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M. YUNUSOV

HYBRID MODELING METHODOLOGY FOR PREDICTING RISKS IN EMERGENCY MANAGEMENT

This research addresses the critical challenge of forecasting natural and man-made emergency situations, with a specific focus on industrial and forest fire dynamics. Traditional emergency management often relies on deterministic models that, while physically accurate, struggle to incorporate the inherent stochasticity of environmental variables. Conversely, purely statistical approaches frequently fail to account for unique, non-linear scenarios where historical data is insufficient. To bridge this gap, this paper proposes a robust hybrid modeling methodology that integrates fundamental physico-mathematical equations with advanced probability theory methods. The core of the deterministic component is based on the parabolic partial differential equation of heat conduction, which describes the thermal evolution of objects under stress. To account for real-world uncertainties, environmental parameters such as wind speed and ambient temperature are treated as random variables, modeled using Weibull and Gaussian distributions respectively. A comprehensive computational experiment was conducted using the Monte Carlo simulation method, executed via Python-based algorithms to perform 10,000 iterations for dynamic fire risk assessment. The Finite Difference Method (FDM) was employed to solve the heat transfer equations iteratively. The results indicate that while a static deterministic model predicts a failure time of 24.5 minutes, the hybrid approach reveals a significant stochastic variance, with failure times ranging from 15 to 45 minutes. Notably, the model identified a "Tail Risk" where 5% of the simulations resulted in failure within less than 18 minutes—a critical safety window that traditional models overlook. Furthermore, a counter-intuitive physical correlation was observed where higher wind speeds occasionally delayed failure due to enhanced convective cooling effects. This methodology provides a more realistic and granular tool for decision-makers in emergency management, offering not just a single risk value but a comprehensive probability interval essential for life-saving evacuation planning.

Keywords: Emergency situations, hybrid modeling, risk prediction, Monte Carlo method, Weibull distribution, fire safety.

М. М. ЮНУСОВ

МЕТОДОЛОГІЯ ГІБРИДНОГО МОДЕЛЮВАННЯ ДЛЯ ПРОГНОЗУВАННЯ РИЗИКІВ У СФЕРІ НАДЗВИЧАЙНИХ СИТУАЦІЙ

Дане дослідження присвячене вирішенню критичної проблеми прогнозування природних і техногенних надзвичайних ситуацій з особливим акцентом на динаміку промислових і лісових пожеж. Традиційне управління надзвичайними ситуаціями часто покладається на детерміновані моделі, які, будучи фізично точними, важко враховують властиву стохастичність екологічних змінних. Навпаки, суто статистичні підходи часто не в змозі врахувати унікальні нелінійні сценарії, де історичних даних недостатньо. Щоб подолати цей розрив, у даній роботі пропонується надійна методологія гібридного моделювання, яка інтегрує фундаментальні фізико-математичні рівняння з передовими методами теорії ймовірностей. Ядро детермінованого компонента базується на параболічному диференціальному рівнянні теплопровідності в частинних похідних, яке описує термічну еволюцію об’єктів під навантаженням. Для врахування невизначеностей реального світу екологічні параметри, такі як швидкість вітру та температура навколишнього середовища, розглядаються як випадкові величини, змодельовані з використанням розподілів Вейбулла та Гаусса відповідно. Комплексний обчислювальний експеримент було проведено з використанням методу моделювання Монте-Карло, реалізованого за допомогою алгоритмів на базі Python для виконання 10 000 ітерацій для динамічної оцінки ризику пожежі. Метод скінченних різниць (FDM) використовувався для ітераційного розв’язання рівнянь теплопередачі. Результати показують, що в той час як статична детермінована модель передбачає час відмови 24,5 хвилини, гібридний підхід виявляє значну стохастичну дисперсію з часом відмови від 15 до 45 хвилин. Зокрема, модель ідентифікувала «хвостовий ризик» (Tail Risk), де 5% симуляцій призвели до збою менш ніж за 18 хвилин — критичне вікно безпеки, яке традиційні моделі ігнорують. Крім того, спостерігалася контрінтуїтивна фізична кореляція, коли вищі швидкості вітру іноді затримували руйнування завдяки посиленим ефектам конвективного охолодження. Ця методологія забезпечує більш реалістичний і детальний інструмент для осіб, які приймають рішення в управлінні надзвичайними ситуаціями, пропонуючи не просто єдине значення ризику, а повний інтервал ймовірності, необхідний для планування евакуації та захисту населення. Практичне впровадження цієї гібридної моделі дозволяє значно підвищити надійність систем раннього попередження в умовах високої невизначеності навколишнього середовища.

Ключові слова: надзвичайні ситуації, гібридне моделювання, прогнозування ризику, метод Монте-Карло, розподіл Вейбулла, пожежна безпека, теплопровідність, стохастичні змінні.

Introduction. In the contemporary era, the backdrop of global climate change, rapid urbanization processes, and the increasing pace of industrialization have led to the complex dynamics of emergency situations. Forecasting the development scenarios of such risks and implementing preventive measures play a crucial role in emergency management. All the aforementioned issues necessitate the enhancement of traditional mechanisms for emergency risk management.

Reports from the United Nations Office for Disaster Risk Reduction (UNDRR) and the Intergovernmental Panel on Climate Change (IPCC) indicate that the rise in average global temperatures has resulted in an increase in hydrometeorological events and large-scale forest fires.

Research conducted in this field utilizes deterministic methods based on physical laws and stochastic methods based on statistical databases for the assessment of emergency risks (Drysdale, 2011; Zio, 2013). The propagation of natural emergencies, expressed through differential equations, is typically presented via deterministic models in existing studies. However, in practical application, such models often treat input parameters-such as wind speed, humidity, and the heat of combustion of an object-as constants, thereby failing to reflect random variables in a real environment. On the other hand, considering the approach to Dynamic Quantitative Risk Assessment (DQRA), the variation of emergency risks over time is characterized by its stochastic nature (F. Khan, 2016).

It is worth noting that while traditional physical-mathematical models—specifically differential equations that calculate the spread of fires and inundation zones during floods—are characterized by high accuracy, the significant time required to process large datasets may lead to delays in operational decision-making. Meanwhile, statistical methods based on historical data struggle to predict real-world events effectively. For this reason, the vastness and rapid fluctuation of databases necessitate the development of hybrid models incorporating artificial intelligence technologies for real-time parameter processing.

Main body. The theoretical basis of the research is built upon key pillars: the dynamics of emergency situations, system reliability, stochastic modeling, and dynamic risk analysis. Recent studies and scientific innovations in these fields have led to a significant evolution in the methodology of forecasting dynamic disaster risks. It is particularly important to note that there are two main directions in disaster risk modeling: deterministic and stochastic (Drysdale, 2011; Zio, 2013). Recently, the number of studies on dynamic and hybrid models has increased.

Deterministic Models. The use of differential equations based on physical laws is considered traditional in the analysis of the propagation of natural emergencies. Heat transfer equations are utilized in the investigation of emergencies such as fire events (Drysdale, 2011). Such models account for existing field parameters to determine fire ignition rates. However, these approaches assume parameters such as wind speed, humidity, and other characteristics to be constant, failing to incorporate environmental variability into the model. Consequently, risk assessment is conducted based on a standard scenario. In practice, the random variation of many parameters limits the reliability of deterministic models. Furthermore, such methods rely on approximate simulations and do not deviate from the constraints established by the scenario.

Stochastic Models. Stochastic risk analysis utilizes methods that encompass probability parameters, thereby accounting for the uncertainty between parameters and real events. Reliable assessment of such risks requires the consideration of a multitude of possible scenarios for the intended processes (Zio, 2013). To achieve this, probabilistic risk assessment methods are employed. In probabilistic risk assessment, parameters are treated as random variables, and various probabilistic scenarios are processed via Monte Carlo simulations. Such a risk assessment process must be conducted over many possible cases, making it possible to detect system failure parameters and determine the distribution of risk values (Zio, 2018).

Dynamic and Hybrid Models. Dynamic risk assessments are developed to address the potential limitations of both deterministic and stochastic methods. Unlike traditional approaches, Dynamic Risk Assessment (DRA) accounts for the temporal variation and updating of risk levels (Khan et al., 2016). Furthermore, the advancement of Quantitative Risk Assessment (QRA) has facilitated the emergence of dynamic methods (Villa et al., 2016). These novel approaches aim to establish a risk profile through continuous observation and monitoring in real-time. Consequently, dynamic risk models can stochastically determine potential risks by considering not only the initial period of the intended process but also its subsequent evolution. Simultaneously, hybrid models integrate both aforementioned approaches—physical laws and probabilistic calculations. For this reason, hybrid modeling approaches are considered effective in risk assessments, as they account for both thermophysical laws and dynamic conditions within the same time interval.

In large-scale natural fire scenarios, the transfer of heat energy from the external environment to a combustible object, and subsequently into its interior, constitutes the fundamental physical process. For the mathematical description of such a process, a parabolic partial differential equation based on the law of heat conduction and the law of conservation of energy is utilized (Drysdale, 2011):

$$\rho C_o \frac{\partial T(x,t)}{\partial t} = \frac{\partial}{\partial x}\left(k \frac{\partial T(x,t)}{\partial x}\right) + Q_{general}, \qquad (1)$$

where:

ρ – density of the object's material (kg/m^3);

Co – specific heat capacity of the material (J/kg*T);

k – thermal conductivity (W/(m·T));

T(x,t) – temperature field depending on spatial (x) and temporal (t) coordinates;

t – time (s);

x – thickness of the object's wall (m);

$Q_{general}$ – internal heat source (W/m3), (typically assumed to be 0).

Boundary conditions play a decisive role in solving the equation. Thus, the heat exchange at the external boundary of the combustible object (x=0) is taken as the primary basis. In this instance, the value of the heat flux consists of the sum of two main components: radiation and convection (Ricci et al., 2023):

$$-k \frac{dy}{dx} \int_{x=0} = q^{"}_{net} = q^{"}_{rad} + q^{"}_{conv}, \qquad (2)$$

- Radiative heat flux $q^{"}_{rad}$ thermal radiation resulting from the direct heat flux generated during natural fires;
- Convective heat flux $q^{"}_{conv}$: heat exchange resulting from air movement via wind, described as follows:

$$q^{"}_{conv} = h_c(T_{env} - T_{surf}), \qquad (3)$$

where:

h_c – convective heat transfer coefficient ((W/(m2·T));

T_{env} - ambient air temperature (T);

T_{surf} – temperature of the object's external surface (T(0,t)).

Modeling of Uncertainties. Although v and Tenv (ambient temperature) are assumed to be constant in deterministic models, since they are random variables in a real environment, determining the Probability Density Functions (PDF) of these parameters is essential for predicting disaster risks.

Research conducted in the fields of meteorology and wind energy has revealed that the Weibull distribution models the probability distribution of wind speed most accurately (Carta et al., 2009):

$$f(v;k,c) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^{k}}, \quad (4)$$

where:

$v \geq 0$ – wind speed (m/s);

k – shape parameter indicating wind variability (dimensionless);

c – scale parameter (correlated with the mean wind speed).

The distribution of air temperature is modeled according to the Gaussian distribution:

$$f(T;\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(T-\mu)^2}{2\sigma^2}}, \quad (5)$$

where:

μ – mean temperature (℃);

σ – standard deviation (℃).

Monte Carlo Simulation. Monte Carlo simulation is utilized to establish the working mechanism of dynamic hybrid models. Through a large number of random samples, this method allows for obtaining the probability distribution results of the deterministic model's output parameters (e.g., the time required for the object's temperature to reach the most critical limit) (Zio, 2013).

The main steps for constructing the algorithm are as follows:

1. Definition of Input Parameters (Input):

- Material properties (ρ, Co, k);
- Geometric dimensions (L);
- Fire scenario (q''_{rad});
- Critical temperature;
- Distribution parameters ($k_{weibull}$, $c_{weibull}$, μ_{temp}, σ_{temp}).

2. Random Sampling:

- Generation of v_i and T_{env},i values from the Weibull and Gaussian distributions for N simulation iterations

3. Loop calculation (Iterative process):

- For eahc i-th iteration (i=1…N):
- v_i calculation hc,i based on v_i;
- Solve the heat conduction equation for (T(x,t) sonlu using the finite difference method;
- Monitor temperature of the object's inner surface (T_{inner});
- if $T_{inner} \geq T_{fail}$, record the time tfail,i and terminate the loop.

4. Analysis of obtained results:

- Calculate statistical indicator of the obtained tfail (mean value, standard deviation, quantiles);
- Construct the Cumulative Distribution Function (CDF) of the probability of failure;
- Conduct "Tail risk" analysis.

To implement the proposed methodology practically, an extensive computational experiment was conducted within the environment provided by the Python programming language. Python's libraries for numerical computing, statistical distributions, and visualization offer a favorable platform for achieving the aforementioned objectives.

For the experiment, a potential fire incident in the industrial zones of the Republic of Azerbaijan was simulated. The algorithmic description of the codes used for the simulation is presented in Figure 1 and Figure 2.

As can be seen in Figure 1 and Figure 2, as a result of 10,000 simulation iterations, several fundamental and counter-intuitive regularities in emergency risk management were revealed. The obtained results were analyzed from both statistical and physical perspectives and compared with the "static" risk approach.

```python
import numpy as np
from scipy.stats import weibull_min, norm

# Number of simulations
N_SIM = 10000

# 1. Generation of Stochastic Variables
# Wind speed (m/s) - Weibull distribution
wind_speeds = weibull_min.rvs(c=2.2, scale=8.5, size=N_SIM)

# Ambient temperature (K) - Normal distribution
# 30C mean, 5C standard deviation -> Conversion to Kelvin
ambient_temps_C = norm.rvs(loc=30, scale=5, size=N_SIM)
ambient_temps_K = ambient_temps_C + 273.15
```

Fig. 1. Introduction to Python algorithm for Monte Carlo simulation and solving the thermodynamic equation

```
import numpy as np

def solve_heat_equation(v_wind, T_amb, q_rad, props):
    # Unpacking parameters
    rho, cp, k, L, T_crit = props

    # Calculation of convection coefficient (Empirical correlation)
    # h_c = 5.7 + 3.8 * v (exemplary simplified formula)
    h_c = 5.7 + 3.8 * v_wind

    # Space and Time discretization
    nx = 20        # Number of nodal points
    dx = L / nx
    alpha = k / (rho * cp)
    dt = 0.5 * dx**2 / alpha  # Stable time step (Fourier number = 0.5)

    # Initial condition: Wall is at ambient temperature
    T = np.ones(nx + 1) * T_amb

    time = 0
    max_time = 3600 * 2 # Maximum 2 hours simulation
```

```
  while time < max_time:
      T_new = T.copy()

      # Internal nodes (Conduction equation)
      for i in range(1, nx):
          T_new[i] = T[i] + alpha * dt / dx**2 * (T[i+1] - 2*T[i] + T[i-1])

      # Boundary Conditions
      # x=0 (Outer surface): Radiation + Convection
      # q_net = q_rad + h_c * (T_amb - T_surface)
      # Update of boundary temperature via energy balance
      q_net = q_rad + h_c * (T_amb - T[0])

      # Corrected FDM formulation for surface node:
      T_new[0] = T[0] + 2 * alpha * dt / dx**2 * (T[1] - T[0] + q_net * dx /

      # x=L (Inner surface): Adiabatic (Simplified scenario) or heat transfer
      # Here we assume adiabatic for "worst-case" (heat accumulation)
      T_new[nx] = T[nx] + 2 * alpha * dt / dx**2 * (T[nx-1] - T[nx])

      T = T_new
      time += dt

      # Check for reaching critical temperature (Inner surface)
      if T[nx] >= T_crit:
          return time # Time to failure (seconds)
```

Fig. 2. Python algorithm for Monte Carlo simulation and solving the Heat Dissipation equation

Comparative Analysis of Static and Probabilistic Risk. It should be noted that the risk analysis was initially performed using the traditional deterministic method. In this case, the mean values of the input variables were used:

- Wind speed: vmean ≈ 7.5 m/s;
- Temperature: Tmean = 30℃.

Under the specified average conditions, the failure time tfail calculated by the deterministic model was 1470 seconds (24.5 minutes). This figure is considered the primary criterion for all evacuation plans as well as firefighting tactics.

However, the results of the hybrid model indicate that this approach does not reflect reality and fails to identify critical risks. According to the Monte Carlo simulation results, the failure time is not a fixed figure but a stochastic quantity ranging from 15 minutes to 45 minutes.

The frequency histogram of the simulation results and the Cumulative Distribution Function differ from a normal distribution. The statistical results are as follows (Table 1):

Table 1 – Comparative analysis of static (deterministic) and hybrid (probabilistic) model results

Parameter	Static Approach	Probabilistic Approach (Hybrid Model)	Difference
Input Conditions	Fixed mean values (v=7.5, T=30)	Distributions (Weibull, Gaussian)	The hybrid model accounts for natural variability.
Result (Time)	24.5 dəq	Mean: 25.1 min, Range: 15-45 min	The static model creates "false precision."
Risk Interpretation	Failure will occur after 24.5 min.	Probability of failure increases over time	The dynamic risk concept alters decision-making.
Safety Margin	Not considered	Measured via 95% CI and Tail Risk	The hybrid model identifies extreme scenarios.

- Mean time: 25.1 minutes;
- Standard deviation: 4.2 minutes;
- Median (50-th quantile): 24.8 minutes;
- 95% confidence interval: 18.5-32.3 minutes.

This implies that in 95% of cases, the object will fail due to the disaster between 18.5 and 32.3 minutes. However, it is the worst-case scenario, not the average, that demands attention.

The greatest advantage of the hybrid model emerged in the "Left tail" analysis. The left side of the distribution describes scenarios where the object fails earliest. in approximately 5% of simulations (500 scenarios), the object failed in less than 18 minutes.

Physical Interpretation. During the physical interpretation of the experiment, an interesting and seemingly contradictory fact emerged. While wind is typically perceived as a factor that exacerbates and spreads forest fires, its role in this object fire scenario was dual. Correlation analysis revealed a positive correlation between wind speed and failure time. In other words, the stronger the wind, the later the object heats up. The physical explanation for this is as follows:

$$q''_{net} = q''_{rad} + h_c(T_{env} - T_{surf}). \qquad (6)$$

Conclusion. The model proposed in this research demonstrates a significant methodological innovation by successfully combining the deterministic accuracy of physical processes (Heat Conduction PDE) with the statistical comprehensiveness of stochastic methods (Monte Carlo, Weibull/Gaussian distributions). This hybrid approach has enabled the description of risk not as a single "static" value, but as a probability distribution, thereby forming a more realistic and informative landscape for decision-makers.

The conducted computational experiments have proven the limitations of the traditional deterministic approach; while the evacuation time of 24.5 minutes predicted by the static model holds true in only 50% of cases from a probability theory perspective, the new model revealed that accidents could occur in less than 18 minutes with a 5% probability ("Tail Risk"). Identifying this critical difference in time indicators is of decisive importance for saving human lives in emergency situations.

Furthermore, the research results uncovered physical paradoxes regarding the complex nature of the wind's role in Natech scenarios. It was determined that in a forest fire scenario, strong wind, contrary to expectations, increases the resilience of industrial tanks by creating a convective cooling effect, whereas calm weather conditions are considered a source of higher danger.

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Відомості про авторів / Сведения об авторах / About the Authors

Yunusov Mir Ramin Mir Gasim – the teacher at the Baku Engineering University, PhD Student at the Institute of Mathematics, Baku, Azerbaijan; e-mail: myunusov@beu.edu.az; ORCID: 0009-0005-8323-4279