# Machine learning method for predicting smoke blockage time at apartment evacuation exits[*]

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**Abstract**

The article explores the application of machine learning methods to study the time of smoke blockage of evacuation routes during the initial stage of a fire in residential premises. A dataset was formed through numerical experiments conducted in the PyroSim software, where 140 fire scenarios were modeled with varying values of the fire spread angle, distance to the exit, total area of opened doors and windows. Correlation analysis was performed to assess relationships between parameters, and polynomial regression of the second degree with variable scaling was employed for modeling, yielding interpretable coefficients. The results were validated using mean squared error (MSE) and coefficient of determination ($R^2$), complemented by visualizations of dependencies. The study demonstrates the effectiveness of combining numerical modeling with machine learning for predicting smoke blockage time, offering practical implications for enhancing evacuation safety.

**Keywords**

machine learning, polynomial regression, PyroSim, numerical experiment, smoke blockage time, evacuation routes, correlation analysis, fire prediction, residential premises, evacuation safety

## 1. Introduction

Fires in residential buildings remain one of the leading causes of human casualties and material losses worldwide, posing a serious threat to the safety of occupants and the stability of urban infrastructure. Statistics indicate that a significant portion of fatalities during fires is linked to evacuation delays in the initial stages of an emergency. These delays stem from residents' inadequate preparedness for critical conditions, inefficient design of fire protection systems, and the influence of building structural features that can complicate safe evacuation.

The first minutes following the outbreak of a fire are critical for saving lives, as this is when the rapid spread of smoke, rising temperatures, and accumulation of toxic gases create conditions capable of blocking evacuation routes. Even a brief delay of a few seconds can sharply increase the risk to life, especially in densely populated buildings. In this context, studying the initial phase of evacuation becomes paramount, as it is during this stage that the preconditions for successful rescue are established.

During the initial evacuation phase from a residential premise (within the first 2–3 minutes of a fire's onset) smoke is the most significant factor among all fire hazards affecting the accessibility of evacuation exits. It forms almost instantly, particularly given that the primary combustible load in residential spaces consists of wood and synthetic materials (furniture and textiles), and can densely fill a space within 1–3 minutes. This rapid spread makes smoke the primary threat, as the loss of visibility directly hinders movement toward doors or other exits. For instance, when visibility drops below 5–10 meters, locating an exit becomes extremely difficult. This typically occurs before

[*] *AdvAIT-2025: 2nd International Workshop on Advanced Applied Information Technologies: AI & DSS, December 05, 2025, Khmelnytskyi, Ukraine, Zilina, Slovakia*

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other factors reach critical levels. Although residents are usually familiar with their surroundings, the psycho-emotional stress of a fire negatively impacts rational decision-making.

Other hazardous factors, such as temperature, carbon monoxide (CO), or carbon dioxide ($CO_2$) concentrations, while posing significant risks, develop more slowly or have an indirect effect on physically blocking exits. For example, temperature reaches critical levels (50–100°C at floor level) only after 3–5 minutes, and even then, passing through a doorway in 1–2 seconds may cause only minor burns without halting evacuation. Carbon monoxide accumulates relatively quickly, but during the brief time (1–2 seconds) it takes to pass through an exit, a person does not receive a lethal dose. Undoubtedly, studying CO's impact during the initial fire stage is necessary, but not solely at the evacuation exit zone. Carbon dioxide, meanwhile, reaches dangerous concentrations (>5%) only after 5–10 minutes, making it less relevant in the initial phase. Thus, investigating the patterns of smoke-related blockage of evacuation exits in residential spaces is a priority task for the early evacuation stage.

Machine learning plays a pivotal role in such studies, unlocking new possibilities for fire and evacuation modeling. With its ability to analyze complex nonlinear relationships and process large datasets, machine learning techniques enable accurate predictions of the dynamics of hazardous fire factors and their impact on evacuation route accessibility.

The combined use of fire modeling software, such as PyroSim, with machine learning tools is highly effective. PyroSim facilitates detailed simulations of various scenarios during the initial fire stage, generating extensive datasets on fire hazards while accounting for room geometry, materials, and ventilation conditions. These datasets serve as a foundation for training machine learning models capable of identifying complex nonlinear relationships between input factors (e.g., fire shape, distance to the exit, area of open door or window spaces) and target outcomes (e.g., the time of smoke blockage of evacuation exits). This approach integrates the precision of physical modeling with the analytical power of machine learning, enabling real-time fire behavior predictions, optimizing evacuation strategies, and enhancing the effectiveness of fire safety measures without the need for costly experiments or simulations for each specific case.

Thus, applying machine learning to study the initial fire stage not only broadens scientific horizons but also holds practical significance for reducing human casualties and material losses in residential buildings. Understanding how smoke and other factors affect evacuation routes, combined with advanced modeling technologies, enables the development of more effective response strategies and the improvement of fire safety systems, making them more adaptable to real-world conditions.

**Research Object** is the process of smoke spread in residential buildings during the initial evacuation stage of a fire.

**Research Subject** is the influence of geometric fire parameters and the area of open window and door openings on the time of smoke blockage of evacuation routes in residential premises during the initial fire stage, as well as methods for predicting this time using machine learning algorithms.

**Research Goal** is to develop a machine learning-based model for predicting the time of smoke blockage of evacuation routes in apartments to enhance the efficiency of fire risk assessment and planning safe evacuation.

To achieve this goal, the following **tasks** must be addressed:

1. Conducting computer modeling of various initial stage of fire scenarios to create a dataset for training a machine learning model.
2. Analyzing the impact of fire shape, distance to the evacuation exit, and the area of open window and door openings on the time of evacuation exit blockage, and identifying patterns of smoke spread based on simulation data.
3. Developing and testing a machine learning model for predicting the time of exit blockage.

## 2. Literature Review

Analysis of research dedicated to the geometric aspects and natural ventilation at the initial stage of fire development, as well as their impact on evacuation processes, allows dividing the existing studies into several directions: numerical modeling of fire hazards; use of statistical methods and machine learning to predict fire safety parameters; combination of numerical modeling and statistical methods to solve the fire safety tasks.

Numerical modeling of fire development using the Fire Dynamics Simulator (FDS) enables the investigation of various aspects of the initial fire stage [1] without conducting costly full-scale experiments. Specifically, several works [2], [3] and [4] are focused on ventilation in the context of modeling fire dynamics. These studies employed numerical methods, including FDS, to analyze the influence of ventilation parameters on smoke and heat flow propagation. In the study by Li et al. [5], a CFD model was developed that accounted for wall thermal conductivity, heat release rate (HRR) variations, and spatial geometric parameters. The use of such models allows for the determination of hazardous fire factor indicators at a specific moment in time for a given space. These articles emphasized patterns of hazardous fire factor propagation rather than the time of their blockage of evacuation exits. Issues of evacuation during the initial stage of fire in residential premises were addressed in works [6] and [7]. These articles are dedicated to general evacuation aspects, as well as the parameters and dimensions of evacuation routes and exits. Several studies demonstrated that ventilation openings significantly affect the dynamics of smoke and heat spread. Cai N. and Chow W.K. [8] utilized numerical modeling to analyze various scenarios of door and window openings. Their results suggest that the size and position of ventilation openings can substantially alter the time it takes for evacuation routes to become unusable. In study [9], the combination of natural and exhaust ventilation and its impact on smoke propagation patterns was used to develop a predictive model, which subsequently enabled smoke spread assessment without relying on FDS.

It is worth noting that machine learning is increasingly applied to model complex physical processes. For instance, in study [10], neural networks were used to improve the consideration of ignition source parameters. In work [11], convolutional neural networks were employed to determine parameters of evacuation flow movement. Other studies, such as [12] and [13], showcase the potential of regression and classification algorithms for assessing fire types and evacuation process parameters. Such approaches enable rapid processing of large datasets and adaptation of models to various fire scenarios. In [14] authors proposed a generative adversarial network (GAN)-based method for rapid automatic generation of diverse and physically plausible fire scenarios in residential buildings, enabling large-scale training datasets for machine-learning fire dynamics models without time-consuming manual CFD simulations.

The analysis of the aforementioned studies leads to the conclusion that the combined use of computer modeling, which conveniently and efficiently generates large amounts of data, and machine learning, which facilitates the analysis of relationships within this data, is a promising and actively developing tool [15, 16]. Together with studies on flame-retardant materials [17] the machine learning methods are able to calculate how material composition can significantly influence fire spread dynamics, which is critical for evacuation modeling. Such approaches can be successfully applied to determine the influence of various factors on fire development and the spread of hazardous factors at the initial stage, particularly the time of smoke blockage of evacuation exits.

## 3. Materials and Methods

To study the time of smoke blockage of evacuation exits during the initial stage of a fire, a dataset of 140 fire scenarios was created using the PyroSim 2024 software package, which is a graphical pre- and post-processor for Fire Dynamics Simulator (FDS) developed by NIST. FDS numerically solves the Navier–Stokes equations for low-Mach-number thermally driven flow using the large eddy simulation (LES) approach with the mixture fraction combustion model and a single-step irreversible reaction. Radiative heat transfer is modelled via the finite volume solution of the radiation transport equation for a non-scattering grey gas, with absorption coefficients determined using the RadCal narrow-band model [18].

Three-dimensional models of typical one-, two- and three-room residential apartments (total area 40–80 m$^2$) were constructed. Walls were defined as 0.5 m thick inert brick layers with thermal inertia $k\rho c = 3.2 \times 10^5$ J$^2$/(m$^4$·K$^2$·s), corresponding to typical clay brick used in Ukrainian residential construction. The fire source was modelled as a fixed-area burner with constant heat release rate per unit area of 200 kW/m$^2$, corresponding to the early flaming stage of upholstered furniture. Fire spread shape was controlled by the burner geometry: 90° sector (corner), 180° (against wall), or 360° (centre placement) [19]. Distance from the fire source to the evacuation door l varied from 2 to 10 m. Total open areas of doors $S_d$ and windows $S_w$ were varied in the ranges 0–1.8 m$^2$ and 0–2.5 m$^2$, respectively. The computational domain was discretised with a uniform cubic mesh of 0.1 m, satisfying the non-dimensional criterion $D^*/\delta x \approx 8–12$ for accurate resolution of the fire plume. The smoke blockage time τ was rigorously defined as the earliest instant when the extinction coefficient K in the layer 1.5–2.0 m above the floor in the doorway reached the value corresponding to visibility of approximately 10 m under typical residential lighting conditions — a widely accepted tenability limit for evacuation. Each simulation ran for 300 s with output recorded every 1 s. The resulting dataset (140 records) was processed in Python 3.11 using Pandas. All four predictors ($a$, $d$, $S_d$, $S_w$) were standardised via StandardScaler. Second-order polynomial features with interaction terms were generated using scikit-learn PolynomialFeatures(degree=2, include_bias=False), yielding 14 predictors. The regression model was fitted using LinearRegression() with default parameters (ordinary least squares). Model quality was assessed by the coefficient of determination $R^2$ and mean squared error (MSE) on the entire dataset. Visualisations were created using Matplotlib and Seaborn.

## 4. Experiment, Results and Discussion

### 4.1. Experiment

Within the framework of this study, the first step was to form a comprehensive dataset that could be used to establish a regression relationship between the characteristics of residential premises and the parameters of hazardous fire factor propagation. The aim of the study was to quantitatively assess the influence of external factors on the time of smoke blockage of an evacuation exit from a dwelling. The obtained data served as the foundation for developing a predictive model using machine learning methods to enhance the efficiency of evacuation planning and optimize fire safety measures in residential buildings.

A numerical experiment simulating fire outbreak scenarios was conducted using the PyroSim software package, which is based on the Fire Dynamics Simulator (FDS) from NIST. In the first stage, a three-dimensional models of typical residential dwellings with an area within the ranges of 40-80 m$^2$ were created, consisting of one, two or three rooms, a corridor, and an evacuation exit. The models' geometry included walls (0.5 m thick, made of brick), doors (0.9 m wide, 2 m high), and windows (area ranging from 0 to 2.5 m$^2$ depending on the scenario). All objects were defined in the PyroSim interface using built-in tools to construct a computational mesh with a cell size of 0.1 m, ensuring a balance between accuracy and computational efficiency.

In the second stage, the scenario parameters were defined. The fire source was modeled as a heat-releasing object with an initial power of 200 kW per m$^2$, corresponding to a typical fire source at the initial stage (e.g., burning furniture). Different placements of the fire source allowed for accounting for various possible fire spread patterns. For instance, if the fire source was located in a corner of the room, its shape resembled a 90° sector; if near one of the walls, a semicircle (180°); and if in the center of the room, a full circle (360°). The area of open doors and windows in the premises was set within ranges of 0–2 m$^2$ and 0–2.5 m$^2$, respectively, to cover various ventilation conditions and evacuation route accessibility. For each scenario, a simulation duration of 300 seconds with a time step of 0.1 s was established, enabling the capture of smoke propagation dynamics during the early fire stage (Figure 1).

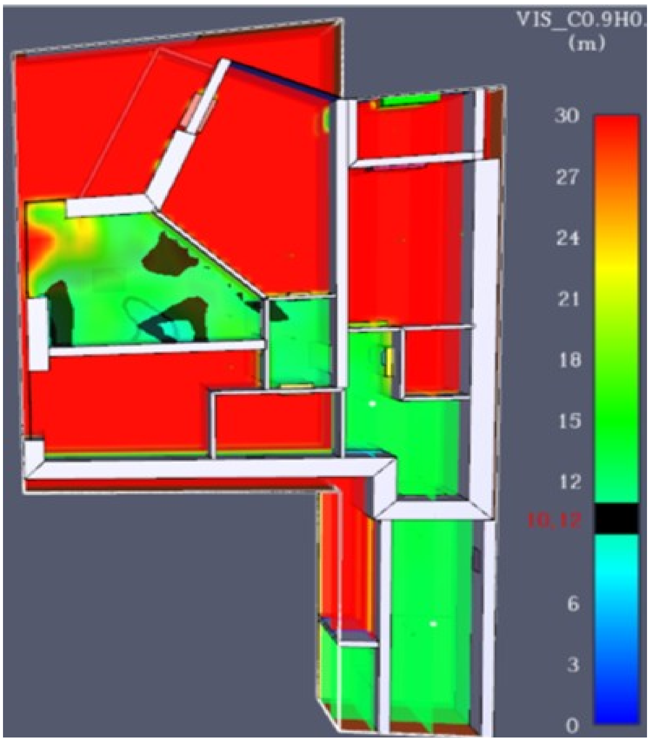


**Figure 1:** Modeling changes in visibility in an apartment during a fire.

The simulation was performed taking into account physical parameters: the air temperature was set at 20°C, the pressure at 101325 Pa, and the ventilation rate varied depending on the openness of windows and doors. The simulation results, including smoke concentration and visibility, were recorded using a virtual sensor placed near the evacuation exit at a height of 0.5 m from the floor (Figure 2).

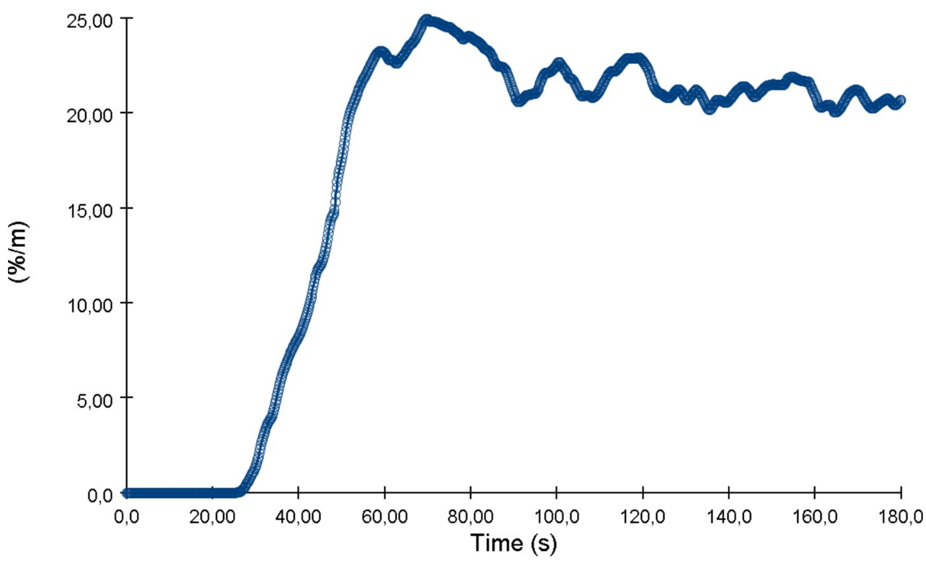


**Figure 2:** Measuring of smoke density changes near the evacuation exit.

The smoke blockage time (Tsmoke) was defined as the moment when visibility dropped below 10 m, corresponding to a soot concentration considered critical for safe evacuation according to regulatory requirements [20]. A total of 140 simulations with various parameter combinations were conducted, and their results were used as a dataset for analysis using machine learning techniques.

### 4.2. Regression Analysis

The first step of the regression analysis involved studying the correlations between the parameters Tsmoke, Angle, Distance, Doors, and Windows. This allowed for the identification of the factors with the greatest influence on the target variable (Tsmoke), the detection of potential linear or nonlinear dependencies, and the assessment of the degree of collinearity among the independent variables. The correlation heatmap is presented in Figure 3.

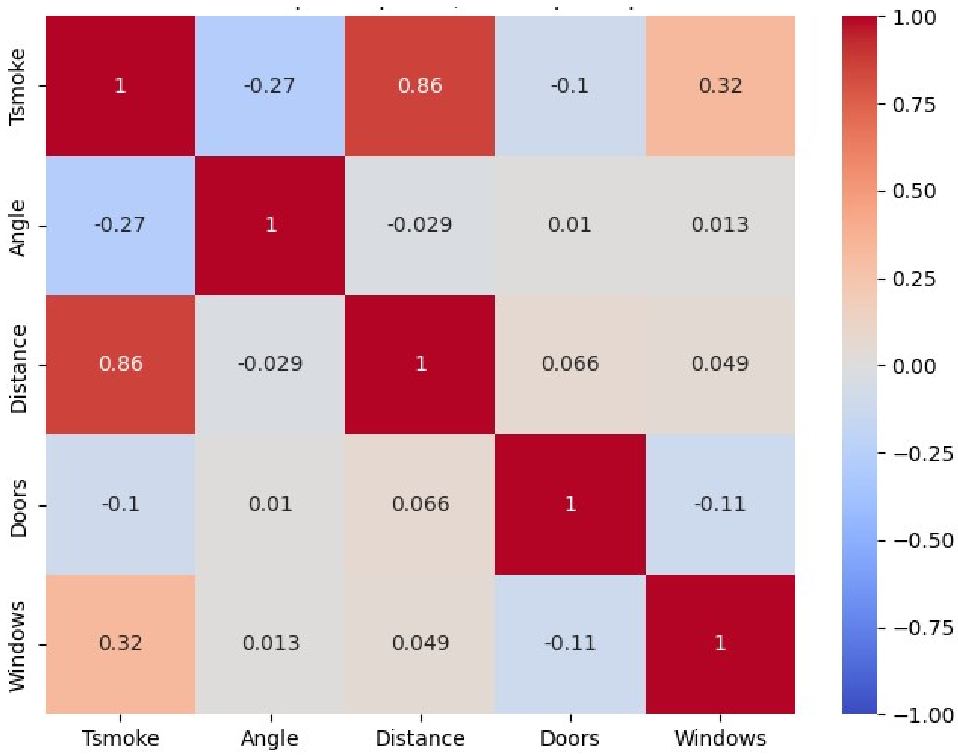


**Figure 3:** Heat map of correlations between parameters.

As observed, the time of smoke blockage (Tsmoke) is most strongly influenced by the distance from the fire source to the evacuation exit (Distance, 0.86), making distance a key factor in the smoke blockage of the exit. The fire shape (Angle) has a significant but lesser impact (−0.27), indicating that a larger fire spread angle results in faster blockage of the evacuation exit. The area of open windows (Windows, 0.32) and doors (Doors, −0.1) exhibits a weaker influence, though their contribution may be significant in nonlinear models. It is noteworthy that opening windows at the initial stage slows down the blockage of evacuation exits, while opening doors slightly accelerates it. This is logical, as an open evacuation exit facilitates smoke egress through it, whereas open windows divert some of the smoke away. The correlations between predictors are minimal, indicating the absence of multicollinearity.

The next step involved creating second-degree polynomial features (linear, quadratic, and interaction terms) using the Scikit-learn library. The data were split into training (80%) and testing (20%) sets with a fixed random_state=42 for reproducibility. A regression model was trained on the polynomial features, followed by predicting the smoke blockage time values for the test set. To evaluate the model's quality, the mean squared error (MSE) and coefficient of determination ($R^2$) were calculated, and visualizations such as a graph showing the dependence of the smoke blockage time of the evacuation exit on the distance from the fire source to the exit under different fire shapes (Figure 4) and a scatter diagram of predicted versus actual values (Figure 5) were constructed.

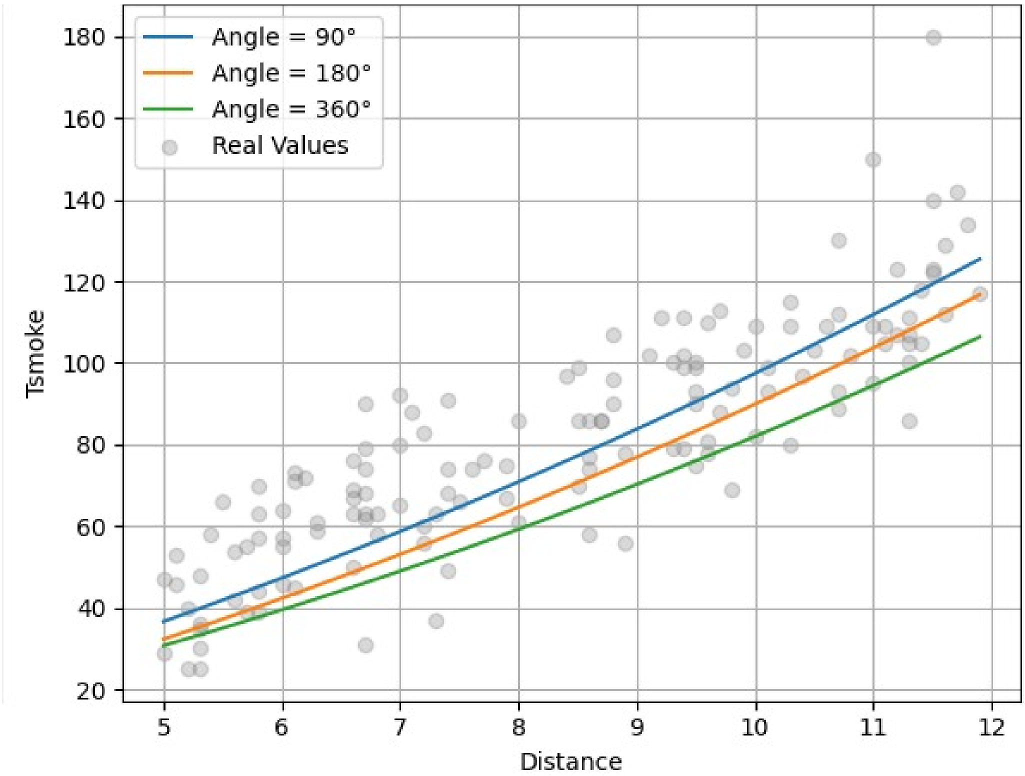


**Figure 4:** Dependence of the an evacuation exit smoke blockage time on the distance from the fire source to the exit under different fire shapes.

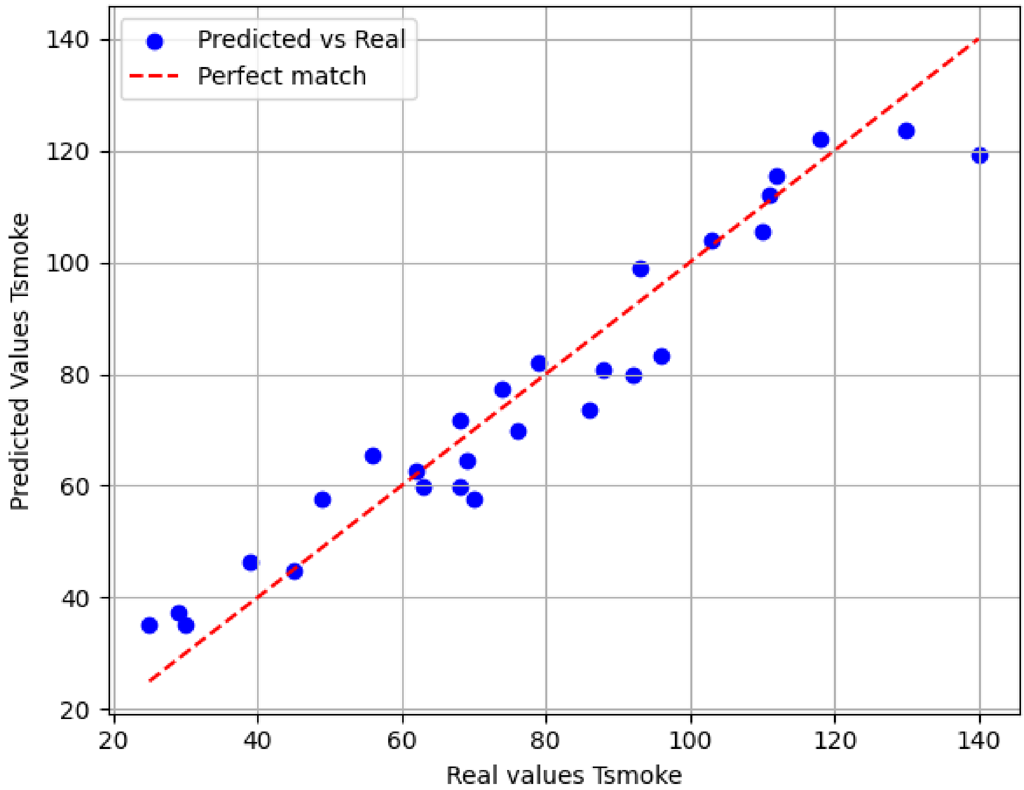


**Figure 5:** Scatterplot of predicted and actual values.

The final regression model describing the nonlinear influence of the input variables on smoke blockage time is given by Equation (1)

$$\tau = 0{,}375\, l^2 + 0{,}435\, lS_d - 0{,}42\, lS_w - 0{,}05\, a + 6{,}47\, l - 1{,}03\, S_d + 8{,}15\, S_w +$$
$$+\ 0{,}00015\, a^2 - 0{,}007\, al + 0{,}00003\, a\, S_d - 0{,}007\, a\, S_w - 3{,}25\, S_d^2 + 0{,}25\, S_d\, S_w + 1{,}93\, S_w^2 + 8{,}19, \quad (1)$$

where

$\tau$ – time of smoke blockage of the evacuation exit during a fire in a residential premise, s;
$l$ – distance from the fire source to the evacuation exit, m;
$a$ – angle of fire spread, degrees;
$S_d$ – area of open doors, $m^2$;
$S_w$ – area of open windows, $m^2$.

As a result, a model with high accuracy was obtained: the MSE was approximately 35.12, and the $R^2$ was about 0.93. The scatter diagram demonstrated a close alignment between predicted and actual values, while the graphs confirmed an increase in Tsmoke with greater Distance and its dependency on Angle, consistent with the physical patterns of smoke propagation.

### 4.3. Discussion

The results of the second-degree polynomial regression obtained in this study indicate high accuracy of the model in predicting the time of smoke blockage of evacuation routes during the initial stage of a fire in residential premises. The coefficient of determination value of $R^2$ = 0.93 explains 93% of the variation in the target variable based on parameters such as the distance from the fire source to the evacuation exit. The mean squared error (MSE) of 35.12 is acceptable and aligns with the natural variability of fire conditions. This confirms the effectiveness of the chosen approach for modeling complex nonlinear dependencies identified through numerical experiments in PyroSim.

Analysis of the model coefficients revealed that the distance to the evacuation exit has the greatest positive impact on the blockage duration: the greater the distance, the longer it takes for smoke to reach a critical concentration near the evacuation exit. The presence of open windows also significantly increases the smoke blockage time, which can be explained by enhanced ventilation and the removal of some smoke. Conversely, open doors produce an opposite effect. With open doors, air circulation intensifies, and a portion of the smoke begins to exit through the evacuation route, thereby increasing its concentration. The fire shape plays a somewhat lesser role, though its interaction with other parameters underscores the importance of a comprehensive analysis.

Visualization of the dependencies confirmed that the smoke blockage time of the evacuation exit increases with the distance to the exit, with this effect becoming more pronounced at higher values of the Angle parameter (360°), possibly related to the direction of smoke spread within the premises. The scatterplot demonstrated a close correspondence between predicted and actual values, indicating the model's reliability for practical application.

## 5. Conclusions

During the study, computer modeling of various scenarios of the initial stage of fire development in a residential premise was conducted using the PyroSim software package. This enabled the creation of a dataset with 140 records for training a machine learning model, incorporating various parameters such as the distance to the evacuation exit, the area of open door and window openings, and the fire shape. Correlation analysis revealed that the distance to the exit and the area of windows have the greatest positive impact on the smoke blockage time, while open doors slightly reduce this time. Nonlinear patterns of smoke spread were identified, including an increase in the evacuation exit blockage time with greater distance and a dependency on fire shape, which was confirmed through visualizations.

The developed second-degree polynomial regression model demonstrated high accuracy in predicting the evacuation exit blockage time ($R^2 \approx 0.93$, MSE ≈ 35.12). Testing showed the model's ability to adequately reflect the influence of the studied factors, making it promising for practical applications in risk assessment and evacuation planning. Thus, all tasks outlined in the article—modeling, analyzing the impact of parameters, and developing a predictive model—were accomplished, confirming the effectiveness of combining numerical modeling with machine learning.

Equation (1) for calculating the time of smoke blockage of an evacuation exit ($\tau$) is useful because it enables quick and accurate prediction of the critical moment when smoke renders safe evacuation from a residential premise impossible. This facilitates fire risk assessment without the need for complex simulations for each scenario, aids in optimizing evacuation planning, and enhances fire safety systems, thereby improving occupant safety. Built on machine learning and numerical modeling, this approach provides a practical tool for making informed decisions in real time.

A limitation of the current study is the relatively modest dataset size (140 scenarios). Nevertheless, this volume proved sufficient to achieve stable training of the second-degree polynomial model with $R^2 > 0.92$ and low MSE. The dataset is being continuously expanded, and future work will incorporate additional influencing factors and more advanced machine-learning architectures. It should also focus on accounting for the influence of wind loads, which can significantly alter smoke propagation dynamics in residential premises, particularly in high-rise buildings where airflows through windows play a critical role. Additionally, it is advisable to investigate the effects of smoke control ventilation systems, designed for high-rise structures, which can delay or redirect smoke, affecting the blockage time of evacuation routes. Integrating these factors into machine learning models will enhance their accuracy and adaptability to real-world building operation conditions.

## Declaration on Generative AI

During the preparation of this work, the authors used X-GPT-4 in order to grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

## References

[1] L. Jiang, A. S. Bøe, T. Li, Numerical simulation of fire spread in a large-scale open CLT compartment, Fire Saf. J. (2024) 104289. doi:10.1016/j.firesaf.2024.104289.

[2] X. Yi, C. Lei, J. Deng, L. Ma, J. Fan, Y. Liu, L. Bai, C.-M. Shu, Numerical Simulation of Fire Smoke Spread in a Super High-Rise Building for Different Fire Scenarios, Adv. Civ. Eng. 2019 (2019) 1–11. doi:10.1155/2019/1659325.

[3] Saber, H., Kashef, A., Bwalya, A., Lougheed, G., & Sultan, M. (2008). A numerical study on the effect of ventilation on fire development in a medium-sized residential room (Report No. NRCC-50357). National Research Council Canada. https://doi.org/10.4224/20377990.

[4] M. D. Lulea, V. Iordache, I. Năstase, Numerical Model Development of the Air Temperature Variation in a Room Set on Fire for Different Ventilation Scenarios, Appl. Sci. 11.24 (2021) 11698. doi:10.3390/app112411698.

[5] J. Li, T. Beji, S. Brohez, B. Merci, CFD study of fire-induced pressure variation in a mechanically-ventilated air-tight compartment, Fire Safety Journal 115 (2020) Article 103126. doi:10.1016/j.firesaf.2020.103126.

[6] E. Guillaume, F. Didieux, A. Thiry, A. Bellivier, Real-scale fire tests of one bedroom apartments with regard to tenability assessment, Fire Safety Journal 70 (2014) 81–97. doi:10.1016/j.firesaf.2014.08.014.

[7] C. S. Lin, M. E. Wu, A study of evaluating an evacuation time, Advances in Mechanical Engineering 10(4) (2018). doi:10.1177/1687814018772424.

[8] N. Cai, W. K. Chow, Air flow through the door opening induced by a room fire under different ventilation factors, Procedia Engineering 43 (2012) 125–131. doi:10.1016/j.proeng.2012.08.022.

[9] Y. Tong, D. Huo, P. Zhu, X. Niu, Prediction of natural and hybrid ventilation performance used for fire-induced smoke control in a large single space, Fire Safety Journal 100 (2018) 20–31. doi:10.1016/j.firesaf.2018.03.005

[10] H. T. Nguyen, Y. Abu-Zidan, G. Zhang, K. T. Q. Nguyen, Machine learning-based surrogate model for calibrating fire source properties in FDS models of façade fire tests, Fire Safety Journal 130 (2022) Article 103591. doi:10.1016/j.firesaf.2022.103591.

[11] O. Khlevnoi, N. Burak, Y. Borzov, D. Raita, Neural network analysis of evacuation flows according to video surveillance cameras, in: S. Babichev, V. Lytvynenko (Eds.), Lecture Notes in Data Engineering, Computational Intelligence, and Decision Making, Springer (2023) 639–650. doi:10.1007/978-3-031-16203-9_35.

[12] A. Balboa, A. Cuesta, J. González-Villa, G. Ortiz, D. Alvear, Online experiments and regression analysis of evacuation decisions in response to fire alarms, Fire Safety Journal 141 (2023) Article 103954. doi:10.1016/j.firesaf.2023.103954.

[13] Q. Cheng, X. Wang, J. Zhuang, W. Liao, L. Xie, Fire scenario simulation method for residential buildings based on generative adversarial network, Developments in the Built Environment 23 (2025) Article 100720. doi:10.1016/j.dibe.2025.100720.

[14] E. A. Refaee, A. Sheneamer, B. Assiri, A deep-learning-based approach to the classification of fire types, Applied Sciences 14(17) (2024) Article 7862. doi:10.3390/app14177862.

[15] B. Y. Lattimer, J. L. Hodges, A. M. Lattimer, Using machine learning in physics-based simulation of fire, Fire Safety Journal 114 (2020) 102991. doi:10.1016/j.firesaf.2020.102991.

[16] B. Ralph, R. Carvel, Coupled hybrid modelling in fire safety engineering: A literature review, Fire Safety Journal 100 (2018) 157–170. doi:10.1016/j.firesaf.2018.08.008.

[17] H. Lavrenyuk, V. Kochubei, O. Mykhalichko, B. Mykhalichko, A new flame retardant on the basis of diethylenetriamine copper(II) sulfate complex for combustibility suppressing of epoxy-amine composites, Fire Safety Journal 80 (2016) 30–37. doi:10.1016/j.firesaf.2016.01.001.

[18] J. Li, L. Bai, J. Bai, Y. Xu, T. Zhang, D. Zhang, Y. Guo, Construction of narrow-band infrared radiation characteristics database for high-temperature hydrocarbon combustion media, Proc. SPIE 133 (2021). doi:10.1117/12.2606124.

[19] L. Xu, Y. Lu, C. Ding, H. Guo, J. Liu, Y. Zhao, A generic flame shape model and analytical models for geometric view factor calculation on the fire exposure surface, International Journal of Thermal Sciences 173 (2022) 107392. doi:10.1016/j.ijthermalsci.2021.107392.

[20] DSTU 8828:2019. Pozhezhna bezpeka. Terminy [Fire safety. Terms], State Standard of Ukraine (2019). URL: http://online.budstandart.com/ua/catalog/doc-page.html?id_doc=82138