increasingly important.

However, analysis of data without generating value offers no contribution to an organization, regardless of whether data are big or small [12]. So, in this article we aimed to present a robust method for

IoT data analysis and forecasting that is specifically designed for the food and beverage industry. By leveraging the unique characteristics of IoT data and addressing the industry's specific operational dynamics, this method seeks to provide managers with actionable insights and improve overall operational efficiency.

After presenting the algorithm, we demonstrated its application using a real-life dataset. The data was first aggregated based on daily seasonality, dividing each day into four distinct periods: night, morning, afternoon, and evening. Deseasonalization of the data was performed to remove inherent seasonal patterns, followed by the application of exponential smoothing to identify optimal smoothing constants. Additionally, learning approach was employed to find the data time spans that yield the most accurate forecast. The results of calculations on this particular dataset showed that greater smoothing constants of 0.7 and 0.9, and shorter time spans (7-day) produced more accurate forecasts. The tracking signal analysis, using a threshold of ±3 MADs, was instrumental in validating the accuracy of the forecasts.

Looking ahead, further research should explore other forecasting methods, such as the moving average and weighted moving average, to compare their effectiveness against the exponential smoothing approach. Also, the integration of advanced machine learning and AI techniques holds significant potential for enhancing forecasting accuracy and efficiency. By focusing on the described algorithm and its practical application, organizations in the food and beverage industry can achieve better forecast accuracy, ultimately leading to improved operational efficiency and customer satisfaction.

References

[1] F. Liu, C. W. Tan, E. T. K. Lim, & B. Choi, "Traversing knowledge networks: an algorithmic historiography of extant literature on the Internet of Things (IoT)", *Journal of Management Analytics*, 4(1), 2016, 3–34. https://doi.org/10.1080/23270012.2016.1214540

[2] E. Ahmed, I. Yaqoob, I. A. T. Hashem, I. Khan, A. I. A. Ahmed, M. Imran, A. V. Vasilakos, "The role of big data analytics in Internet of Things", *Computer Networks*, 129(2), 2019, 459-471, ISSN 1389-1286. https://doi.org/10.1016/j.comnet.2017.06.013

[3] A. M. Andrushko, "Leveraging smart measurement technologies for enhanced food and beverage servicing: a case study of the KYPS system" // COLLECTIVE MONOGRAPH "CAD IN MACHINERY DESIGN IMPLEMENTATION AND EDUCATIONAL ISSUES. XXXI INTERNATIONAL CONFERENCE", Publishing House of Bialystok University of Technology, Białystok, Poland, 2024, 161-171. DOI: 10.24427/978-83-68077-19-3

[4] P. Kansakar, F. Munir & N. Shabani, "Technology in the Hospitality Industry: Prospects and Challenges", *IEEE Consumer Electronics Magazine*, 8(3), 2019, 60-65. doi: 10.1109/MCE.2019.2892245

[5] Y. Bouzembrak, M. Klüche, A. Gavai & Hans J. P. Marvin, "Internet of Things in food safety: Literature review and a bibliometric analysis", *Trends in Food Science & Technology*, 94, 2019, 54-64, ISSN 0924-2244. https://doi.org/10.1016/j.tifs.2019.11.002

[6] [Electronic resource] M. Diaz, "How to manage hotel food and beverage services: redefining F&B in the hospitality industry", 2019, https://joinposter.com/en/post/hotel-food-and-beverage [Jul 11, 2023].

[7] Y. Sasaki, "A Survey on IoT Big Data Analytic Systems: Current and Future", *IEEE Internet of Things Journal*, 9(2), 2022, 1024-1036. doi: 10.1109/JIOT.2021.3131724

[8] E. Ostertagova & O. Ostertag, "The Simple Exponential Smoothing Model" // MODELLING OF MECHANICAL AND MECHATRONIC SYSTEMS 2011, The 4th International conference, Faculty of Mechanical engineering, Technical university of Košice, September 20 – 22, 2011, Herľany, Slovak Republic, 380-384.

[9] B. Render, R. M. Stair Jr., M. E. Hanna, T. S. Hale, "Quantitative Analysis for Management", 13th Edition, Pearson Education Limited, Edinburgh Gate, Harlow, Essex CM20 2JE, England, 2018.

[10] H. V. Ravinder, "Forecasting With Exponential Smoothing – What's The Right Smoothing Constant?", *Review of Business Information Systems*, 17 (3), 2013, 117-126.

[11] I. Tuncer, "Customer Experience in the Restaurant Industry: Use of Smart Technologies", Handbook of Research on Smart Technology Applications in the Tourism Industry, IGI Global, 2020. DOI: 10.4018/978-1-7998-1989-9.ch012

[12] R. H. L. Chiang, V. Grover, T. P. Liang, & D. Zhang, "Special Issue: Strategic Value of Big Data and Business Analytics", *Journal of Management Information Systems*, 35(2), 2018 383–387. https://doi.org/10.1080/07421222.2018.145195

Андрій Андрушко[1], Василь Том'юк[2]

[1]Кафедра систем автоматизованого проектування, Національний університет "Львівська політехніка", вул. Степана Бандери 12, Львів, Україна, E-mail: andrii.m.andrushko@lpnu.ua, ORCID 0000-0003-4229-7589
[2]Кафедра систем автоматизованого проектування, Національний університет "Львівська політехніка", вул. Степана Бандери 12, Львів, Україна, E-mail: vasyl.v.tomiuk@lpnu.ua, ORCID 0000-0003-4999-7019

ВИКОРИСТАННЯ IoT ДАНИХ ДЛЯ ТОЧНОГО ПРОГНОЗУВАННЯ ТЕМПЕРАТУРИ В СЕКТОРІ ГРОМАДСЬКОГО ХАРЧУВАННЯ

Отримано: Листопад 20, 2024 / Переглянуто: Листопад 25, 2024 / Прийнято: Листопад 30, 2024

Анотація. У секторі громадського харчуваня підтримка оптимальних температурних умов має вирішальне значення для забезпечення якості та безпеки продукції. Поява Інтернету речей (IoT) зробила можливим моніторинг температури в режимі реального часу за допомогою сенсорних мереж, надаючи велику кількість даних, які можна використовувати для прогнозної аналітики. У цьому дослідженні представлено метод аналізу даних IoT та прогнозування температури на основі цих даних. Метод спеціально адаптований до специфіки операційної динаміки сектору громадського харчуваня. Використовуючи експоненційне згладжування у поєднанні із елементами машинного навчання, у статті представлено алгоритм, здатний надавати точні прогнози температури для підтримки проактивного прийняття рішень.

Ключові слова: IoT, дані, прогноз температури, сектор громадського харчуваня, експоненційне згладжування, аналіз часових рядів, сезонність.