

# Forecasting fire emergencies using historical regional data: an experimental comparison of probabilistic-statistical methods

Oleh Staso<sup>1</sup>, Nazariy Burak<sup>1</sup>

<sup>1</sup> Lviv State University of Life Safety, 35, Kleparivska St., Lviv, Ukraine

## Abstract

Accurate forecasting of fire emergencies is essential for proactive decision-making in civil protection systems. This paper presents an experimental comparison of probabilistic-statistical forecasting methods applied to real regional fire incident data. The study is based on official records from the Lviv region of Ukraine covering the period from 2019 to 2024.

Historical data from 2019–2023 were used for model training and calibration, while forecasts for 2024 were evaluated using out-of-sample temporal validation. Within a unified experimental framework, four classes of methods were examined: seasonal naive time-series forecasting, machine learning regression, Bayesian probabilistic graphical models, and stochastic simulation-based approaches. Forecasting performance was assessed using standard accuracy metrics and computational efficiency indicators.

The results demonstrate meaningful differences in forecasting accuracy and computational cost across the evaluated approaches. Methods that explicitly account for uncertainty and stochastic variability show improved robustness in predicting aggregated fire incident counts, while simpler baseline models remain competitive in terms of efficiency. The findings support informed selection of forecasting methods for safety-oriented decision support systems under practical operational constraints.

## Keywords

Emergency forecasting, Fire emergencies, Probabilistic-statistical methods, Decision support system

## 1. Introduction

Emergency situations, particularly fires, remain one of the most frequent and destructive types of crises, posing significant threats to human life, infrastructure, and the environment. Effective emergency management increasingly depends not only on rapid response but also on the ability to anticipate potential incidents and allocate resources proactively. As emergency systems generate large volumes of heterogeneous data, traditional reactive approaches are often insufficient for supporting timely and well-grounded managerial decisions [1].

In recent years, probabilistic and statistical methods have become a cornerstone of modern decision support systems in crisis management. These approaches enable the modeling of uncertainty, estimation of risk levels, and forecasting of event dynamics under incomplete and noisy data conditions [1,2]. Machine learning models, time-series forecasting techniques, probabilistic graphical models, and Monte Carlo simulations are widely applied to disaster prediction, risk assessment, and scenario analysis across various domains, including safety engineering, infrastructure management, and environmental protection [3].

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<sup>\*</sup> Corresponding author.

<sup>†</sup> These authors contributed equally.

✉ staso.oleh@gmail.com (Oleh STASO); n.burak@ldubgd.edu.ua (Nazariy BURAK);

ORCID 0009-0005-6049-6161 (Oleh STASO); 0000-0002-3880-4077 (Nazariy BURAK)



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A comprehensive theoretical overview of probabilistic-statistical methods in crisis management, including their advantages, limitations, and application areas, was presented in our previous work [4]. That study demonstrated the potential of such methods for modeling crisis scenarios and supporting managerial decision-making under uncertainty. However, most existing research, including review-oriented studies, primarily focuses on methodological descriptions or isolated case applications, while comparative experimental evaluations on real emergency datasets remain limited [5, 6].

One of the key challenges identified in the literature is the lack of unified experimental frameworks for objectively comparing different classes of probabilistic-statistical methods [6]. Many studies rely on synthetic data, short time horizons, or single modeling approaches, which restricts the generalizability of their conclusions [7, 8]. Moreover, baseline models are often omitted, making it difficult to assess the actual predictive gain of complex techniques over simpler statistical approaches [3, 9].

This gap is particularly evident in the context of regional-level emergency forecasting, where long-term historical data are available but rarely used for systematic out-of-sample validation. Forecasting future emergency events using past observations and directly comparing predicted outcomes with real incidents provides a robust basis for evaluating model accuracy and practical applicability [10].

The present study addresses this limitation by conducting an experimental comparison of four major classes of probabilistic-statistical methods for forecasting fire emergencies: machine learning models, seasonal naive time-series forecasting, probabilistic graphical models, and Monte Carlo simulations. The experiments are based on an official dataset of all recorded fire incidents in the Lviv region of Ukraine from 2019 to 2024, provided by the regional emergency authority. Data from 2019-2023 are used for model training and parameter estimation, while forecasts for 2024 are evaluated against real observed events.

The main contributions of this paper are as follows:

- the use of a real, complete regional emergency dataset covering a six-year period;
- a unified experimental design for comparing fundamentally different probabilistic-statistical approaches;
- out-of-sample temporal validation using an unseen forecasting year;
- a quantitative assessment of prediction accuracy and error characteristics across methods.

By providing an objective experimental comparison, this study aims to support the selection of appropriate forecasting methods for safety-oriented decision support systems and contribute to the practical deployment of predictive analytics in emergency management.

## 2. Related Work

Forecasting emergency events, including fire incidents, has been widely studied in the fields of safety engineering, risk analysis, and disaster management. Existing research explores a broad spectrum of statistical, probabilistic, and data-driven approaches aimed at predicting emergency occurrence, supporting early warning systems, and improving resource allocation under uncertainty [1,11]. Most studies rely on historical data aggregated at national or regional levels, demonstrating the feasibility of forecasting-based decision support in civil protection systems.

Classical time-series models remain a common choice in emergency forecasting due to their simplicity and interpretability. Numerous studies emphasize the importance of seasonal patterns in fire occurrence, motivating the use of seasonal baselines and autoregressive approaches [9,10]. However, several authors note that many comparative studies omit simple baseline models, which complicates the objective evaluation of more complex techniques and obscures the actual

predictive gain of advanced methods [3,9]. As a result, the practical advantage of sophisticated forecasting approaches over naive seasonal assumptions often remains unclear.

Machine learning methods have been increasingly applied to disaster prediction and emergency management tasks, particularly for modeling non-linear relationships in large and heterogeneous datasets [3,11]. Applications include fire risk assessment, flood forecasting, and emergency demand prediction [7,8]. Despite their flexibility, existing studies report challenges related to model interpretability, sensitivity to feature selection, and limited generalization when applied to sparse or highly aggregated data [3,8]. Moreover, machine learning models are frequently evaluated in isolation, without systematic comparison to simpler statistical or probabilistic baselines, limiting their operational interpretability.

Probabilistic approaches play a central role in emergency forecasting by explicitly modeling uncertainty and stochastic variability in event occurrence. Bayesian models, particularly Poisson-based formulations, are well suited for count data and have been successfully applied to risk modeling and emergency prediction tasks [2,5]. Such models provide interpretable parameter estimates and enable uncertainty quantification, which is essential for safety-oriented decision support systems. Several studies highlight the robustness of Bayesian methods under limited data conditions and their suitability for operational deployment [2,14].

Monte Carlo simulation techniques further extend probabilistic models by enabling scenario-based forecasting and exploration of rare but high-impact events [12,13]. These approaches are especially relevant in emergency management, where extreme outcomes can dominate operational risk. However, simulation-based methods are often evaluated independently and rarely compared directly with machine learning and time-series approaches within a unified experimental framework [13,14].

Despite the extensive body of literature, systematic experimental comparisons across different classes of probabilistic-statistical methods remain limited. Many studies rely on synthetic data, short observation periods, or single modeling paradigms, and only a few employ out-of-sample temporal validation using real-world regional datasets [6,7,10]. This lack of unified evaluation frameworks hinders the objective assessment of relative strengths, limitations, and practical applicability of forecasting methods in emergency management.

The present study addresses these limitations by conducting a unified experimental comparison of seasonal time-series baselines, machine learning regression, Bayesian probabilistic graphical models, and Monte Carlo simulation approaches using a complete regional fire emergency dataset and consistent evaluation metrics.

### **3. Dataset Description**

#### **3.1. Data Source and Scope**

The empirical analysis is based on an official dataset of fire emergencies provided by the regional emergency authority of the Lviv region, Ukraine. The dataset contains comprehensive records of all registered fire incidents from 2019 to 2024 and represents both urban and rural areas within the region. Historical data from 2019–2023 were used for model training and calibration, while data from 2024 were reserved exclusively for out-of-sample validation.

Each record corresponds to a single fire incident and includes temporal, spatial, and categorical attributes describing the circumstances of the event. The availability of a multi-year regional archive enables realistic forecasting and objective evaluation of predictive models under operational conditions.

#### **3.2. Data Preprocessing and Attribute Selection**

The original dataset includes a large number of operational attributes related to administrative codes, location details, object characteristics, fire causes, and response information. For the

purposes of forecasting fire incident counts, only attributes directly relevant to spatiotemporal event occurrence were retained.

The selected attributes include the calendar date of the incident, settlement name extracted from the textual address field, administrative district code, fire type identifier, and fire object category. Settlement names were extracted and normalized using regular expression-based parsing to ensure consistency across records and years.

Records containing missing or invalid values in any of the selected attributes were excluded to ensure data reliability. After preprocessing, the resulting dataset consisted of complete and structurally consistent observations suitable for aggregation and modeling.

### **3.3. Data Aggregation**

To align with the forecasting objectives, incident-level data were aggregated into count-based representations. Fire incidents were grouped by date, fire type, and spatial region, and the total number of incidents was calculated for each unique combination. The spatial region was defined using a composite identifier derived from administrative district and settlement information, allowing flexible regional aggregation while preserving local specificity.

This aggregated representation provides a unified input format for regression-based machine learning models, probabilistic graphical models, Monte Carlo simulations, and seasonal time-series baselines, enabling a fair and consistent comparison across different forecasting approaches.

### **3.4. Ethical Considerations**

The dataset does not contain personal identifiers used for analytical purposes. All analyses were conducted on anonymized and aggregated data, focusing exclusively on event occurrence patterns and complying with ethical standards for data handling.

## **4. Methodology**

### **4.1. Experimental Design**

The experimental design of this study is based on a temporal out-of-sample validation framework aimed at objectively evaluating the forecasting performance of different probabilistic-statistical methods. The primary objective is to assess how accurately historical emergency data can be used to predict future fire incidents under real-world conditions.

The dataset consists of official records of fire emergencies in the Lviv region of Ukraine covering the period from 2019 to 2024. To avoid information leakage and ensure realistic forecasting conditions, the data were divided chronologically into two non-overlapping subsets. Records from 2019 to 2023 were used exclusively for model training, parameter estimation, and calibration, while data from 2024 were reserved for testing and validation.

Each forecasting method was trained using identical historical input data and evaluated on the same target period. This unified experimental setup ensures comparability across methods and eliminates biases caused by differences in data availability or preprocessing. No information from the validation period was used during model development.

The forecasting task was formulated as a time-dependent prediction problem, where the goal was to estimate the expected number of fire emergencies for future time intervals. Depending on the method, forecasts were generated either deterministically or probabilistically, producing point estimates or distributions of possible outcomes. In the case of probabilistic methods, expected values were derived from simulated or inferred distributions for comparison with observed data [2, 5].

A seasonal naive time-series model was included as a baseline benchmark to provide a reference level of predictive performance. More complex approaches—machine learning models, probabilistic

graphical models, and Monte Carlo simulations—were evaluated relative to this baseline to quantify the added predictive value of advanced modeling techniques [3, 9].

The forecasting horizon was fixed to one calendar year (2024), allowing the assessment of both short-term fluctuations and seasonal effects. Model performance was evaluated by comparing predicted values with actual observed fire incidents using a consistent set of quantitative error metrics described in the following section.

This experimental design reflects realistic operational conditions for emergency management systems, where models are trained on historical data and applied to future periods without access to real-time corrections. As a result, the obtained performance estimates provide a reliable basis for assessing the practical applicability of probabilistic-statistical forecasting methods in decision support systems for emergency management [1].

## 4.2. Evaluation Metrics

To ensure an objective and comprehensive comparison of forecasting methods, multiple evaluation metrics were employed. The selected metrics assess not only predictive accuracy but also computational efficiency, which is a critical factor for practical deployment in emergency management decision support systems [1].

### 4.2.1. Error-Based Accuracy Metrics

Prediction accuracy was evaluated using three widely adopted error metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), which are commonly used in time-series forecasting and disaster prediction studies [9, 10]. These metrics provide complementary perspectives on model performance and are commonly used in time-series forecasting and disaster prediction studies.

The Mean Absolute Error (MAE) measures the average magnitude of prediction errors without considering their direction and is defined as:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (1)$$

where  $y_i$  represents the observed number of fire incidents,  $\hat{y}_i$  denotes the predicted value, and  $n$  is the number of observations. MAE is particularly useful due to its interpretability and robustness to outliers [9].

The Root Mean Squared Error (RMSE) penalizes larger errors more strongly and is calculated as:

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

RMSE is sensitive to extreme deviations and is therefore effective for identifying models that occasionally produce large forecasting errors, which is critical in emergency management contexts [10].

The Mean Absolute Percentage Error (MAPE) expresses prediction errors as a percentage of the observed values:

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (3)$$

MAPE facilitates relative comparison between methods and allows intuitive interpretation of forecasting accuracy. However, its limitations for small or zero values were considered during analysis, and results were interpreted accordingly [9].

### 4.2.2. Computational Performance Metrics

In addition to predictive accuracy, computational efficiency was evaluated using training time and prediction time metrics. These indicators reflect the practical feasibility of deploying forecasting models in real-world emergency management systems, where timely decision-making is essential [13].

Training time represents the total computational time required to train or calibrate a model using historical data from 2019-2023. This metric captures model complexity and scalability, particularly relevant for machine learning and probabilistic graphical approaches [2, 3].

Prediction time measures the time required to generate forecasts for the target period (2024) after the model has been trained. Low prediction latency is crucial for operational decision support systems that may require frequent updates or near real-time forecasting [1, 13].

By jointly analyzing accuracy-based and computational metrics, the evaluation framework enables a balanced comparison between model precision and operational efficiency. This multi-criteria assessment supports informed selection of forecasting methods for safety-oriented decision support systems, where both accuracy and responsiveness are critical [1].

### 4.3. Machine Learning Models

Machine learning models were employed to capture complex and potentially non-linear relationships in historical fire incident data and to provide quantitative forecasts of future emergency occurrences. In this study, the forecasting task was formulated as a supervised regression problem, where the objective was to estimate the expected number of fire incidents for predefined spatiotemporal and categorical combinations [3, 11].

#### 4.3.1. Problem Formulation

The original incident-level dataset was transformed into an aggregated form to enable regression-based modeling. Records were grouped by date, type of fire, and administrative region, and the total number of fire incidents was calculated for each unique combination. As a result, each observation in the training dataset represents an aggregated count of fire events corresponding to a specific date-type-region tuple.

Formally, the learning task can be expressed as estimating a function:

$$\hat{y} = f(d, t, r) \quad (4)$$

where  $d$  denotes the date,  $t$  represents the fire type,  $r$  corresponds to the administrative region, and  $\hat{y}$  is the predicted number of fire incidents for the given combination.

#### 4.3.2. Training and Forecasting Procedure

Historical data from 2019 to 2023 were used for model training and parameter estimation. The regression models were trained on aggregated observations covering all valid combinations of dates, fire types, and regions within this period. Categorical variables were encoded in a consistent manner across training and forecasting phases to ensure comparability and avoid structural inconsistencies [3].

Once trained, the models were applied to generate forecasts for the year 2024. The output of the machine learning approach consists of predicted fire incident counts for each date-type-region combination in the forecasting horizon. These predictions provide a fine-grained representation of expected emergency activity and allow subsequent aggregation at higher temporal or spatial levels if required.

### 4.3.3. Role within the Experimental Framework

Within the experimental comparison, machine learning regression models serve as a flexible data-driven approach capable of modeling complex patterns that may not be adequately captured by simpler statistical or baseline methods. Their performance is evaluated against alternative probabilistic-statistical approaches using identical training data, forecasting horizons, and evaluation metrics, ensuring a fair and unbiased comparison [3].

Although machine learning models can achieve high predictive accuracy, their increased computational cost and reduced interpretability compared to simpler approaches are explicitly considered through the inclusion of training time and prediction time metrics in the evaluation. This allows the assessment of trade-offs between accuracy and operational feasibility in safety-oriented decision support systems [1].

## 4.4. Seasonal Naive Time-Series Model

A seasonal naive time-series model was employed as a baseline forecasting approach to capture recurring seasonal patterns in fire emergency occurrences. Baseline models play a critical role in forecasting studies, as they provide a reference level of performance against which more complex methods can be objectively evaluated [3, 9].

### 4.4.1. Model Formulation

The seasonal naive model was constructed using a day-of-year seasonal mapping, where each calendar day is associated with the historical average number of fire emergencies observed on that day, which is a standard approach in time-series forecasting for crisis prediction [9, 15]. Historical data from 2019 to 2023 were used to estimate these seasonal averages.

For each day of the year  $d \in \{1, \dots, 365\}$ , the expected number of fire incidents was computed as:

$$\mu_d = \frac{1}{N_d} \sum_{i=1}^{N_d} y_{i,d} \quad (5)$$

where  $y_{i,d}$  denotes the observed number of fire incidents on day  $d$  in year  $i$ , and  $N_d$  is the number of available observations for that calendar day across the training period. This mapping establishes a deterministic seasonal profile reflecting recurring annual patterns in fire activity [9].

### 4.4.2. Forecasting Procedure

Forecasts for the year 2024 were generated by assigning each day the corresponding historical average value  $\mu_d$  based on its position within the calendar year. As a result, the predicted number of fire incidents depends solely on the day of the year and does not incorporate trend components, external covariates, or adaptive updates.

### 4.4.3. Role as a Baseline Model

Within the experimental framework, the seasonal naive model serves as a transparent and interpretable benchmark that explicitly captures seasonal effects. While its simplicity limits its ability to respond to structural changes or anomalous events, it provides a meaningful lower bound for acceptable forecasting performance [3].

Comparing advanced probabilistic-statistical methods against this baseline allows the assessment of whether increased model complexity yields tangible improvements in predictive accuracy. This is particularly important in emergency management applications, where simpler models may be preferred if their performance is comparable to more computationally demanding alternatives [1].

## 4.5. Probabilistic Graphical Model (Bayesian Poisson-Gamma)

To explicitly model uncertainty and stochastic variability in fire emergency occurrences, a Bayesian probabilistic graphical model based on the Poisson-Gamma conjugate framework was employed, which aligns with established applications of Bayesian networks in crisis and risk modelling [14]. This approach is well suited for count-based event data and enables probabilistic inference while remaining computationally efficient [2, 5].

### 4.5.1. Model Assumptions and Structure

Fire incidents were modeled as discrete count events occurring over time. For each combination of fire type and administrative region, the number of observed fire incidents on a given date was assumed to follow a Poisson distribution:

$$y_{d,t,r} \sim \text{Poisson}(\lambda_{t,r}) \quad (6)$$

where  $y_{d,t,r}$  denotes the number of fire incidents on date  $d$  for fire type  $t$  in region  $r$ , and  $\lambda_{t,r}$  represents the latent event intensity for the corresponding type-region combination [5].

To incorporate uncertainty and enable Bayesian inference, the Poisson rate parameter  $\lambda_{t,r}$  was assigned a Gamma prior distribution:

$$\lambda_{t,r} \sim \text{Gamma}(\alpha, \beta) \quad (7)$$

This conjugate prior-likelihood pairing allows analytical derivation of the posterior distribution and facilitates efficient parameter updating using observed data [2,5].

### 4.5.2. Model Calibration

Historical data from 2019 to 2023 were aggregated by date, fire type, and region, producing daily count observations for each type-region combination. For each combination, posterior parameters were estimated based on observed event counts, resulting in a posterior Gamma distribution:

$$\lambda_{t,r} | y \sim \text{Gamma}(\alpha + \sum y_{d,t,r}, \beta + N) \quad (8)$$

where  $N$  is the number of observed days in the training period. This formulation captures both the average intensity of fire incidents and the associated uncertainty derived from historical variability [id2].

### 4.5.3. Forecasting Procedure

Forecasts for 2024 were generated by drawing expected values from the posterior distributions of  $\lambda_{t,r}$ . For each date in the forecasting horizon, the predicted number of fire incidents for a given date-type-region combination was computed as the posterior mean:

$$E[\lambda_{t,r}] = \frac{\sum y_{d,t,r}}{\beta + N} \quad (9)$$

This results in a probabilistic forecast that reflects long-term intensity patterns learned from historical data while explicitly accounting for uncertainty. The model does not assume deterministic trends or seasonality but instead provides a statistically grounded expectation of event occurrence [2].

#### 4.5.4. Role within the Experimental Framework

Within the experimental comparison, the Bayesian Poisson-Gamma model represents a probabilistic alternative to both deterministic baselines and data-driven machine learning approaches. Its strengths lie in interpretability, robustness to sparse data, and the ability to quantify uncertainty without requiring large datasets or complex training procedures [2, 5].

The model's performance is evaluated using the same accuracy and computational metrics as other methods, enabling a direct comparison of predictive precision, training time, and inference efficiency. This allows assessment of whether probabilistic interpretability and uncertainty modeling provide advantages over purely deterministic or data-intensive approaches in emergency forecasting tasks [1].

#### 4.6. Monte Carlo Poisson-Gamma Simulation

To extend probabilistic inference beyond point estimates and enable scenario-based forecasting, a Monte Carlo simulation framework based on the Poisson-Gamma model was applied. This approach allows the generation of multiple stochastic realizations of future fire emergency counts, explicitly capturing uncertainty and variability in event occurrence [12, 13].

##### 4.6.1. Simulation Framework

The Monte Carlo simulation was built upon the Bayesian Poisson-Gamma formulation described in the previous section. For each combination of fire type and administrative region, the posterior Gamma distribution of the Poisson rate parameter  $\lambda_{t,r}$  was first estimated using historical data from 2019 to 2023 [5].

For each simulation run, a latent intensity value was sampled from the posterior distribution:

$$\lambda_{t,r}^{(s)} \sim \text{Gamma}(\alpha', \beta') \quad (10)$$

where  $\alpha'$  and  $\beta'$  denote the posterior shape and rate parameters obtained during model calibration. Conditional on the sampled intensity, daily fire incident counts were generated according to:

$$y_{d,t,r} \sim \text{Poisson}(\lambda_{t,r}^{(s)}) \quad (11)$$

This two-stage sampling process was repeated across multiple Monte Carlo iterations, producing a distribution of possible outcomes for each date-type-region combination [12].

##### 4.6.2. Forecast Generation

Forecasts for the year 2024 were obtained by aggregating simulation results across all iterations. For each date and type-region combination, the expected number of fire incidents was computed as the mean of the simulated counts:

$$\hat{y}_{d,t,r} = \frac{1}{S} \sum_{s=1}^S y_{d,t,r}^{(s)} \quad (12)$$

where  $S$  denotes the total number of Monte Carlo simulations. This procedure yields a probabilistic forecast that reflects both parameter uncertainty and intrinsic randomness in fire incident occurrence [12, 13].

### 4.6.3. Role within the Experimental Framework

Within the comparative experiment, the Monte Carlo Poisson-Gamma approach represents a scenario-based probabilistic forecasting method, bridging analytical Bayesian inference and simulation-driven uncertainty analysis. Unlike deterministic baselines and point-estimate models, this approach provides a distribution of plausible outcomes rather than a single forecast value [13].

The method is evaluated using the same accuracy and computational metrics as other approaches, allowing direct comparison of predictive performance, training time, and prediction time. Its ability to represent uncertainty and generate multiple future scenarios makes it particularly relevant for safety-oriented decision support systems, where understanding the range of potential outcomes is as important as predicting expected values [1].

### 4.6.4. Role within the Experimental Framework

Within the comparative experiment, the Monte Carlo Poisson-Gamma approach represents a scenario-based probabilistic forecasting method, bridging analytical Bayesian inference and simulation-driven uncertainty analysis. Unlike deterministic baselines and point-estimate models, this approach provides a distribution of plausible outcomes rather than a single forecast value [13].

## 5. Experimental Results

### 5.1. Quantitative Performance Comparison

The forecasting performance of the evaluated methods was assessed using the accuracy and computational metrics defined earlier. Table 1 summarizes the results obtained for the 2024 forecasting horizon after updating and re-running the experimental pipeline.

**Table 1**

Comparative performance of forecasting methods

Method	MAE	RMSE	MAPE(%)	Training Time (s)	Prediction Time (s)
Machine Learning (Regression)	11.61	16.33	99.57	63.84	11.89
Seasonal Naive Time Series	10.59	15.59	89.38	0.02	2.80
Probabilistic Graphical (Poisson-Gamma)	10.55	15.54	88.55	0.37	4.09
Monte Carlo Poisson-Gamma	9.31	14.60	79.79	0.21	86.08

## 5.2. Accuracy Analysis

The updated experimental results confirm consistent performance differences between the evaluated forecasting approaches. Among all methods, the Monte Carlo Poisson-Gamma simulation achieved the lowest error values across all accuracy metrics, demonstrating the highest predictive accuracy. This indicates that explicitly modeling stochastic variability and parameter uncertainty through repeated simulations provides a clear advantage in forecasting fire emergency counts.

The probabilistic graphical model (Poisson-Gamma) and the seasonal naive time-series model produced very similar results, both significantly outperforming the machine learning regression model. Their comparable MAE and RMSE values suggest that much of the predictive power in this dataset originates from stable long-term intensity patterns and seasonal effects rather than complex non-linear dependencies.

The machine learning regression model yielded the highest error values and the largest MAPE, indicating limited generalization capability in this experimental setting. Despite its flexibility, the model struggled to capture sharp temporal fluctuations and extreme events, likely due to the absence of additional explanatory variables beyond aggregated historical counts.

## 5.3. Computational Performance

Significant differences were observed in computational efficiency across the evaluated methods. The seasonal naive model exhibited negligible training time and very low prediction latency, making it the most computationally efficient approach overall.

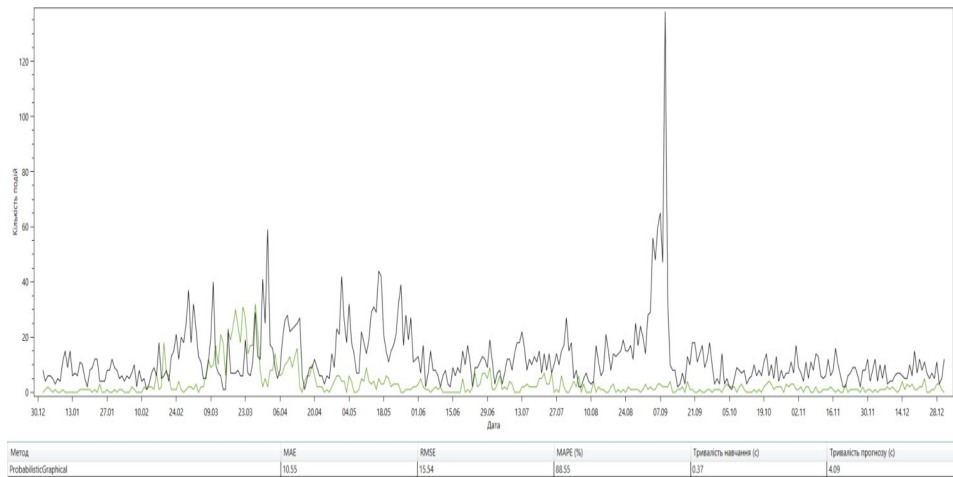
The probabilistic graphical model maintained low training and prediction times while achieving higher accuracy than the seasonal baseline. This balance between efficiency and performance highlights its suitability for operational decision support systems with limited computational resources.

The Monte Carlo Poisson-Gamma approach, although highly accurate, incurred a substantially higher prediction time due to the large number of stochastic simulations required. While training time remained low, the inference cost may restrict its applicability in real-time scenarios unless parallel computation or reduced simulation counts are employed.

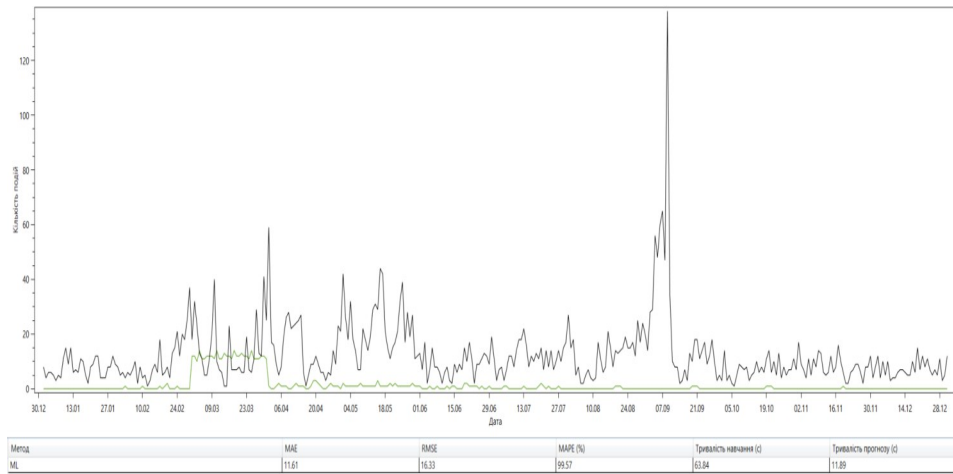
The machine learning model required the longest training time among all methods, reflecting the overhead associated with model fitting and parameter optimization. Its prediction time, although moderate, did not compensate for the comparatively lower forecasting accuracy.

## 5.4. Visual Comparison of Forecasts

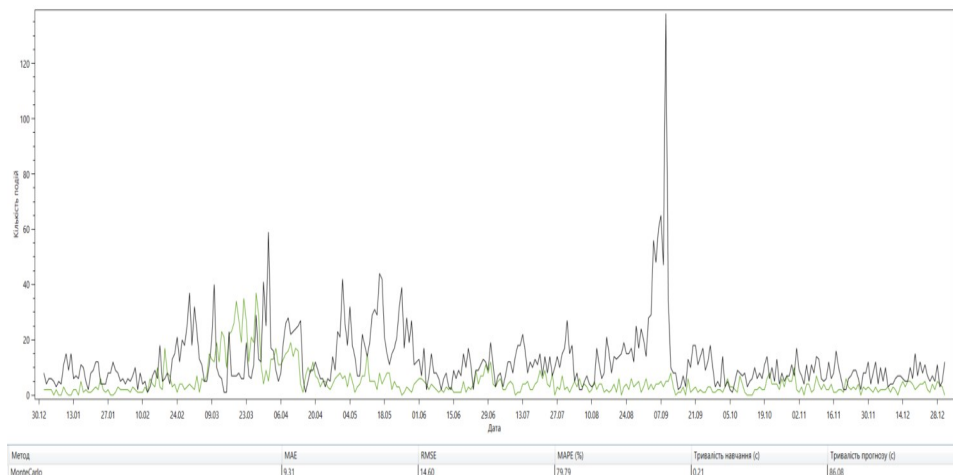
To complement the quantitative evaluation, visual comparisons between observed and predicted fire incident counts were conducted for each method. Figures 1-4 illustrate the temporal alignment between real data and model forecasts for the year 2024.



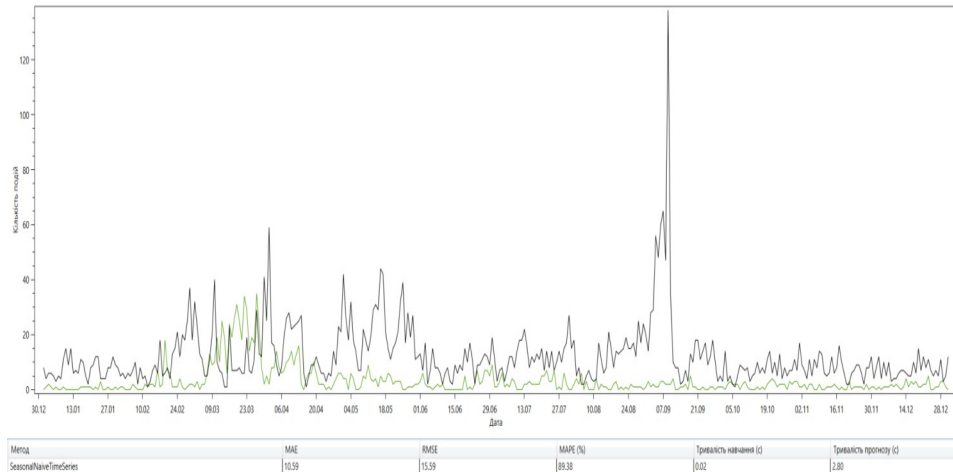
**Figure 1:** The probabilistic graphical model results, showing stable tracking of baseline activity but limited responsiveness to extreme spikes.



**Figure 2:** The machine learning regression forecasts, which exhibit smoothing effects and underestimation of high-intensity periods.



**Figure 3:** The Monte Carlo simulation results, where stochastic variability enables closer approximation of both average behavior and peak values.



**Figure 4:** The seasonal naive time-series forecasts, effectively capturing recurring seasonal patterns but failing to adapt to anomalous events.

Overall, the visual analysis supports the numerical findings and highlights qualitative differences in model behavior, particularly in handling peak fire activity and abrupt temporal changes.

### 5.5. Summary of Results

The experimental evaluation reveals a clear trade-off between predictive accuracy and computational efficiency. Simulation-based probabilistic methods provide superior accuracy but require higher inference time, whereas simpler statistical and probabilistic models offer competitive performance with minimal computational cost. Machine learning regression, in contrast, does not demonstrate advantages under the current feature set and aggregation strategy.

These findings emphasize the importance of aligning forecasting method selection with operational constraints and decision-making requirements in emergency management systems.

## 6. Discussion

The experimental results demonstrate clear and consistent differences in forecasting performance among the evaluated probabilistic-statistical methods. These differences can be interpreted in terms of model assumptions, data representation, and the nature of fire emergency occurrence as a stochastic process.

### 6.1. Interpretation of Accuracy Differences

The superior performance of the Monte Carlo Poisson-Gamma simulation indicates that explicitly modeling uncertainty and stochastic variability is highly beneficial for forecasting fire emergencies. By generating multiple realizations of future scenarios, the Monte Carlo approach captures both average behavior and rare but impactful fluctuations more effectively than deterministic or single-estimate models. This is particularly important in emergency management contexts, where extreme events can dominate operational risk despite being infrequent [12].

The Bayesian Poisson-Gamma probabilistic graphical model achieved accuracy comparable to the seasonal naive baseline while maintaining low computational cost. This suggests that fire incident occurrence at the regional level can be reasonably approximated by stable intensity parameters conditioned on fire type and region. The probabilistic formulation provides interpretability and uncertainty awareness without the need for extensive simulation, making it a strong candidate for operational use [5].

The seasonal naive time-series model performed competitively despite its simplicity. Its effectiveness confirms the strong seasonal structure inherent in fire emergency data, particularly

when aggregated at daily resolution. This finding highlights that, in the absence of external covariates, capturing seasonality alone can yield substantial predictive power [9].

In contrast, the machine learning regression model did not outperform simpler statistical approaches. Although capable of modeling non-linear relationships, the model struggled to generalize to unseen data, as reflected by higher MAE, RMSE, and MAPE values. This outcome suggests that aggregated count-based features without additional explanatory variables may be insufficient for unlocking the full potential of machine learning methods in this context [3].

## 6.2. Accuracy-Efficiency Trade-Off

A key insight from the experiments is the pronounced trade-off between predictive accuracy and computational efficiency. While the Monte Carlo simulation achieved the best accuracy, it required substantially higher prediction time due to repeated stochastic sampling. This limits its applicability in real-time or near-real-time systems unless computational resources are sufficient or the number of simulations is reduced.

Conversely, the seasonal naive and probabilistic graphical models offer rapid training and prediction, making them suitable for time-critical decision support scenarios. Their competitive accuracy suggests that simpler models may be preferable when computational constraints or operational timelines are strict.

Machine learning regression exhibited the highest training time without delivering corresponding accuracy gains. From a decision-support perspective, this raises questions about the cost-benefit balance of deploying such models when simpler probabilistic approaches provide more reliable and interpretable results.

### Practical Implications for Emergency Services

The obtained results have direct practical relevance for regional emergency services, including the State Emergency Service of Ukraine (DSNS). The evaluated forecasting methods can support proactive planning by providing advance estimates of expected fire emergency activity at the regional and subregional levels.

Forecasts generated at the date-type-region resolution enable emergency authorities to anticipate periods of increased risk, adjust duty schedules, pre-position resources, and prioritize preventive measures. In particular, probabilistic forecasts allow decision-makers to assess not only expected event counts but also the likelihood of adverse scenarios, which is essential for risk-aware operational planning [1].

The findings indicate that lightweight probabilistic models and seasonal baselines may already provide sufficient accuracy for many routine decision-making tasks, reducing the need for computationally intensive solutions in daily operations.

## 6.3. Integration into Decision Support Systems (DSS)

The proposed forecasting framework is well suited for integration into decision support systems for emergency management. Due to its modular structure, different forecasting methods can be deployed depending on system requirements and available computational resources [1].

Seasonal naive and probabilistic graphical models can serve as core forecasting components in near-real-time DSS environments, providing fast and interpretable predictions. Monte Carlo simulation can be integrated as an auxiliary module for offline risk assessment, scenario analysis, and strategic planning, where computational latency is less critical.

Such a layered DSS architecture enables flexible method selection and supports multi-level decision-making, ranging from operational response to long-term risk mitigation planning. Importantly, all evaluated methods rely on routinely collected historical data, facilitating practical adoption without changes to existing reporting workflows.

#### **6.4. Limitations of the Experimental Study**

Despite the robustness of the experimental design, several limitations should be acknowledged. The forecasting models were trained exclusively on historical fire incident data and did not incorporate external explanatory variables such as weather conditions, population density, or land-use characteristics. The absence of such covariates may limit the ability of models to anticipate abrupt changes driven by exogenous factors.

Additionally, the analysis focused on independently modeling type-region combinations and did not explicitly capture spatial dependencies between neighboring areas. Extreme events caused by exceptional circumstances may therefore remain difficult to predict accurately regardless of the modeling approach.

#### **6.5. Generalizability of the Approach**

Although the experimental evaluation was conducted using data from a single region, the proposed methodology is generalizable and can be applied to other regions or types of emergency events. The reliance on standard count-based representations and probabilistic modeling makes the framework adaptable to different administrative structures and reporting systems [2].

The approach can be extended to other categories of emergencies, provided that sufficient historical data are available. As such, the proposed framework offers a transferable foundation for safety-oriented decision support systems beyond the specific case study considered in this research.

#### **6.6. Directions for Future Research**

Future work should focus on extending the proposed framework by integrating exogenous variables, exploring spatially explicit probabilistic models, and evaluating hybrid approaches that combine machine learning with probabilistic inference. Additionally, optimizing Monte Carlo simulation strategies to reduce prediction latency could further enhance their applicability in operational environments.

### **7. Conclusions**

This study presented an experimental comparison of probabilistic-statistical methods for forecasting fire emergencies using a comprehensive regional dataset covering the period from 2019 to 2024. The analysis was conducted on official historical records and employed a unified experimental framework with out-of-sample validation, enabling an objective assessment of forecasting accuracy and computational efficiency across different methodological approaches.

The experimental results demonstrate that probabilistic-statistical methods outperform machine learning regression models when forecasting aggregated fire emergency counts in the absence of external explanatory variables. In particular, the Monte Carlo Poisson-Gamma simulation achieved the highest predictive accuracy across all evaluated error metrics, confirming the effectiveness of stochastic simulation for modeling variability and uncertainty in emergency event occurrence.

At the same time, the results highlight that model complexity does not necessarily translate into improved forecasting performance. Simple baseline approaches, such as the seasonal naive time-series model, showed competitive accuracy, underscoring the strong seasonal structure inherent in fire emergency data. The Bayesian Poisson-Gamma probabilistic graphical model provided a favorable balance between accuracy, interpretability, and computational efficiency, making it especially suitable for operational forecasting tasks.

From a practical perspective, the findings emphasize the importance of aligning forecasting method selection with operational requirements in emergency management decision support systems. Simulation-based approaches are best suited for offline risk analysis and scenario planning, where capturing uncertainty and extreme outcomes is critical. In contrast, simpler probabilistic and seasonal models offer reliable performance with minimal computational overhead, making them appropriate for routine forecasting and time-sensitive decision-making.

Several limitations of the present study should be acknowledged. The analysis relied solely on historical fire incident data and did not incorporate external factors such as meteorological conditions, demographic characteristics, or land-use information. Additionally, spatial dependencies between neighboring regions were not explicitly modeled. Addressing these limitations represents a promising direction for future research.

Future work will focus on integrating exogenous variables, extending the framework to spatially explicit probabilistic models, and exploring hybrid approaches that combine machine learning with probabilistic inference. Such extensions have the potential to further improve forecasting accuracy while maintaining practical applicability in safety-oriented decision support systems.

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The views and conclusions expressed in this paper are those of the authors and do not necessarily reflect the official position of the State Emergency Service of Ukraine.

## Declaration on Generative AI

During the preparation of this work, the authors utilized Gemini to identify and rectify grammatical, typographical, and spelling errors. Following the use of this tool, the authors conducted a thorough review and made necessary revisions, and accept full responsibility for the final content of this publication.

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