



GRADO EN INGENIERÍA EN TECNOLOGÍAS
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TRABAJO DE FIN DE GRADO

FIRE DYNAMICS ANALYSIS FOR ASSESSING RESILIENCE IN VULNERABLE DWELLINGS

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June 2024

Declaro, bajo mi responsabilidad, que el Proyecto presentado con el título
FIRE DYNAMICS ANALYSIS FOR ASSESSING RESILIENCE IN
VULNERABLE DWELLINGS

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Collaborating Entity: ICAI – Universidad Pontificia Comillas

SUMMARY OF THE PROJECT

Fire safety has undergone significant transformations since its initial introduction in the 1930s within industrial settings. Over the years, a complex approach to fire prevention and mitigation has been developed. This approach includes different strategies like the use of smoke alarms, the adoption of effective evacuation plans, fire education initiatives, the use of advanced fire-retardant building materials, the implementation of regulations, etc. These efforts have aided in the reduction of fire incidence and resulting casualties. However, despite these evolutionary aspects, certain areas and demographic groups are still vulnerable to the devastating effects of fires.

Due to recent massive fire catastrophes, researchers have been investigating the characteristics of vulnerable populations and how fires affect them. Focus has been placed on informal dwellings, which portray challenges when referring to fire safety. Informal settlements, often referred to as slums, are housing arrangements that do not conform with the established housing regulations of the community. Typically, these dwellings lack formal land tenure and often go without essential utilities. Nevertheless, there are other types of dwellings, which although compliant with the legal requirements, still present risks. In substandard dwellings, living and building conditions fall significantly short of optimal, offering only bare minimum habitability. Both informal and substandard housing share the common characteristic of heightened vulnerability to fires. This stems from factors such as overcrowding, limited fire safety awareness, compromising construction materials, and energy poverty.

In an effort to assess the risk that this vulnerable type of household has, a simulation tool that utilizes the GAMA software and is obtained from previous research [1] is refined. This is done through the introduction of several numerical temperature models to capture the spread of the fire. In addition to this, the partition algorithm is improved to add geometric realism to the simulations. The importance of a tool as such is paramount, as being able to predict how a

potential fire would spread aids in the design of fire safety measures. A real-life example block of buildings located in a mid to low-income area of Madrid, Spain is selected for the risk assessment. Simulations of potential fires beginning at the ground floor of the buildings are carried out. The spread of the fire is monitored, and data of the affected apartments, floors and area is obtained after 1 hour. The risk of these buildings becomes apparent when analyzing the outcome of the simulations. The smallest buildings, situated at the center of the block, which consist of one apartment each, are completely burned down for almost every simulation. In addition to this, the statistics obtained from the results showcase the danger that this block of buildings possesses. An average burned area of 115 m² through the simulations, while approximately 4-5 apartments and 2 floors are affected on average. There exist some extreme situations with around 14 affected apartments, 6 burned floors and an affected area close to 450 m². The distribution of data for these variables shown in Figure 1 indicates the high presence of scenarios with low to medium risk, while there are some extreme cases with a high level of risk.

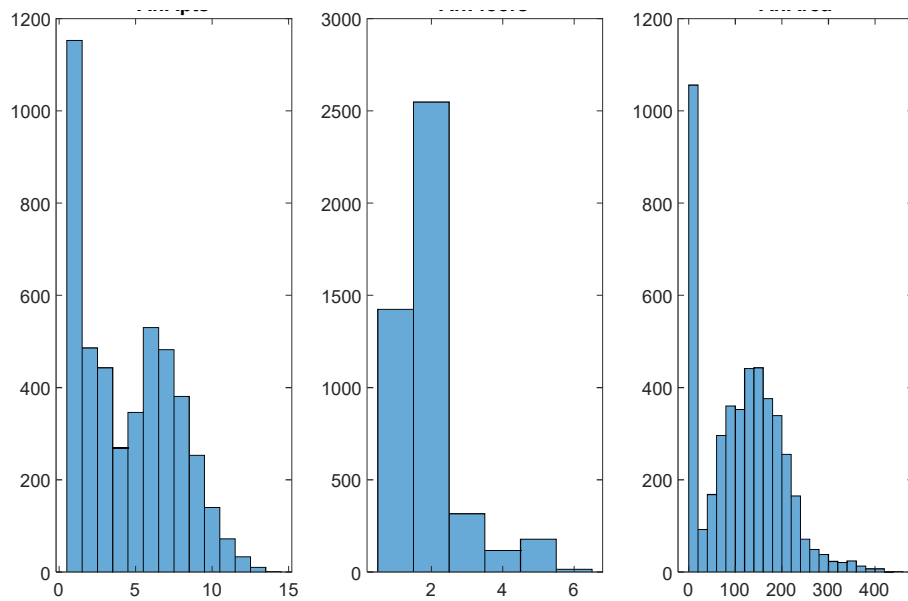


Figure 1. Histograms of a) affected apartments, b) affected floors, and c) affected area

Furthermore, two linear regression models are created, each one with a specific purpose. The first model aims to understand the variables that affect the level of risk that a room within a building possesses. The second, serves as a tool to predict the risk that rooms in other scenarios may have. A risk factor is defined, related to the room where the fire begins and measured as a factor that combines the three variables from Figure 1. The three are considered as they measure different characteristics. While the number of affected apartments measures the amount of families that are affected by the fire, the number of affected floors can difficult the

actions of the fire brigade, and the total affected area represents the extent of the damage that the fire causes. Variables related to the building parameters, wind conditions, fire parameters (including fire load density and fire growth rate), and the state of the doors and windows are considered as the independent variables in the models.

The explanatory model includes the variables that are considered statistically significant. It determines that the variables that have a highest impact on the risk factor are related the number of open doors in the rooms. Furthermore, the presence of windows also increases the risk factor, as oxygen is part of the fuel necessary for the fire to spread. Building parameters such as the size and number of floors impact the risk. Nevertheless, while a higher area increases the risk factor, the number of floors decreases it. A conclusion from this is that the fire spreads more horizontally (within the same floor) than vertically (to top floors), according to the outcome of the simulations and the model. The model has moderate explanatory power, presenting an adjusted R-squared of 0.66 and a Root Mean Square Error of 0.123 and a p-value of the F statistic close to 0.

The predictive model is built with more variables and presents a higher adjusted R-squared (0.69) and a lower RMSE (0.119), the p-value of the F statistic remains close to 0. This determines that the model has a moderate predictive power. Figure 2 provides a graph of the actual values against the predicted values of the test set. As can be seen, the values with an actual value close to zero, which represent extremely low risk, are below 0.2 in predicted value. Furthermore, high actual risk factor values (over 0.8) have a predicted value over approximately 0.5. The underestimation of the values with a high risk factor should be taken into account when using the model, knowing that a predicted value over 0.5 may be related to a high risk scenario. Values that are extreme can thus, be identified in this way. Two different groups can be identified in Figure 2. The separation of them into two models was considered, nevertheless, the performance of the model was not improved by this.

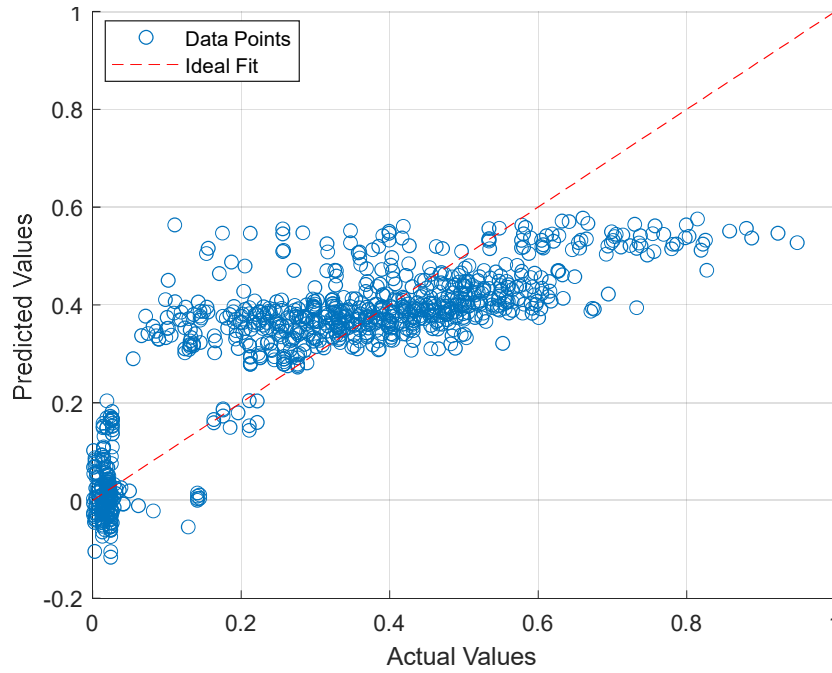


Figure 2. Actual vs. Predicted values of test set

This study provides a tool to assess fire resilience in vulnerable substandard dwellings through simulation and risk modelling. The results obtained through the evaluation of the case study underscore the importance of tailored safety measures for vulnerable housing types, contributing to enhanced fire prevention and mitigation strategies. The explanatory model highlights the significant impact of building and room characteristics on fire risk. Its moderate explanatory power suggests that, while it provides valuable insights, additional factors may influence fire risk. The predictive model also provides moderate prediction results, making it possible to identify scenarios with low and high risk.

Furthermore, there exist limitations of the simulation tool, as assumptions had to be made to make the tool functional. As for the model, validation with real experiments would be beneficial to verify and adjust the model. Additionally, the use of data from a larger number of buildings (in this case it was limited to 12), could improve the fit of the models.

ANÁLISIS DE LA DINÁMICA DEL FUEGO PARA EVALUAR LA RESILIENCIA EN VIVIENDAS VULNERABLES

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RESUMEN DEL PROYECTO

La seguridad contra incendios ha experimentado transformaciones significativas desde su introducción en la década de 1930 en entornos industriales. Con el tiempo, se ha desarrollado un enfoque complejo para la prevención y mitigación de incendios. Este enfoque incluye diferentes estrategias, como el uso de detectores de humo, adopción de planes de evacuación, introducción de iniciativas de educación sobre incendios, uso de materiales de construcción avanzados retardantes al fuego, implementación de normativas, etc. Estas medidas han ayudado a reducir la incidencia de los incendios y el número de víctimas. Sin embargo, a pesar de estos aspectos evolutivos, ciertas áreas y grupos demográficos siguen siendo vulnerables a los efectos devastadores de los incendios.

Debido a las recientes catástrofes provocadas por incendios masivos, los investigadores han estudiado las características de las poblaciones vulnerables y cómo les afectan los incendios. La atención se ha centrado en las viviendas informales, que plantean desafíos en materia de seguridad contra incendios. Los asentamientos informales, a menudo denominados barrios marginales, son viviendas que no se ajustan a las normas establecidas en materia de vivienda. Normalmente estas viviendas carecen de la propiedad formal de suelo y a menudo no cuentan con los servicios esenciales. Sin embargo, existen otros tipos de viviendas que, aunque cumplen con los requisitos legales, presentan riesgos. En las infraviviendas las condiciones de vida y construcción son muy inferiores a las óptimas, ofreciendo solo una habitabilidad mínima. Tanto las infraviviendas como las precarias comparten la característica común de una mayor vulnerabilidad a los incendios. Esto se debe a factores como el hacinamiento, la escasa conciencia sobre la seguridad contra incendios, los materiales de construcción utilizados y la pobreza energética.

En un esfuerzo por evaluar el riesgo que tiene este tipo vulnerable de hogar, se perfecciona una herramienta de simulación que utiliza el software GAMA y se obtiene de una investigación

anterior [1]. Esto se realiza mediante la introducción de varios modelos numéricos de temperatura de incendios para capturar su propagación. Además, se mejora el algoritmo de partición para añadir realismo geométrico a las simulaciones. La importancia de una herramienta como ésta es fundamental, ya que poder predecir cómo se propagaría un incendio ayuda en el diseño de medidas de seguridad. Para realizar la evaluación del riesgo se selecciona un bloque de edificios real situado en una zona de renta media-baja de Madrid, España. Se realizan simulaciones de incendios que comienzan en la planta baja de los edificios, se monitoriza su propagación y se obtienen datos de los apartamentos, número de plantas y áreas afectadas tras 1 hora. El riesgo de estos edificios se hace evidente al analizar los resultados de las simulaciones. Los edificios más pequeños, situados en el centro de la manzana, que constan de un apartamento cada uno, se queman por completo en casi todas las simulaciones. Además, las estadísticas obtenidas de los resultados muestran el peligro que posee esta manzana de edificios. Con el análisis estadístico, en las simulaciones se obtiene un área promedio quemada de 115 m² y un promedio de 4-5 apartamentos y 2 plantas afectados. Se dan algunas situaciones extremas con alrededor de 14 apartamentos afectados, 6 plantas quemadas y un área afectada cercana a los 450 m². La distribución de datos para estas variables, mostrada en la Figura 1, indica la alta presencia de escenarios con riesgo bajo a medio, mientras que hay algunos casos extremos con un nivel de riesgo alto.

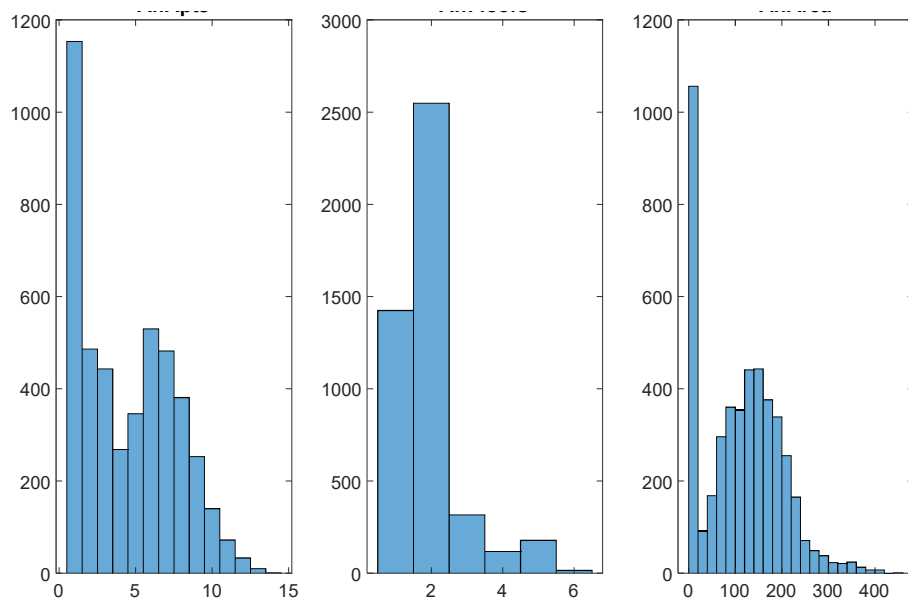


Figura 1. Histogramas de a) apartamentos afectados, b) plantas afectadas, y c) área afectada

A partir de estos datos, se crean dos modelos de regresión lineal, cada uno con un propósito específico. El primer modelo tiene como objetivo analizar las variables que afectan el nivel de riesgo que posee una habitación dentro de un edificio. El segundo sirve como herramienta para predecir el riesgo que pueden tener las habitaciones en otros escenarios en caso de incendio. Se define un factor de riesgo, relacionado con la habitación donde comienza el incendio y medido como un factor que combina las tres variables de la Figura 1. Se consideran las tres pues miden características diferentes. Mientras que el número de apartamentos afectados mide la cantidad de familias que se ven afectadas por el incendio, el número de plantas afectadas puede dificultar las acciones de los bomberos y el área total afectada representa, de una manera más general, la magnitud de los daños que causa el incendio. Las variables relacionadas con los parámetros del edificio, las condiciones del viento, los parámetros del incendio (incluyendo la densidad de carga de fuego y la tasa de crecimiento del incendio) y el estado de las puertas y ventanas se consideran como variables independientes en los modelos.

El modelo explicativo incluye las variables que se consideran estadísticamente significativas. Determina que las variables que tienen un mayor impacto en el factor de riesgo están relacionadas con el número de puertas abiertas en las habitaciones. La presencia de ventanas también aumenta el factor de riesgo, ya que el oxígeno es necesario para que el incendio se propague. Parámetros del edificio, como el tamaño y el número de plantas, afectan al riesgo. Sin embargo, mientras que un área mayor aumenta el factor de riesgo, el número de plantas lo disminuye. Una conclusión de esto, según los resultados de las simulaciones y del modelo, es que el incendio se propaga más horizontalmente (dentro del mismo piso) que verticalmente (a los pisos superiores). El modelo tiene un poder explicativo moderado, presentando un R-cuadrado corregido de 0.66 y un Error Cuadrático Medio (ECM) de 0.123 y un p-valor del estadístico F cercano a 0.

El modelo predictivo se construye con más variables y presenta un R-cuadrado corregido más alto (0.69) y un ECM más bajo (0.119), el p-valor del estadístico F permanece cercano a 0. Esto determina que el modelo tiene un poder predictivo moderado. La Figura 2 muestra un gráfico de los valores observados frente a los valores estimados o predichos del conjunto de prueba. Como se puede ver, los valores con un valor observado cercano a cero, que representan un riesgo extremadamente bajo, están por debajo de 0.2 en cuanto a valor predicho. Por otro lado, los valores reales de alto factor de riesgo (superiores a 0,8) tienen un valor estimado mayor que 0.5 en la mayoría de los casos. La subestimación de los valores con un alto nivel de

riesgo debe tenerse en cuenta a la hora de utilizar el modelo, sabiendo que un valor estimado de 0.5 podría estar relacionado con un alto factor de riesgo. En la Figura 2 se pueden identificar dos grupos diferentes de datos, un grupo que permanece con un valor observado menor que 0.1, y otro con valores mayores. La separación de estos datos en dos modelos se consideró, sin embargo, el rendimiento del modelo no mejoró.

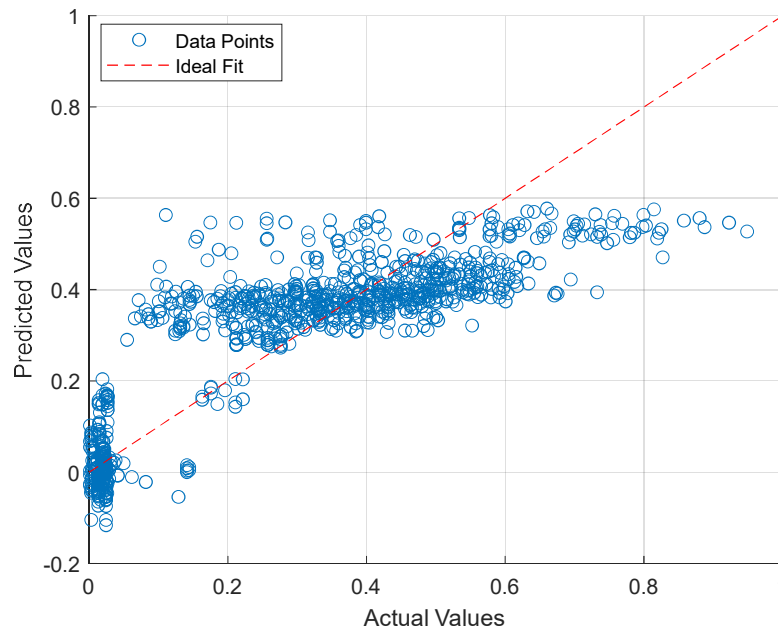


Figura 2. Valores observados vs. estimados del conjunto de prueba

Este estudio proporciona una herramienta para evaluar la resiliencia contra incendios en infraviviendas vulnerables mediante simulación y modelos de riesgos. Los resultados obtenidos a través de la evaluación del estudio de caso subrayan la importancia de medidas de seguridad adaptadas para los tipos de viviendas vulnerables, contribuyendo a mejorar las estrategias de prevención y mitigación de incendios. El modelo explicativo destaca el impacto significativo de las características del edificio y de las habitaciones en el riesgo de incendio. Su poder explicativo moderado sugiere que, si bien proporciona información valiosa, otros factores adicionales pueden influir en el riesgo de incendio. El modelo predictivo también ofrece resultados de predicción moderados, haciendo posible identificar escenarios con riesgo bajo y alto.

Además, existen limitaciones en la herramienta de simulación, ya que se tuvieron que hacer suposiciones para asegurar la funcionalidad de la herramienta. En cuanto al modelo, sería beneficioso validarlo con experimentos reales para verificar y ajustar el modelo.

Adicionalmente, el uso de datos de un mayor número de edificios (en este caso, se limitó a 12) podría mejorar el ajuste de los modelos.

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I would like to thank Alexis and Pablo for their continuous help and support throughout the project and for always finding time to answer my questions. I am extremely grateful for the invaluable knowledge you have instilled in me during these years.

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1. Introduction

Fire safety has undergone significant transformations since its initial introduction in the 1930s within industrial settings. Over the years, a complex approach to fire prevention and mitigation has been developed. This approach includes different strategies like the use of smoke alarms, the adoption of effective evacuation plans, fire education initiatives, the use of advanced fire-retardant building materials, the implementation of regulations, etc. These efforts have aided in the reduction of fire incidence and resulting casualties. However, despite these evolutionary aspects, certain areas and demographic groups are still vulnerable to the devastating effects of fires.

Due to recent massive fire catastrophes, researchers have been investigating the characteristics of vulnerable populations and how fires affect them. Focus has been placed on informal dwellings, which portray challenges when referring to fire safety. Informal settlements, often referred to as slums, are housing arrangements that do not conform with the established housing regulations of the community [2]. Typically, these dwellings lack formal land tenure and often go without essential utilities.

On the other hand, there are other types of dwellings, which although compliant with the legal requirements, still present risks. In substandard dwellings, living and building conditions fall significantly short of optimal, offering only bare minimum habitability [3]. Both informal and substandard housing share the common characteristic of heightened vulnerability to fires. This stems from factors such as overcrowding, limited fire safety awareness, compromising construction materials, and energy poverty, which will be explained in detail in the following section.

2. Fire Risk Factors

Fire risk factors are conditions that increase the likelihood of a fire occurring or intensifying its potential to cause harm. They have been researched at the beginning of this century to be able to focus all efforts on certain groups that need special protection. Below, Figure 1 shows a general view of the topics discussed in scientific papers related to fire risk factors for residential buildings. This aids in the selection of important topics, their interrelationships, and their relevance in recent literature.

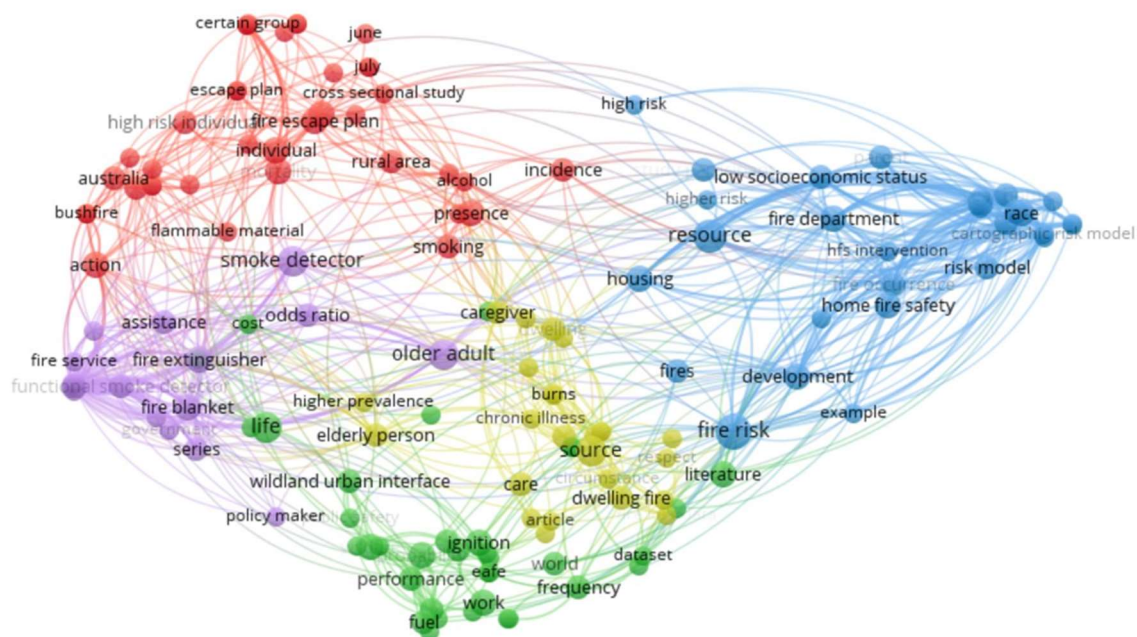


Figure 1. Diagram of Researched Topics [4,5].

Topics related to fire safety, such as fire escape plans, action, preparation, and fire suppressors such as extinguishers, fire blankets, and smoke detectors (red and purple dots) are mentioned. Also, subjects such as housing, low socioeconomic status, elderly persons, flammable materials, older adults, perceived risk, race, smoking, and alcohol use... (yellow and blue) are all reviewed in the papers. Terms referring to the study and modelling of these fires are also displayed: risk model, odds ratio, fire escape plan, and cross-sectional studies.

This diagram was created with the VOS viewer tool [4]. As for the graphics, related topics are grouped into the same categories and portrayed in the same colors. The size of the dot symbolizes the presence of the topic in the texts. The connections between terms written in the same paper are the colored lines between dots.

Current research lists dwelling characteristics and the demographics of residents as the two primary determinants affecting the risk of fire. In many cases, these factors are closely related, as socioeconomic vulnerability often leads to inadequate living conditions. As for the demographics of residents, several factors have been considered. A low income has been linked to fire risk by many studies. This relationship has been observed and studied as far back as 1977 with a pilot study in New Orleans, Louisiana [5]. A fairly negative linear association was observed in low-median household incomes. Recent research carried out in the United States concludes that high levels of poverty may increase between two and three times the average fire rates [6]. This factor is considered a general increase in risk and it is highly linked to others [7]. Substandard housing is very prevalent among economically vulnerable groups.

Poor construction materials, specifications, and maintenance make buildings more prone to more numerous, dangerous and fast spreading fires [7]. These factors are mostly found in old buildings (built when fire safety standards were lower), but also in newer constructions (using cheap materials and synthetics).

An example is the Grenfell Tower, a 24-storey residential building in West London. It was built for social purposes, and it housed up to six hundred, mostly low-income people and immigrants. The building underwent a renovation in 2016, which included changes in the insulation system and windows. In June 2017, a flat on the fourth floor caught fire and rapidly spread to higher floors. The insulation, which was made from composite metal cladding, was what quickened the spread of the fire [8]. In addition to this, the building did not comply with some of the fire safety regulations [9] (contained in the Building Regulations 2010 document [10]), which caused a delay in the actions of the fire brigade. This incident caused seventy-two deaths and immediately put focus on social housing conditions and fire safety legislation [11].

After events such as the previously described, studies have been published analyzing the gaps and needs in the regulation of buildings. As apartments and buildings become owned by particulars, inspections become more difficult. Inhabitants of substandard dwellings tend to overlook issues because of the added cost of maintaining the home according to standards [12]. Depreciated electrical and gas installations are a leading cause of residential fires, with 8% of fires in the United States generated by electrical wiring [13]. Fire safety measures are at many times forgotten and, in case of a fire, the situation becomes more

dangerous and deadly. In addition to maintenance issues, energetically poor households tend to utilize dangerous practices to cook and heat, posing a fire risk [14].

An example of these issues is the Bronx apartment fire, happening in 2022. This residential fire is considered the third worst in the United States in the last four decades, with seventeen deaths. The cause of the fire was a defective space heater. Malfunctioning self-closing doors made the smoke spread quickly, which was what ultimately made the fire deadly. As the failure of the main fire safety system was the cause of the disaster, experts concluded that the deaths were preventable [15].

These types of buildings tend to be overcrowded and have small rooms, which leads to several problems, some of them regarding fire safety. Leung and Chow [16] performed a study about subdivided units, identifying housing characteristics that increase fire risk. Narrow corridors, combustible objects in escape routes, and blocked fire escapes are common in overcrowded dwellings, and all contribute to a higher number of deaths and injuries in case of fire.

Examples of fires in overcrowded buildings include the recent Johannesburg fire, which happened in 2023. This illegal settlement was state-owned and “hijacked”. It was subdivided and overcrowded and was considered “a firetrap and a disaster waiting to happen”, according to experts and locals [17]. It lacked steady access to electricity and housed approximately 600 people. Although the exact cause of the fire is not yet clear, it is known that this incident killed at least 76 people [18].

2.1. Situation in Spain

Focusing on Spain, statistical data is found to support the information given in the previous section. The extensive study carried out by Fernandez-Vigil et al. [19] uses different Spanish official databases to statistically exemplify the fire risk factors.

In Figure 2, the evolution of the fire death rate in Spain from 1980 to 2022 is shown.

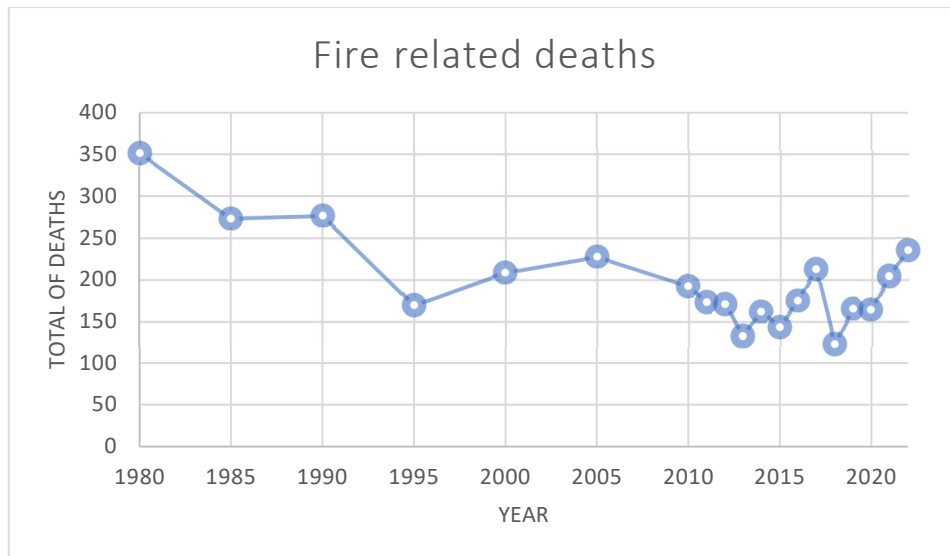


Figure 2. Fire death rate in Spain in all types of fires through the years [20].

According to this graph, since the 1980s this cause of death has reduced to more than half its casualties. Three-fourths of the total deaths happened in residential buildings, which highlights the importance of analysis and action in dwellings. The visible reduction observed in the last decades of the last century is due to the improvement of fire safety methods, as formerly explained. Nevertheless, starting in 1995, a stabilization is perceived and each year deaths vary in a range of 125-225 deaths per year.

The data from the 2019 statistical study highlights the prevalence of risk factors: income level, age of the building, and age of the inhabitants.

Income range	Population (%)	Deaths	R.R. deaths
10,000–15,000	3.6	12 (9.7%)	2.70
15,001–20,000	20.6	26 (21%)	1.02
20,001–25,000	30.8	49 (39.5%)	1.28
25,001–30,000	29.8	29 (23.4%)	0.79
Over 30,000	15.3	8 (6.5%)	0.42
Total	100.0	124 (100%)	

Table 1. Fire-related deaths by the income range of the location, 2016 [19,20].

Table 1 shows that households with an income between 10.000 and 15.000 suffer a fire risk increase by a factor of 2.7. Even though this population group is the smallest when compared to the four others, the risk difference among groups is significant.

The age of the building also portrays an interesting statistical outcome as can be observed in Figure 3.

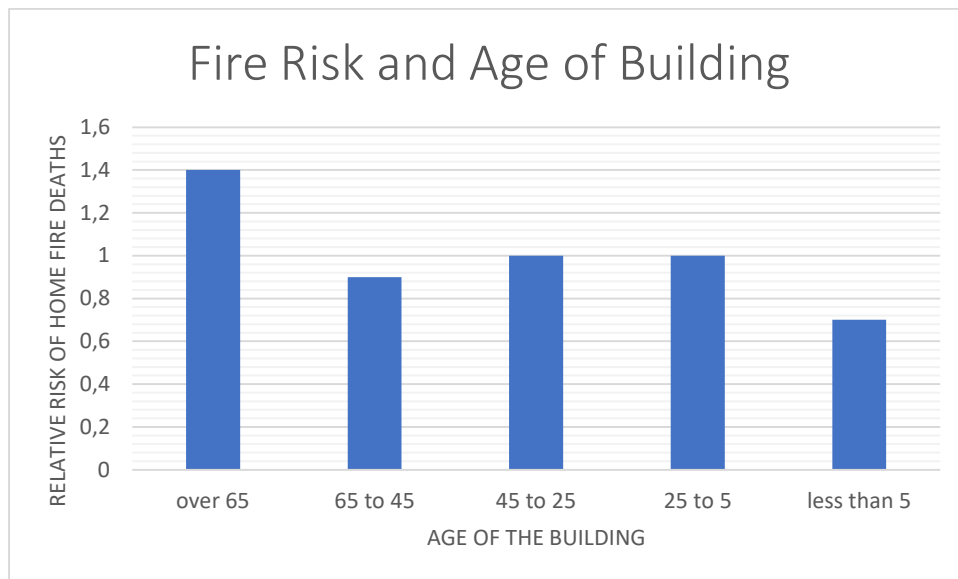


Figure 3. Relative risk of home fire deaths by the age of the building in Spain, 2016 [19].

Buildings that are over the age of sixty-five are 1.4 times more at risk for fire. This is proven statistically significant to a value of 5%. As aforementioned, older, and deteriorating buildings have been difficult to regulate, and many present outdated fire safety measures and dangerous installations.

Lastly, the analysis of fire risk depending on age group rendered the information presented in Figure 4. In orange, is the population among age groups [21], in blue, the deaths by fire for each age group, and in green, the risk or fire death or ratio can be seen.

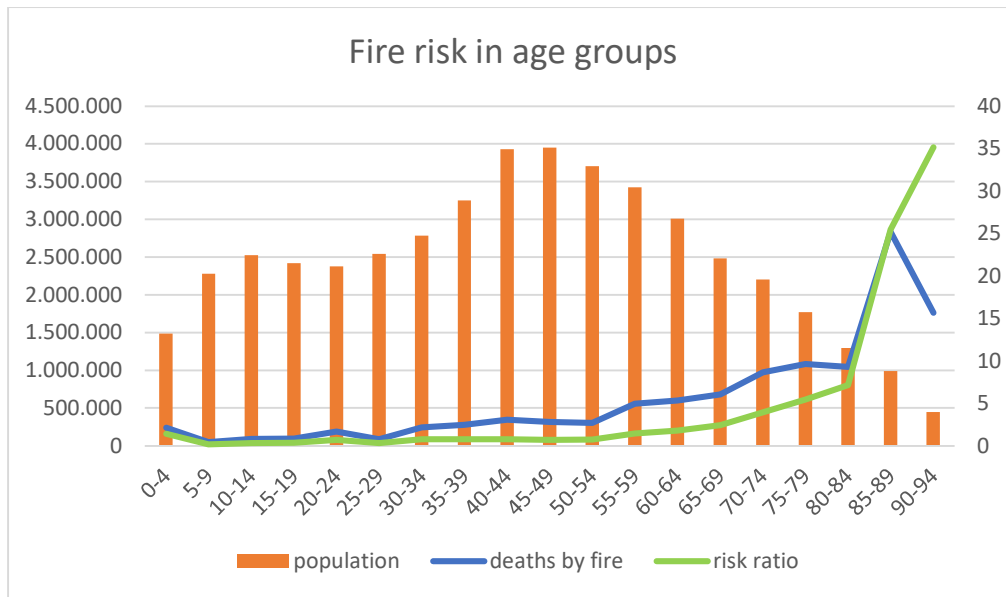


Figure 4. Fire Deaths in Home Fires in Spain by Age Group. 2021 [20,22].

The ages sixty-five and over, conforming approximately 20% of the population accounted for more than 60% of deaths. It is also significant to notice the sharp increase in the fire death ratio (obtained by dividing the death per million indices by the population for each age group). From the age of eighty, fire death risk increases notably.

2.2. Case of Study

For this project, a block of homes in the Tetuán district in Madrid, Spain, was chosen. This area of Madrid consists of six very heterogeneous neighborhoods close to the financial center of the city. This community shows certain characteristics that can be grouped into two categories:

Urban

The design of homes in this neighborhood is characterized by being smaller (74,1 m²) than Madrid's average (80.7 m²). These homes tend to house a higher-than-average number of people [23]. Because of this, population density is as high as 293 in the district and averages 410 inhabitants per hectare in Bellas Vistas, the neighborhood where the case study is located: more than ten times the municipal average [24].

Social

The socio-economic level of the population in Tetuán is mid-low, with high percentages of elderly (about 10%, older than 75) and immigrant population (20.2%) [24]. In addition to this, and because of the cultural diversity and the presence of Latin gangs in some neighborhoods within this district, coexistence problems arise often [25]. Another problem that this district faces is the presence of what is referred to “dark kitchens”, which are industrialized kitchens that only offer delivery services [26]. Issues regarding informal settlements and occupied buildings have also caused preoccupation among the inhabitants. The social issues mentioned are most prevalent in the neighborhoods of Bellas Vistas and Berruguete. There have been various fire incidents documented in the area. Most of them occurred in informal settlements, such as the ones portrayed in Figure 5

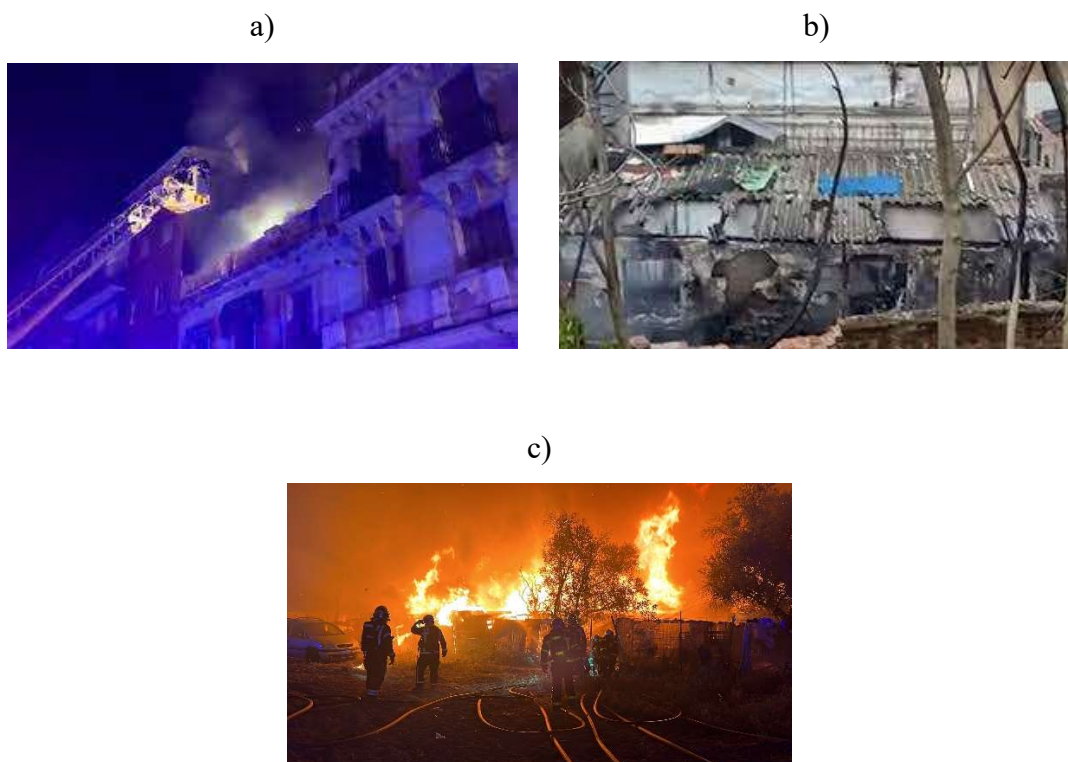


Figure 5. Pictures of different fires in informal settlements in Tetuán, Madrid: a) [27], b) [28], c) [29].

On the other hand, there have been fires registered in substandard housing, such as the following in Figure 6.

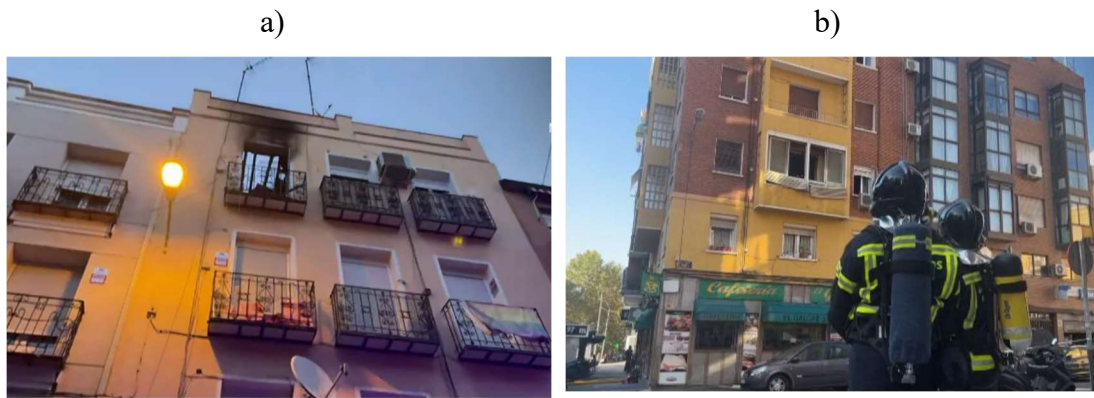


Figure 6. Pictures of different fires in substandard housing in Tetuán, Madrid: a) [27] b) [28].

The chosen block of buildings is limited by the streets: Carolinas, Alvarado, Topete, and Bravo Murillo, and it is shown in Figure 7. This block is characterized by having different shapes of buildings, some with internal courtyards. In addition to this, balconies tend to accumulate trash, furniture, and clothing lines.

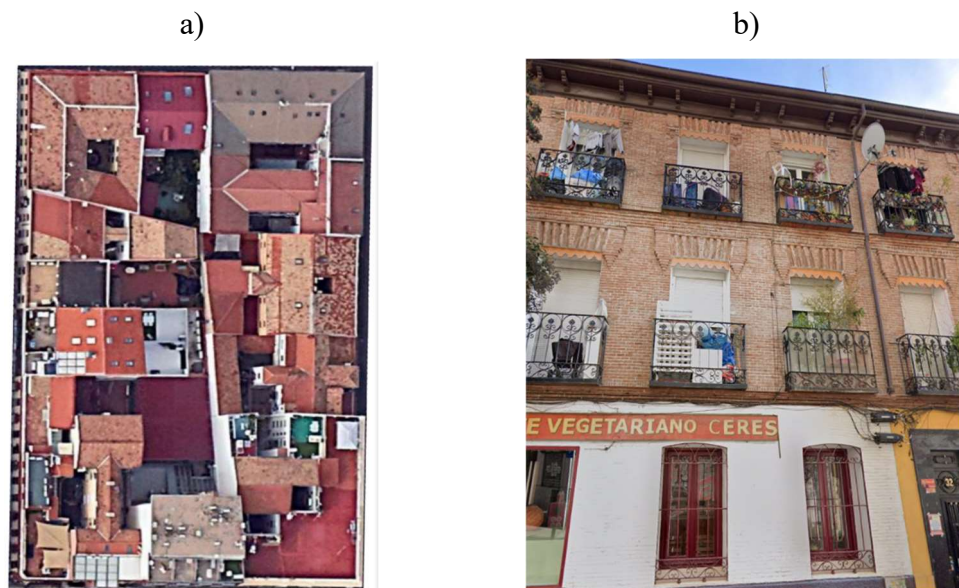


Figure 7. Pictures of the block of buildings selected [29]: a) top view b) facade view.

These buildings were constructed between 1910 and 1993, most of them with an old architectural style. Corridors are narrow and apartments, small. In Figure 8, one of the hallways and stairs can be seen, as well as a kitchen.

a)



b)

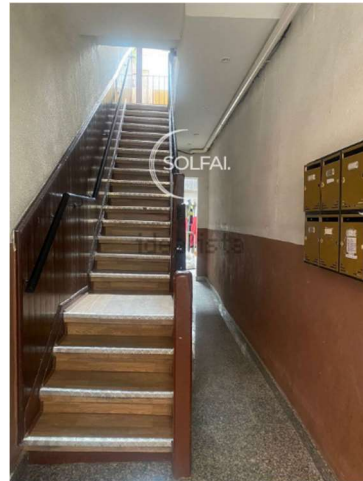


Figure 8. Pictures of the inside of buildings [30]: a) kitchen b) staircase.

3. Fire Dynamics

Fire dynamics is the study of fire behavior: ignition, growth, and evolution over time. This field draws upon principles from chemistry, fire science, material science, physics, fluid mechanics, and heat transfer. The study of this field is of key importance for firefighting strategies, design of structures, fire detection, analysis of human behavior in fires, and overall fire safety.

Computational Fluid Dynamics (CFD) has been one of the most crucial advancements in the field of fire dynamics. Fire Dynamics Simulator (FDS) is a powerful CFD software that has aided in the prediction of fire behavior, smoke movement, and the impact of fires on structures in a more realistic and visual manner. Because of this, predictive and analytic capabilities have been strengthened. In the specific case of this project, FDS is not considered because of the long simulation times for such a complex geometry and the model domain size.

3.1. Compartment Fires

According to the Society of Fire Protection Engineers (SFPE), “compartment fires are defined as fires in enclosed spaces, which are commonly thought of as rooms in buildings but may include other spaces such as those found in transportation vehicles such as ships, planes, trains, and the like” [31]. The general stages of this type of fire are ignition, growth, flashover, fully developed fire, and decay; represented in Figure 9.

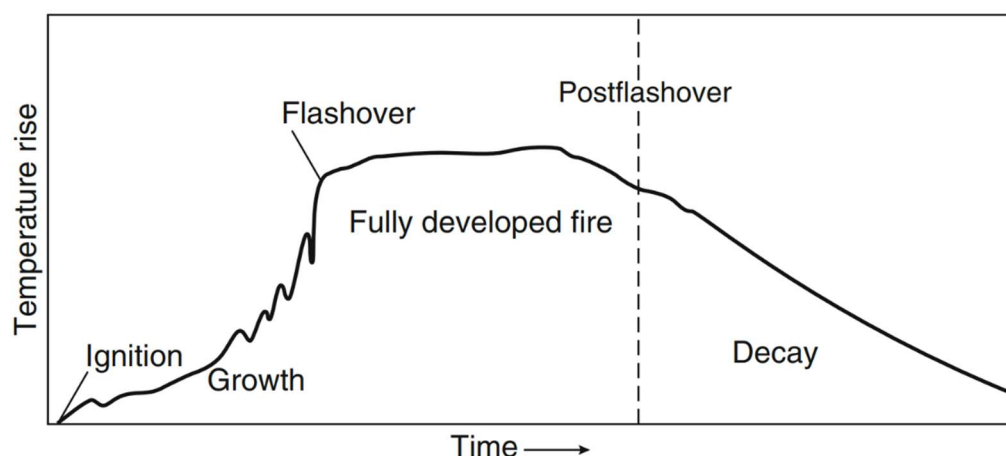


Figure 9. Stages of fire development [31].

The fire begins within the compartment (ignition). Following this stage, the fire grows, mainly influenced by the fuel contained in the compartment and ventilation. If enough fuel and oxygen are present, the temperature rises until it reaches flashover at about 500-600°C. In this stage, the temperature is sufficient for all objects within the compartment to catch fire, even if they are not affected by a direct flame. Because of this, during the flashover stage, flames may emerge from the compartment's openings. The behavior in the fully developed phase depends on factors such as the size of the compartment, construction materials, openings, and the amount and distribution of fuel. In this stage, two different types of fires are identified. Frequently, and due to the size and opening conditions of the compartment, there exists more fuel than can be burned with the oxygen available. These fires are denominated ventilation controlled. On the other hand, if there is sufficient oxygen available for all the fuel to be burned, the fire is said to be fuel controlled. As the fuel available becomes less, the fire's temperature decreases, and the fire decays [31].

Compartment fires are frequently described with a two-layer model, as seen in Figure 10. The upper layer is made up of hot gases, and the lower, of cold air. Energy and products from the fire are released into the top layer, towards the ceiling. Energy is also transferred towards and from the compartment's surfaces by convection and radiation. As the fire grows and more fuel is consumed, the hot layer becomes thicker and eventually reaches the openings. Hot gases from the upper layer flow out through the openings, and cold air flows inwards, providing more oxygen for the fuel to burn.

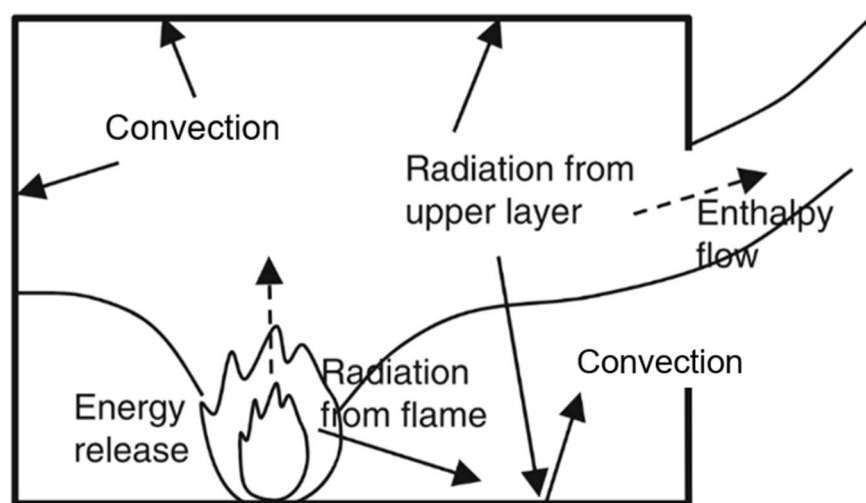


Figure 10. Energy transfer during compartment fires [21].

Energy and mass conservation equations are defined to solve for the temperature during the distinct stages of fire. Nevertheless, numerical models, explained in the following section introduce assumptions and simplify expressions for more direct calculations [31].

3.2. Numerical Models

Numerical models have emerged as powerful tools in the field of fire safety, offering a systematic and detailed approach to understanding fire dynamics, predicting fire behavior, and optimizing fire protection measures. These models utilize mathematics and computations to simulate the complex physical and chemical processes involved in fires. They provide invaluable insights for designing safer buildings and analyzing existing ones. The fundamental role of numerical models in fire safety is explored, highlighting the significance of studying and mitigating risks associated with fires.

In the case of compartment fires with naturally ventilated openings, numerical models aim to simplify calculations and provide an approximation of the upper layer temperature. Most numerical models created starting in the 1980s, contained in the SFPE Handbook [31] are still in use nowadays.

A summary of the temperature numerical models collected in the SFPE, highlighting some of the most important characteristics, can be found in Table 2.

	Author	Specifications, limitations, and characteristics
PRE-FLASHOVER	McCaffrey, Quintiere, and Harkleroad [32]	Specific for fuel-controlled fires (during the growth phase, fires are considered fuel-controlled). Temperature limit of about 600°C.
	Foote, Pagni, and Alvares	Improves MQH for forced-ventilation fires.
	Beyler and Deal	Correlation for known forced-ventilation flow rate.
	Peatross and Beyler	Specific for highly conductive walls.
	Beyler [33]	Specific for non-ventilated compartments.
	Babrauskas	Utilizes a series of factors such as combustion efficiency and opening height effect to calculate the temperature of the upper gas layer.
POST-FLASHOVER	Law [34]	Calculates the maximum upper gas layer temperature based on compartment and opening geometry conditions.
	Delichatsios et al.	Calculates upper gas layer temperature through a calculation of the adiabatic temperature leaving through the opening.
	Swedish	Experiments involved wood crib fires. Method is performed through the SFIRE computer program.
	Japanese [35]	Based on the MQH, it is extended for post-flashover ventilation-controlled fires.

Table 2. Temperature Numerical Model Summary.

The most widely used and oldest is the method of McCaffrey, Quintiere, and Harkleroad (MQH) [32], presented in 1981 which uses a simple energy conservation expression and correlations. Its main inputs are the heat release rate of the fire, and enclosure and opening measurements. The method of Law (1983) [34] uses fuel and opening characteristics to calculate a maximum average temperature and provides correlations for both ventilation and fuel controlled compartment fires. The Japanese method [36],

developed in 1998, utilizes a burning type index to obtain a heat release rate to further include in the temperature expression. Through comparison, it was proven to provide better results for ventilation-controlled fires. Lastly, Delichatsios [37] proposed a new model in 2009 using the adiabatic temperature leaving through the opening, as well as the heat release rate to obtain the room's temperature. When compared with MQH, this model obtained better results when dealing with ventilation-controlled fires. All models share similarities when referring to outcomes; nevertheless, they each have certain limitations and specific uses to be considered. There exist more compartment fire models [31], although they are for specific conditions such as forced ventilation, no ventilation, specific wall materials, etc.

Fire plumes eject from openings such as windows when the fire reaches flashover. Several models have been created to study the height of these flames (Figure 11), as they may cause ignition in the upper levels of a building. Most correlations are designed for small compartments, of approximately 0.1-1 cubic meter [38]. Since this project deals with rooms inside a home, larger scales are needed. Quintere and Cleary [39] offer a model to calculate fire plume height for room scale compartments utilizing the heat release rate of the fire and the opening's characteristic length as inputs. A more recent research paper deals with similar room scales through the improvement of a previous model through the input of new data to obtain a better correlation [40].

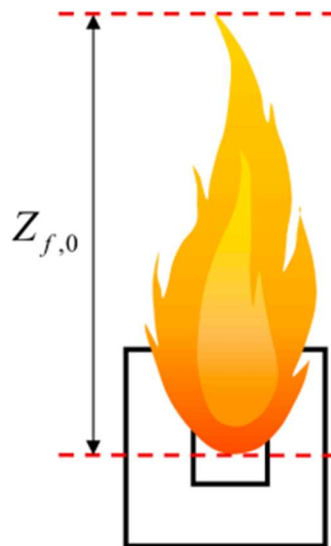


Figure 11. Representation of characteristic height of flame [38].

3.3. Vulnerable Dwellings

After dramatic incidents, such as the ones explained in Section 2, action was taken to analyze and prevent them in the future. Since the Grenfell Tower fire, there have been several research efforts to reconstruct the fire and understand its spread. Vertical [41] and horizontal [42] spread have been analyzed using FDS and close simulations of the fire have been found.

Moreover, informal settlements, having a higher risk and more dangerous incidents than substandard housing, have been more extensively studied. Several experimental studies and new fire spread models have been created since 2017. Experiments have been carried out on smaller [43] and larger scales [44], providing data for the later development of models. Complexity is noted, as fire loads may vary, and wind can greatly affect fire spread.

Studies and models regarding substandard housing are scarce. Nevertheless, Cantizano et al. [1] provide an analysis of the introduction of Human and Organizational Factors (HOF) into the assessment of resilience to fire.

4. Motivation

The motivation for this project comes from the need for research and implementation of fire dynamics analysis and risk assessment on buildings with vulnerable populations. Moreover, fire risk factors may be key in the correct evaluation of the resilience of these types of dwellings. Substandard housing has not been as thoroughly investigated as non-vulnerable or informal settlements. In Spain, buildings in certain urban areas tend to be old, unmaintained, and in harsh conditions.

5. Objectives

The main aim of this project is to assess fire resilience in vulnerable substandard dwellings. To do so, a real-life example block of buildings in a mid to low-income area in the city of Madrid, Spain has been selected. The research carried out in the study performed by Cantizano et al. [1] will be used as the basis for further investigation. This paper utilizes the GAMA software to conduct simulations, mainly because of the long simulating times of FDS. The code developed during this research will be used as a starting point to reach the following sub-objectives:

- Improvement of the partition algorithm for more realism.
- Implementation of different numerical models for predicting fire growth in compartment fires.
- Assessment of resilience through the calculation of a risk factor.
- Creation of linear regression models to assess the impact of different variables on the risk factor.

6. Partition algorithm

The already implemented partition algorithm works to simplify the geometry and obtain a close-to-real partition of the inside of the building (into corridors, apartments, and rooms within apartments). The algorithm utilizes squared cells with the size of the average room. The model contained the following features:

- Use of Geographic Information System (GIS) to work with the real building geometry.
- Number of apartments per floor according to cadastral data.
- Same geometry for all floors in each building.

Furthermore, the following characteristics were introduced to provide more closeness to reality:

- The ground floor is different from the top floors, geometrically, mainly due to the main entrance.
- The top floor of some buildings is different from the bottom floors, some of them include penthouses.
- The geometry of the inside of the buildings was compared to reality using cadastral data.

The mentioned changes and improvements on the algorithm can be seen in **¡Error! No se encuentra el origen de la referencia..** The differences between ground and top floors can be observed, as well as the addition of different levels within a building which depict penthouses.

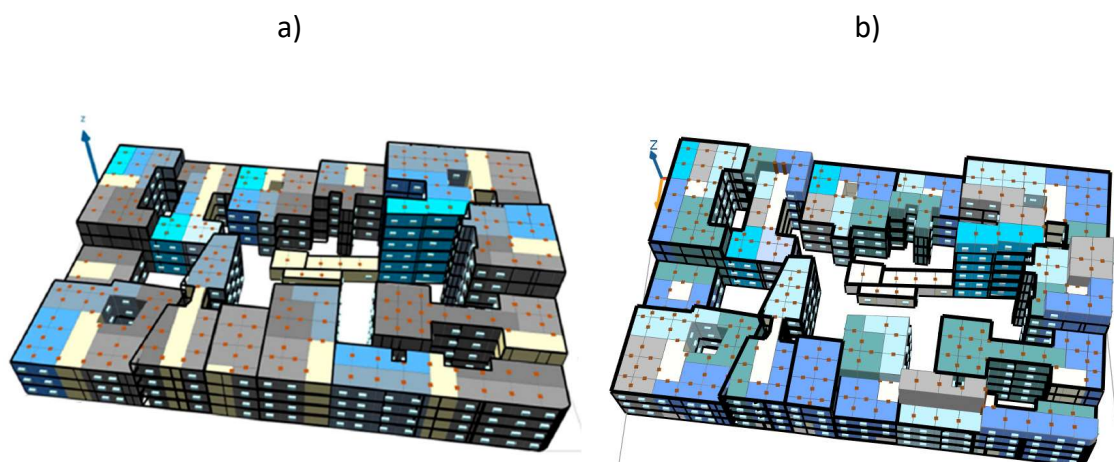


Figure 12. Up-front view of the block a) before and b) after the changes.

In Figure 13, the geometry of the block of buildings after the changes were put in place can be seen, with a focus on the differences between ground the ground floor and the rest. Four streets delimit the rectangular block of buildings. In white, the courtyards and the entrances to the buildings. In different tones of blue and grey, each building is partitioned into apartments. The beige areas represent staircases and corridors. Lastly, each square delimited by a black outline represents a room.

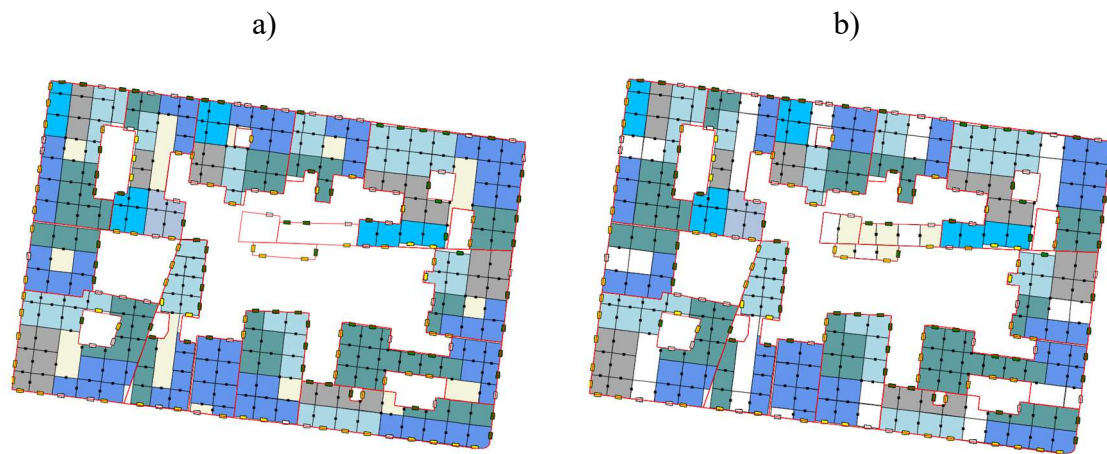


Figure 13 . Geometry of the block a) top floors, b) bottom floors.

The difference in geometry between the bottom floor and the others can be seen. The bottom floor's corridor reaches the street, to create an entrance. On the other hand, the top floors' corridor is smaller, as the entrance is through elevators or the staircase.

7. Numerical models

7.1 Definition of temperature models

To calculate the temperature and stage of the fire in each room at any given moment and, thus, further analyze the fire spread, several models for compartment fires have been used [31]. In the following section, their uses and limitations will be explained.

Method of McCaffrey, Quintiere, and Harkleroad (MQH) [32]

This numerical model was created for the calculation of pre-flashover temperatures. Its intended use is for fuel-controlled fires as the correlation contains extensive data on this typology of fires. The beginning of a compartment fire can be categorized as fuel controlled, as there is exceeding oxygen. The MQH model is characterized using the Heat Release Rate ($\dot{Q}$) curve and the heat transfer coefficient (h_k), as well as opening size and shape variables for the calculation of temperature. One of the main limitations of this model is the maximum temperature of compartment upper-layer gas, at around 600°C.

The MQH equation is the following:

$$\Delta T_g = 480 \left(\frac{\dot{Q}}{\sqrt{g} c_p \rho_\infty T_\infty A_o \sqrt{H_o}} \right)^{2/3} \left(\frac{h_k A_T}{\sqrt{g} c_p \rho_\infty A_o \sqrt{H_o}} \right)^{-1/3}$$

Being:

$\dot{Q}$ = Heat release rate of the fire (kW)

A_T = Total area of the compartment enclosing surfaces (m²)

A_o = Area of opening (m²)

H_o = Height of opening (m)

h_k = Effective heat transfer coefficient (kW/m²·K)

And the ambient air variables:

g = Acceleration due to gravity (m/s²), 9.81 [45]

c_p = Specific heat of ambient gas (kJ/kg·K), 1.005 [46]

ρ_∞ = Ambient air density (kg/m³), 1.2 [47]

T_∞ = Ambient temperature (K), 293 [48]

Where:

$$\dot{Q} = \alpha t^2$$

$$h_k = k/\delta \quad (t > t_p)$$

$$h_k = \left(\frac{k\rho c}{t} \right)^{1/2} (t \leq t_p)$$

$$t_p = \left(\frac{\rho c}{k} \right) \left(\frac{\delta}{2} \right)^2$$

Being:

α = Fire growth rate (kW/s²)

t = Exposure time (s)

t_p = Thermal penetration time (s)

Related to the compartment's surface material, in this case, brick:

k = Thermal conductivity (kW/m·K), 0.0006 [49]

δ = Thickness (m), 0.02 [50]

ρ = Density (kg/m³), 2000 [51]

c = Specific heat (kJ/kg·K), 0.9 [52]

Method of Beyler [33]

Similarly to MQH, this method is designed for use in the pre-flashover range of temperatures. Nevertheless, it is introduced for calculating the temperatures of compartments without ventilation. As MQH, it makes use of the Heat Release Rate curve to obtain reasonable temperatures. The “closed” compartment is considered to have certain small openings, such as door cracks, which prevent pressure buildup. However, the leakage, and the mass of the fuel, are disregarded when calculating the temperature.

$$\Delta T_g = \frac{2K_2}{K_1^2} (K_1\sqrt{t} - 1 + e^{-K_1\sqrt{t}})$$

Where:

$$K_1 = \frac{2(0.4\sqrt{k\rho c}A_T)}{mc_p}$$

$$K_2 = \frac{\dot{Q}}{mc_p}$$

Being:

m = Mass of the gas in the compartment (kg)

The other variables are already mentioned.

Japanese Method [35]

The Japanese method is used for post-flashover fire temperature predictions. It does not have limitations when it comes to the typology of fire, as it allows for different cases ranging from fuel to ventilation-controlled fires. It utilizes fire load density, and compartment and opening shape and size to obtain the temperature of the compartment.

$$\Delta T_g = 1.280 \left(\frac{\dot{Q}}{\sqrt{A_T \sqrt{k \rho c}} \sqrt{A_o \sqrt{H_o}}} \right)^{2/3} t^{1/6}$$

Being:

$\dot{Q}$ = Heat release rate by combustion (MW)

t = Time (min.)

All other variables are already defined.

Where:

$$\dot{Q} = A_{fuel} \times \begin{cases} 1.6\chi & (\chi \leq 0.081) \\ 0.13 & (0.081 < \chi) \\ 2.5\chi \exp(-11\chi) + 0.048 & (0.1 < \chi) \end{cases}$$

$$t_D = \frac{1}{60} \frac{F_L A_r}{\dot{Q}}$$

$$\chi = \frac{A_o \sqrt{H_o}}{A_{fuel}}$$

$$A_{fuel} = 0.26 F_L^{\frac{1}{3}} A_r$$

t_D = Fire duration (min) until the end of the development phase

F_L = Fire load density (MJ/m²)

A_r = Floor area of the room (m²)

χ = Burning type index

A_{fuel} = Fuel surface area (m²)

With all other variables defined previously.

The fire duration refers to the duration of the fully developed phase of the fire. Afterwards, as explained in section 3.1., the fire enters the decay phase, in which the temperature decreases to reach the initial temperature.

Decay and Cooling [53]

The Lucherini et al. article [53] provides guidelines to define the decay and cooling phase of post-flashover compartment fires. It reviews previous research and introduces a more precise way to characterize the behaviour of the fire during the final phases. During the decay phase, the temperature can be assumed to decrease lineally until it reaches ambient temperature. The decay is assumed to begin as 70% of the fuel has been consumed. The Japanese Method, explained previously, provides a calculation of t_D , which is the duration of the fire until the end of the development phase. This time is to be used as the beginning of the decay phase. The total duration of the fire, including the decay phase is assumed to be the time until the complete burning of the fuel has occurred.

The total energy and, thus, the fuel, consumed by the fire can be calculated as the integral of the HRR curve. As explained in the MQH method, the HRR curve can be assumed to follow an αt^2 tendency, until a maximum value is reached. Afterwards, the curve falls with the symmetric αt^2 tendency until it reaches the value of zero. An example of a curve is displayed in Figure 14.

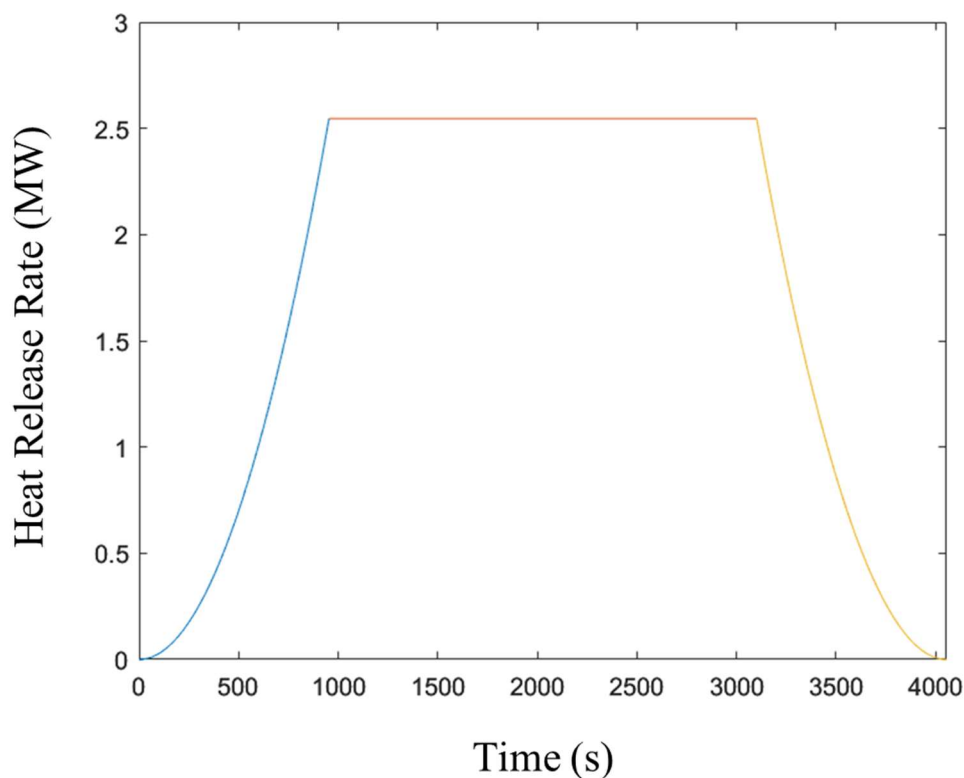


Figure 14. Example HRR Curve.

For compartment fires, the maximum $\dot{Q}$ in MW that can be reached can be calculated as follows:

$$\dot{Q}_{max} \cong 1.5A_o\sqrt{H_o}$$

Thus, the total duration of the fire (t_{total}) can be calculated as:

$$t_{total} \cong \frac{F_L \cdot A_r - \frac{2}{3}\alpha\sqrt{\frac{\dot{Q}_{max}}{\alpha}} + \dot{Q}_{max} \cdot \sqrt{\frac{\dot{Q}_{max}}{\alpha}}}{\dot{Q}_{max}} + \sqrt{\frac{\dot{Q}_{max}}{\alpha}}$$

α = Fire growth rate (MW/s²)

With all other variables and units defined previously.

7.2 Application of temperature models

The different possible cases in the context of this project were identified and the temperatures from ignition to the end of the fire were calculated utilizing combinations of the three models. The following cases and combinations of models displayed in Table 3 were detected. The table contains information about the phases comprised between the beginning of the fire until the end of the full development phase.

The first column indicates the number allocated to each of the cases. The following two columns indicate the presence of open windows and doors, with a “Y” meaning that they are present and an “N” meaning they are all closed. This table considers more specific situations regarding windows within a room, for example the absence of windows, as in cases 1 and 2 with a “-”, or the presence of more than one window, such as cases 7 and 8, where there is one open window and one closed one represented with the symbol “Y*”. When analyzing the doors, there are less possibilities, as all rooms have at least one door. What is important in this case is to know if there is at least one door that is open (Y), as this can affect the ventilation in the room. At the bottom of Table 3, the definition of the time variables can be found.

	Open windows	Open doors	Beyler	MQH	Japanese	500 °C
1	-	N	t_1-t_3	-	-	t_3-t_4
2	-	Y	-	t_1-t_3	t_3-t_4	-
3	N	N	t_1-t_2	t_2-t_3	t_3-t_4	-
4	N	Y	-	t_1-t_2/ t_2-t_3	t_3-t_4	-
5	Y	N	-	t_1-t_3	t_3-t_4	-
6	Y	Y	-	t_1-t_3	t_3-t_4	-
7	Y*	Y	-	t_1-t_2/ t_2-t_3	t_3-t_4	-
8	Y*	N	-	t_1-t_2/ t_2-t_3	t_3-t_4	-
t ₁ : start of fire / t ₂ : breaking of windows / t ₃ : flashover / t ₄ : end of development						

Table 3. Cases for Temperature Numerical Models.

The temperature models and curves are assumed to have continuity, as one model is used after another when a certain temperature is reached. This is an assumption as, for example, when a window breaks, there would be a peak increase in temperature. What is more, when carrying out the experiments to obtain the correlations for each model, the opening conditions did not change. Nevertheless, this increase is not easily quantifiable so the closest reproduction of the real temperature would be using the temperature models available.

The breaking of windows is assumed to occur at 512 K (239 °C) [54] and flashover is assumed to occur at 773 K (500 °C) [55]. The Beyler model is considered for closed compartments, that is, if all windows and doors are closed. If the compartment has closed windows and the window-breaking temperature is reached or if the compartment has open doors or windows, the MQH model is used. The Japanese model is used for most situations of post-flashover fire. The only exception would be if the room is closed throughout all stages of the fire. When this is the case, the fire ends because of a lack of oxygen and does not spread to adjoining rooms. The decay and cooling phase is the same for every case where there is some type of ventilation (all of them except case 1), as the fuel is allowed to burn completely. In case 1 the temperature is assumed to drop more quickly as there is no ventilation in the compartment.

To validate the use of these models, visualize the temperature curves on a smaller scale and provide more detailed examples, some cases were tested with MATLAB [56]. The variation of absolute temperature in time was calculated and graphed for a single room with different characteristics. The following three cases were chosen from Table 3, each representative of a different situation and use of models (it should be noted that, as

explained in the following section, all windows will be considered closed at the beginning of the simulations):

- Case 4: One open door and one closed window.
- Case 3: One closed door and two closed windows.
- Case 1: No windows and no open doors.

Case 4: One open door and one closed window

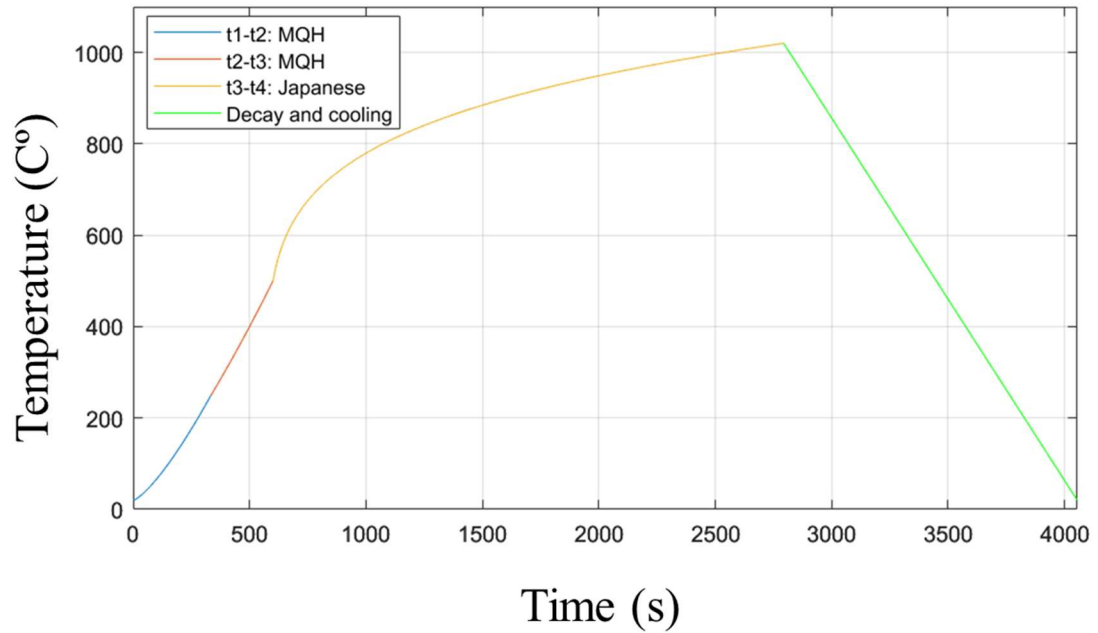


Figure 15. Validation Case 4 Temperature Curve [56].

In Figure 15, four separate parts can be seen. The two first sections (blue and orange) represent the MQH model, with the only change of an increase in compartment opening variables, as the window breaks. This change does not have a significant effect on the temperature curve. The breakage of windows and, thus, increase in opening area, somewhat lowers the slope of the curve, making for a slower increase in temperature. The third part of the figure is calculated utilizing the Japanese method [35] and, as seen, has a decreasing slope. The curve is consistent with the examples displayed in Matsuyama et al. [35].

Case 3: One closed door and two closed windows

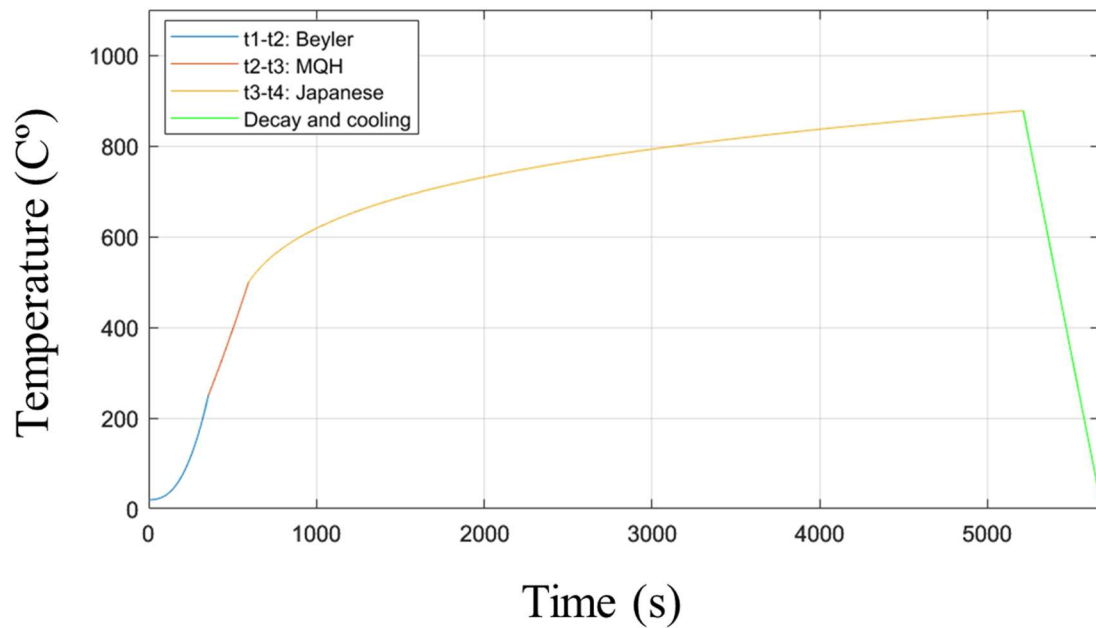


Figure 16. Validation Case 3 Temperature Curve [56].

The example shown in **¡Error! No se encuentra el origen de la referencia.** exemplifies the case of having a closed compartment at the beginning with windows that break once a certain temperature is reached. The Beyler model used for the closed compartment provides a changing slope that begins at zero and quickly becomes greater. The MQH model used as the window breaks has a much steadier slope that is lower than the Beyler slope at the end of the curve. It is interesting to notice how the duration of the fire is much greater than in Case 4. This is due to the change in geometrical characteristics, mainly areas and heights of openings. The maximum temperature reached is also lower than in Case 4, also because of the smaller opening area and height.

Case 1: No windows and no open doors

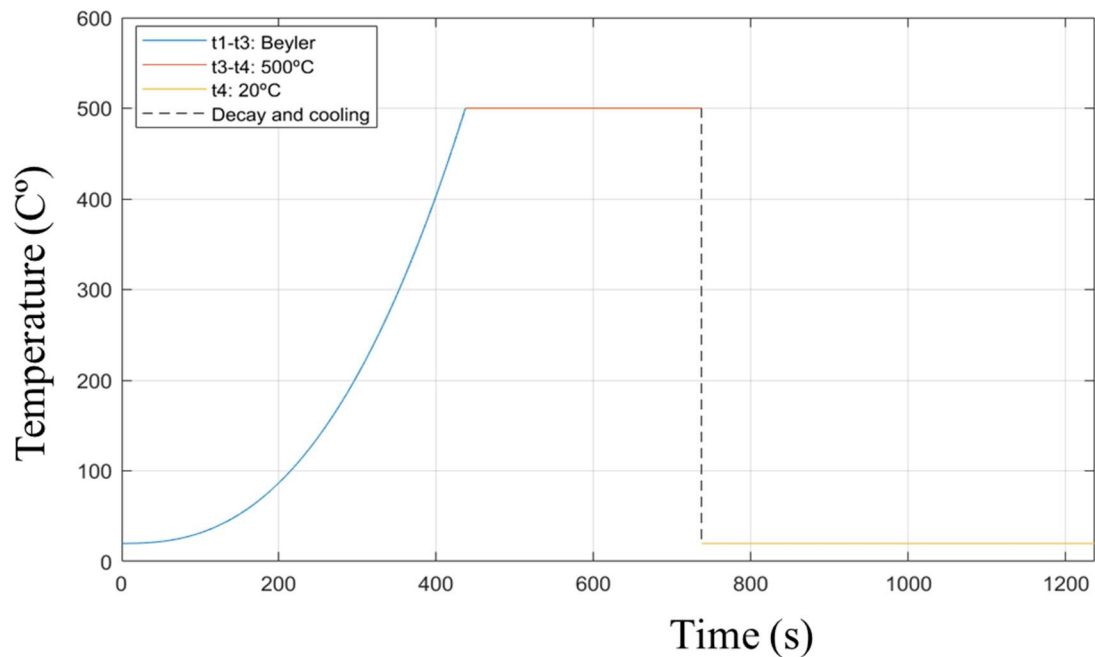


Figure 17. Validation Case 1 Temperature Curve [56].

This last validation case exemplifies a completely closed compartment. In this case, the temperature rises according to the Beyler model until it reaches flashover temperature at 773 K, as seen in Figure 17. Furthermore, the temperature remains constant for 300 seconds, which is an assumption made regarding the time in which all the oxygen present in the compartment is consumed. After this, the fire would end, and the temperature would return to ambient conditions. This decrease would not be instantaneous, although at a faster rate than the decay and cooling phase for the rest of the cases. Nevertheless, the behavior is outside of the scope and the needs for this analysis.

7.3 Fire plumes

Fire plumes exit the window when a fire reaches flashover, assumed here at 773 K[55], until burning ends. The geometry of the flame outside of the window can depend on factors such as the speed and direction of the wind and the characteristics of the façade, as well as characteristics of the fire [38]. Several models have been developed to calculate different geometrical characteristics of fire plumes, although, for this purpose, only the height of the flame tip will be taken into consideration. The different models were designed for specific compartment sizes and shape scales. Because of this, the selected model was the one developed by Stevens et al. [40], which provides an

adaptation to the original model by Law and O'Brien [34] and can be applied to large-scale residential fires.

The following equations which provide values of flame height and width through the window were utilized for situations with low wind:

$$z = \begin{cases} -0.049u + 9.8 \left(\frac{R}{w} \right)^{\frac{2}{3}} - h & 0 \leq u \leq 24 \\ 0 & u \geq 24 \end{cases}$$

$$x = \begin{cases} 0.043u + 0.55h \left(\frac{1.175}{h} \right)^{\frac{1}{3}} & 0 \leq u \leq 10 \\ 1.276 & u \geq 24 \end{cases}$$

Where:

z = Flame height from the upper edge of the opening (m)

R = Mass loss rate of the compartment fire (kg/s)

w = Sum of all compartment opening widths (m)

h = Area-weighted average height of compartment openings (m)

x = Flame length (m)

u = Wind speed in a perpendicular direction away from the opening (m/s)

8. Modes of Fire Propagation

There exist two main modes of fire spread in the case of residential fires. These are horizontal and vertical fire spread. These two mechanisms will be discussed in the following sections.

Horizontal Fire Spread

Horizontal fire spread, as seen in Figure 18, occurs when fire spreads to adjacent rooms. This is mainly caused by increasing temperatures and smoke traveling from one room to another through openings such as doors. In the case of this project, to simplify calculations and reduce computational power, the horizontal fire spread is calculated based on temperatures and smoke propagation is disregarded. To do so, it is assumed that, once the fire reaches flashover, it spreads to contiguous rooms in case the door that connects them is open. This assumption can be made based on the results of various experimental and numerical studies [57–59].



Figure 18. Horizontal spread in residential fire [60].

Vertical Fire Spread

Vertical fire spread, exemplified in Figure 19, occurs when flames exit the compartments through the windows and impinge on the upper windows. This event takes place as flashover begins and, because of its dependence on different variables, it has been more thoroughly studied than horizontal fire spread. For the purpose of this project, it will be assumed that the fire spreads vertically to upper rooms when the flame tip of the fire plume

reaches the upper-level window. This assumption is also based on experimental and empirical studies such as Fang et al. [21], Quintiere et al. [39], and Heskestad et al. [61].

a)



b)



Figure 19. Vertical spread in residential fires a) [54] b) [55].

9. Simulations and variables

Before focusing on the simulations, an explanation of the main variables and parameters is be given.

9.1 Independent variables and parameters

The main parameters and potential variables to be defined are divided into general and specific conditions, divided into room and building. General conditions apply to the block as a whole, while specific conditions are different for every room or building.

- General conditions: wind conditions (speed and direction) and duration of the simulation.
- Specific conditions (room): state of the windows and doors (open or closed), fire growth rate (or value of alpha), and fire load density.
- Specific conditions (building): number of rooms, number of apartments, number of floors, total area, number of windows, and year of construction.

9.1.1 General conditions

Wind conditions

Wind conditions consist of two parameters: wind speed and wind direction. These values have an important impact on the geometry of the fire plume outside of the window as the fire reaches the flashover state. In the process of setting parameters that correspond to reality, data from the closest meteorological station that collects wind information, Hortaleza [64], was analyzed. Daily wind speed and wind direction parameters from the beginning of 2019 to the end of 2023 are published [48]. The maximum and minimum of this set of data is obtained. When it comes to wind direction, it is variable and the whole possible range (from 0 to 359) is observed. Using the random operator [65], the wind speed and direction are randomized for each simulation within the ranges: [0, 359] in the case of wind direction and [0.29, 3.76] m/s for wind speed [48], which are the maximum and minimum registered in the area.

Duration of the simulations

The duration of the simulations corresponds to the time between the start of the fire and the moment in which it would end as firefighters arrive at the scene. This amount of time may vary greatly depending on several factors. First, there is a lapse of time as the

fire starts until a citizen calls the local authorities. This could vary greatly as, for example, at night, it would be more difficult for someone to notice the presence of fire. What is more, depending on where the fire originates, it may take some time until it is visible from the outside of the building. After the warning has been placed by calling the authorities, the fire brigade must prepare and reach the premises. The current average response time of the fire brigade in Madrid is 8 minutes and 30 seconds, with an even lower statistic of just under 7 minutes for urgent interventions [66]. As for the time to extinguish the fire, there is also a high variability. Depending on the nature and progression of the fire, the time to have the fire under control and, ultimately, the terminal can vary, starting from around 10 minutes [67]. Having these stages in mind and thinking about a worst-case scenario in which it would take around 30 to 40 minutes for the authorities to be notified and for the fire brigade to prepare, an estimation of one hour has been set for the duration of the simulations.

9.1.2 Specific room conditions

State of windows and doors

The state of windows and doors may greatly influence the spread and progression of the fire. Therefore, it is an interesting variable to study. From the point of view of doors, their state influences the rate of increase of temperature inside a room, as well as the expansion of the fire to contiguous rooms. Windows also affect the increment of temperature, and their geometry influences the flame projected to the outside of the building when flashover is reached.

The simulated fire is assumed to occur during the winter months, as fires are more frequent in this season [68]. Because of this, windows are assumed to be closed at the beginning of the fire, which translates to the initialization state of the simulation. Irrespective of the season, some doors in homes tend to be closed and others open, depending on the preference of the resident and the rooms that connects [69]. As this variable may change conditioned on different factors, its effect on the progression of the fire will be studied. To do this, the doors are configured to be randomly open or closed (using the random operator in the software [65]).

Fire growth rate (or value of alpha)

This parameter characterizes the speed of fire spread. According to the American Fire Protection Association [70], the classification of fire growth rates is shown in Table 4.

Combustible material	Fire type	Fire growth rate α (kW/s ²)
Wood-cement panels Polyisocyanurate foam	Slow speed fire	0.0029
Non-cotton product Polyester mattress	Medium speed fire	0.0117
Plastic foam Stacked wood	Fast speed fire	0.0469
Methanol Upholstered seats	Ultra-fast speed fire	0.1876

Table 4. Fire growth rate classification [71,72].

Figure 20 below represents the HRR curves for each of the four scenarios presented in Table 4.

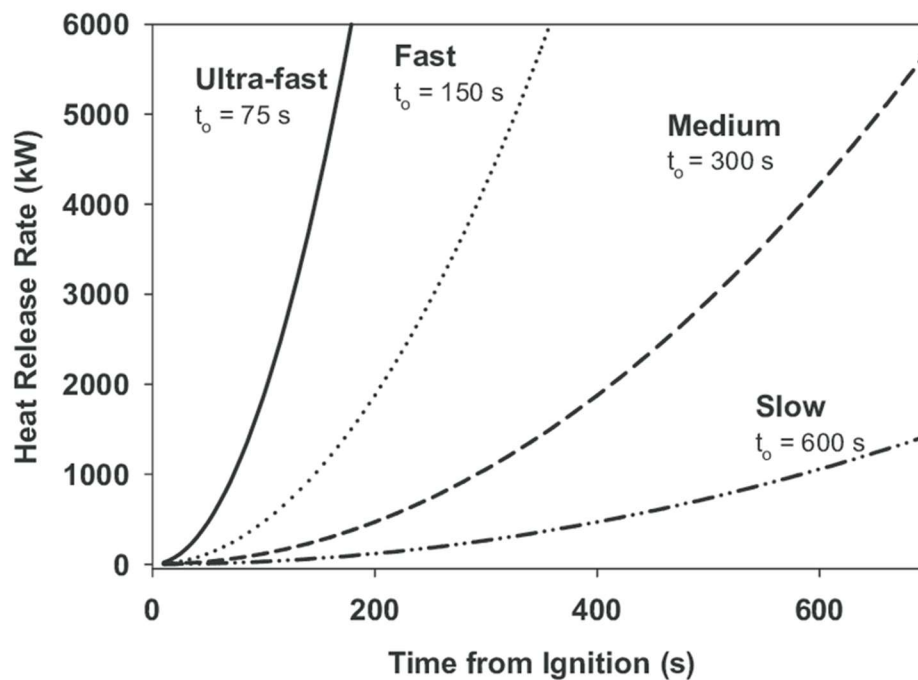


Figure 20. HRR growth for Different α Values.

After having an overview of the ranges of fire growth rates and their classification, specific data applied to dwellings can be found in Hopkin et al. [73]. The authors developed a lognormal distribution for this parameter, utilizing fire datasets from the UK. The results obtained were the following: a mean growth rate in the range of $[0.0022, 0.0034]$ kW/s² and a standard deviation of $[0.0071, 0.0132]$ kW/s². The following Figure 21 displays the density functions of probability and cumulative probability.

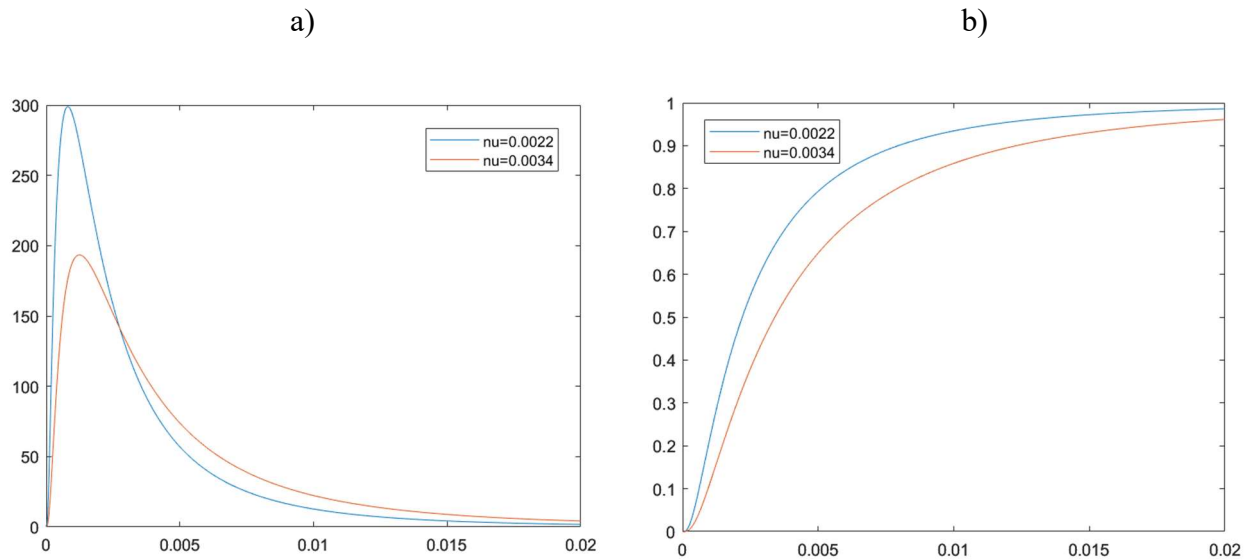


Figure 21. Lognormal distribution of fire growth rate [57, 74]. a) PDF (Probability Density Function) b) CDF (Cumulative Density Function).

Only the mean growth rate was varied when graphing the functions, as the standard deviation had an effect on the curves that could not be appreciated in the scale depicted.

As can be concluded, there is a high variability in growth rate values, with around 15-25% in the slow speed fire range, approximately 45-65% in the medium, and 20-40% in the high speed. Even though these distributions are derived from UK data, because of the unavailability of specific data in Spain and similarities in architecture and regulations, this distribution is employed. First, two random numbers within the ranges of the mean value and standard deviation are chosen. With these, a value of alpha following the lognormal distribution is obtained for each of the rooms in the block of buildings.

Fire load density

The fire load density is a measure of the quantity of energy released in the combustion of the materials in a compartment fire [74]. It influences the temperature evolution of the fire, so much so, that some models such as the Japanese or the method of Law use this value to obtain the temperature fields [34,35]. These values have been standardized depending on the use of the compartment, as it has to do with the materials and their quantity found inside, by analyzing a large amount of data. Typically, these calculations are specific to a specific country, and the parameters obtained are usually found in fire safety regulatory codes. In the case of Spain, values of fire load densities depending on the type of building are found in the Building Technical Code [75] and were found to be the following: 650 MJ/m² for residential buildings and 730 MJ/m² for commercial premises. With the knowledge that the ground floors of the buildings selected for the case are commercial spaces such as hairdressers, small shops, and restaurants, the fire load density is set to 730 MJ/m² for all rooms located on the bottom floor. The rest of the apartments and rooms are considered residential and have a value of 650 MJ/m² for this parameter. Corridors have a much lower fire load density as there is usually little to no furniture or combustible materials. Nevertheless, it is known that in substandard settlements, it is common to find some waste and furniture. Because of this, a value of 200 MJ/m² is specified in the case of corridors.

Since it is known that these values have variability because of their high dependency on the objects, such as furniture, and materials found inside, a 20% randomness is added to them for the purpose of this project.

9.1.3 Specific building conditions

The parameters related to specific building conditions have to do with the geometry of the building, such as the total number of rooms, apartment, floors and floor areas, as well as the year of construction. These are set for each building and remain the same for each of the simulations within the same building.

Figure 22 displays the number allocation for each building, which will be utilized to refer to them and to be able to analyze their position and shape with relation to the variables.

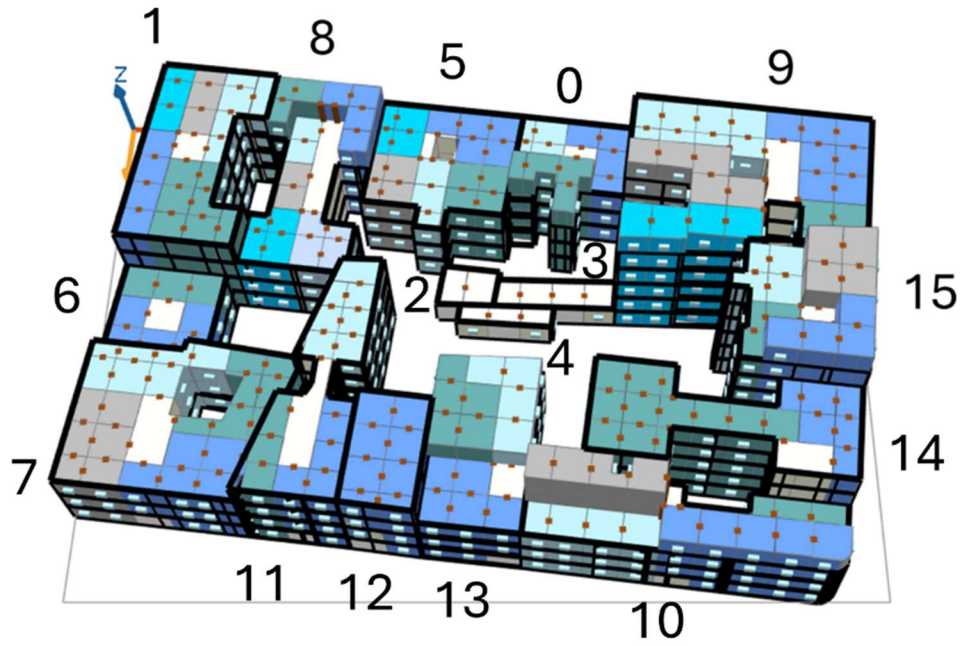


Figure 22. Number allocation.

The parameters for every building are summarized in Table 5.

Building Number	Year of Construction	Number of Rooms	Number of Apts.	Number of Floors	Total Area (m²)
0	1910	55	17	5	472
1	1920	91	24	4	832
2	1920	2	2	1	26
3	1910	4	2	1	40
4	1955	3	2	1	22
5	1920	62	18	3	528
6	1915	17	6	2	210
7	1945	77	15	3	891
8	1970	66	23	4	621
9	1925	153	32	6	1843
10	1920	61	17	4	681
11	1930	63	16	4	608
12	1988	32	4	4	304
13	1955	53	14	4	551
14	1940	94	15	5	860
15	1993	97	32	7	966

Table 5. Building information: year of construction, size and geometry characteristics.

9.1.4 Selected independent variables

The selected independent variables are obtained from the parameters and potential variables presented in the previous sections.

A summary of the independent variables and parameters is presented in Table 6. The variable index will be used to refer to the variables from this point forward.

Variable	Variable Index	Description
Windows within the building	Windows _B	Total number of windows in the building
Windows within the first ignited room	Windows _R	Total number of windows in the room
Open doors within the building	Doors _B	Total number of open doors in the building
Percentage of open doors within the building	%Doors _B	Ratio of open doors to the total of doors in the building
Open doors of the first ignited room	Doors _R	Presence of open doors in the room (0: no, 1: yes)
Average alpha values of the rooms within the building	AvgAlpha _B	Alpha calculated as a value in the lognormal ([0.0022, 0.0034], [0.0071, 0.0132]) kW/s ²
Value of alpha of the first ignited room	Alpha _R	
Average value of FLD within the building	AvgFld _B	FLD calculated as: - Floor 1: 730 ± 20% MJ/m ² - Floor 2+: 650 ± 20% MJ/m ² - Corridor: 200 ± 20% MJ/m ²
Value of FLD within the first ignited room	Fld _R	
Wind Speed	WindSpeed	Random value [0, 359]
Wind Direction	WindDir	Random value [0.29, 3.76]
Projected Wind Speed	WindP	Wind speed in the perpendicular direction from windows
Total number of rooms in the building	Rooms _B	-
Total number of apartments in the building	Apts _B	-
Total number offloors in the building	Floors _B	-
Total area of the building	Area _B	-
Year of construction	Year	-

Table 6. Independent variables.

9.2 Dependent variables

Dependent variables are defined to statistically analyze fire resilience and obtain the risk factors of each room and building. The variables obtained from each simulation to be analyzed are the following:

1. Number of affected floors.
2. Number of affected apartments.
3. Number of affected buildings.
4. Affected area (m²).

When defining these variables more specifically, burning and already burnt down are considered as “affected”. Once a single room within an apartment and building is ignited, that apartment is considered “affected”. The affected area is calculated by adding the floor areas of all the affected rooms. The number of affected floors is important when analyzing the extent of the vertical fire spread within a building. The number of affected apartments is regarded as an interesting variable to obtain, as it measures the number of households affected by the fire. The possibility that some of these variables have a high correlation is considered. Nevertheless, they are measured to later analyze and select the most significant.

9.3 Simulations

Each simulation is carried out by igniting one of the rooms on the ground floor for the analysis of the effects after an hour. The ground floor is selected as a fire starting in this location is thought to be the most dangerous, since the fire can more easily propagate upwards. All the ground floor rooms, in total 215, are analyzed to obtain a more comprehensive view of the situation in each of the buildings. Twenty-two simulations are carried out for each room, so, in total 215x22 (4.730) simulations are run. This will allow to obtain statistically significant average values of the dependent variables, and to analyze the random independent variables (wind speed and direction, door distribution, fire growth rate and fire load density). It should be noted that fires beginning in corridors are not considered because they are not a common event.

10. Results

This section is aimed at the analysis of the dependent variables obtained through the simulations explained in the previous section from the point of view of the independent variables. A linear regression model is used to analyze the dependent variables related to fire outcomes, such as the affected area or the risk index, and to quantify the effect of the various independent variables including building characteristics and fire characteristics. Another use of this tool is to predict or estimate values of the dependent variable from the independent variables.

A linear model is a statistical tool used to model the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data. The equation takes the form:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon$$

Where y represents the dependent variable and $x_1, x_2, \dots, x_n$ are the independent variables. β_0 is the intercept, represents the value of y when all x variables are zero, providing a baseline level of the dependent variable. $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients, quantifying the relationship between each independent variable and the dependent variable, indicating how much y changes with a one-unit increase in x_i while holding other variables constant. The error term (ϵ) captures the difference between the observed values and the values predicted by the model, accounting for the variability in y that cannot be explained by the independent variables. This approach is chosen because it allows for the quantification of the impact of each independent variable on the dependent variable, providing insights into which factors most significantly influence fire outcomes. To estimate the β coefficients, the Ordinary Least Squares (OLS) method is utilized. The goal of this method is to find the best-fitting line through the set of data points by minimizing the sum of the residuals (squared differences) between the observed values and the values predicted by the model.

The assumptions of linear regression are fundamental to ensure the validity and reliability of the model. These assumptions include linearity, which means that there is a linear relationship between the independent and dependent variables; independence, where observations are independent of each other; homoscedasticity, indicating that the variance of residuals (errors) is constant across all levels of the independent variables; normality of residuals, implying that the residuals are normally distributed; and no multicollinearity, meaning that independent

variables are not highly correlated with each other. Violations of these assumptions can lead to biased or inefficient estimates, making the model's predictions unreliable.

10.1 Exploratory Data Analysis

The first step for the creation of the linear model is to analyze the dependent and independent variables available. This first analysis is carried out to obtain insights into the distributions of each variable, as well as its correlation with the others to make the appropriate decisions when creating the model.

Firstly, a summary of the main statistics of each variable: mean and median values, standard deviation, minimum and maximum values are analyzed. Furthermore, a histogram is presented for each variable to understand their distribution and obtain the skewness, which is a measure of the asymmetry of a distribution [76]. This is of high importance, as skewness should be corrected to improve the performance of the model and the interpretability of the coefficients. Afterwards, a correlation matrix is presented to identify possible multicollinearity between the variables. This statistical phenomenon occurs when two or more independent variables in a regression model are highly correlated with each other [77]. After analyzing the independent variables, the potential dependent variables are looked at and a final one is selected. Furthermore, scatter plots of the different independent variables versus the dependent variable are presented to investigate possible quadratic transformations.

10.1.1 Summary of statistics

Table 7 presents the statistics of the different dependent and independent variables available. In the case of the variable that indicates the number of affected buildings, all the statistical values remain at 1. This means that, in the case of all simulations, the fire does not spread to contiguous buildings.

<i>Variable</i>	Mean	Median	Standard Deviation	Maximum	Minimum
<i>AffApts</i>	4.54	4	3.03	14	1
<i>AffFloors</i>	1.94	2	0.94	6	1
<i>AffArea</i>	115.47	118.26	82.11	446.17	4.03
<i>Windows_B</i>	61.36	54	34.09	142	10
<i>Windows_R</i>	0.78	1	0.60	3	0
<i>Doors_B</i>	10.25	10	4.18	24	0
<i>Doors_P</i>	49.05	48.78	11.62	100	0
<i>Doors_R</i>	1.10	1	0.82	4	0
<i>AvgAlpha_B</i>	0.00275	0.00275	0.00009	0.00311	0.00222
<i>Alpha_R</i>	0.00276	0.00275	0.00072	0.00400	0.00150
<i>AvgFld_B</i>	671.51	670.74	12.07	738.63	623.14
<i>Fld_R</i>	730.83	732.35	74.47	859.99	600
<i>WindSpeed</i>	2.02	2.04	0.98	3.72	0.29
<i>WindDir</i>	179.19	179	103.77	360	0
<i>Rooms_B</i>	80.31	66	33.45	153	17
<i>Apts_B</i>	19.79	17	7.46	32	4
<i>Floors_B</i>	4.26	4	1.22	7	2
<i>Area_B</i>	833.60	681	430.27	1843	210
<i>Year</i>	1938.89	1930	23.87	1993	1910
<i>Wind_P</i>	1.27	1.08	0.92	3.68	0

Table 7. Statistics of dependent and independent variables.

It is interesting to analyze the first three rows, related to the affected apartments, floors and area with the simulations. They portray the extent of the damage that is suffered when a fire occurs. An average of 4-5 apartments are affected, while the mean number of floors is close to two. Approximately 115 m² are calculated to be burnt on average when a fire originates on the ground floor and lasts for 1 hour.

To have an idea of the changes per building and detect any inconsistencies, the affected area variable is analyzed in Table 8. Its mean value, as well as maximum and minimum values are obtained for each building. In addition to this, the total floor area of the buildings is presented in the last column. All numbers have m² units.

Building	Mean	Maximum	Minimum	Total Area
0	78	171	4	472
1	101	279	6	832
2	23	25	11	25
3	33	39	8	39
4	18	21	6	21
5	153	249	5	528
6	71	153	10	210
7	125	339	4	891
8	123	270	4	621
9	184	500	8	1843
10	86	243	5	681
11	90	197	5	608
12	64	102	5	304
13	124	238	8	551
14	106	231	4	860
15	122	225	5	966

Table 8. Affected area statistics depending on building.

Various building sizes can be observed. For example, building 9 is the biggest in floor area, with almost double the area of the second largest building (15). Buildings 2, 3, and 4 have the smallest total area, ranging from 20 to 40 m². When looking at the mean, maximum and minimum numbers for the affected area variable, it is interesting to notice that in buildings 2, 3, and 4, the fire reaches the total floor area. This means that, for some simulations, these buildings are completely burnt. Furthermore, the mean value is close to the maximum value for the three buildings, meaning that there are a lot of instances where the totality of the building is affected. Because of this, the decision of disregarding buildings 2, 3, and 4 is made. There are two main reasons for this decision. The first is that these buildings do not represent a common type of construction. These buildings are located in the main courtyard of the block and are very small (as seen in Figure 23), consisting of two to four rooms each. Secondly, the fact that the area is quite limited does not allow the fire to spread and the dependent variable values such as the affected area would depend directly on the total of the building. Even though these buildings are not considered for this analysis, their results exemplify the high risk for these types of constructions.

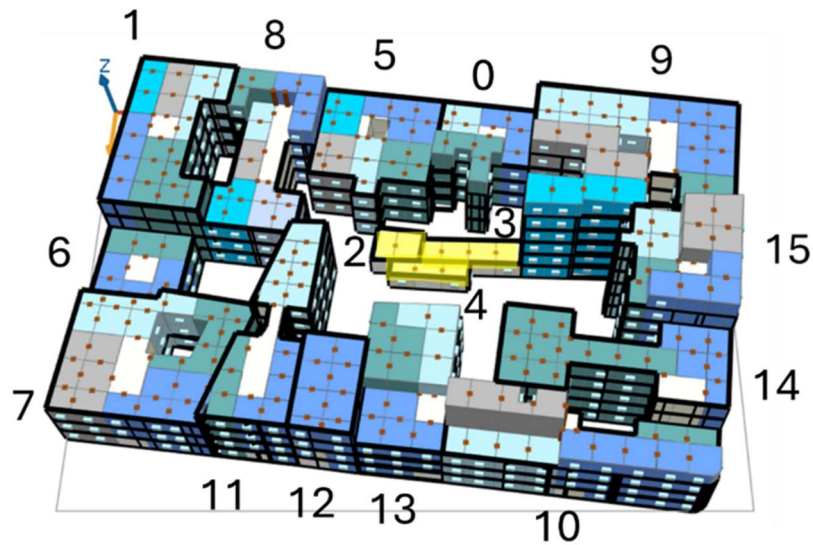


Figure 23. Location of buildings 2, 3 and 4.

10.1.2 Histograms and skewness

Analyzing histograms and skewness of independent variables before creating a linear model is crucial for understanding the distribution and characteristics of the data. Histograms provide a visual representation of the data's distribution, revealing patterns such as normality, uniformity, or the presence of outliers. Skewness indicates the asymmetry of the data distribution, with highly skewed data potentially leading to biased estimates, affecting the model's performance. By assessing these factors, one can decide whether transformations or other preprocessing steps are necessary to improve the model's accuracy and to ensure the normality assumption of linear regression is met.

Figure 24 displays histograms of the independent variables.

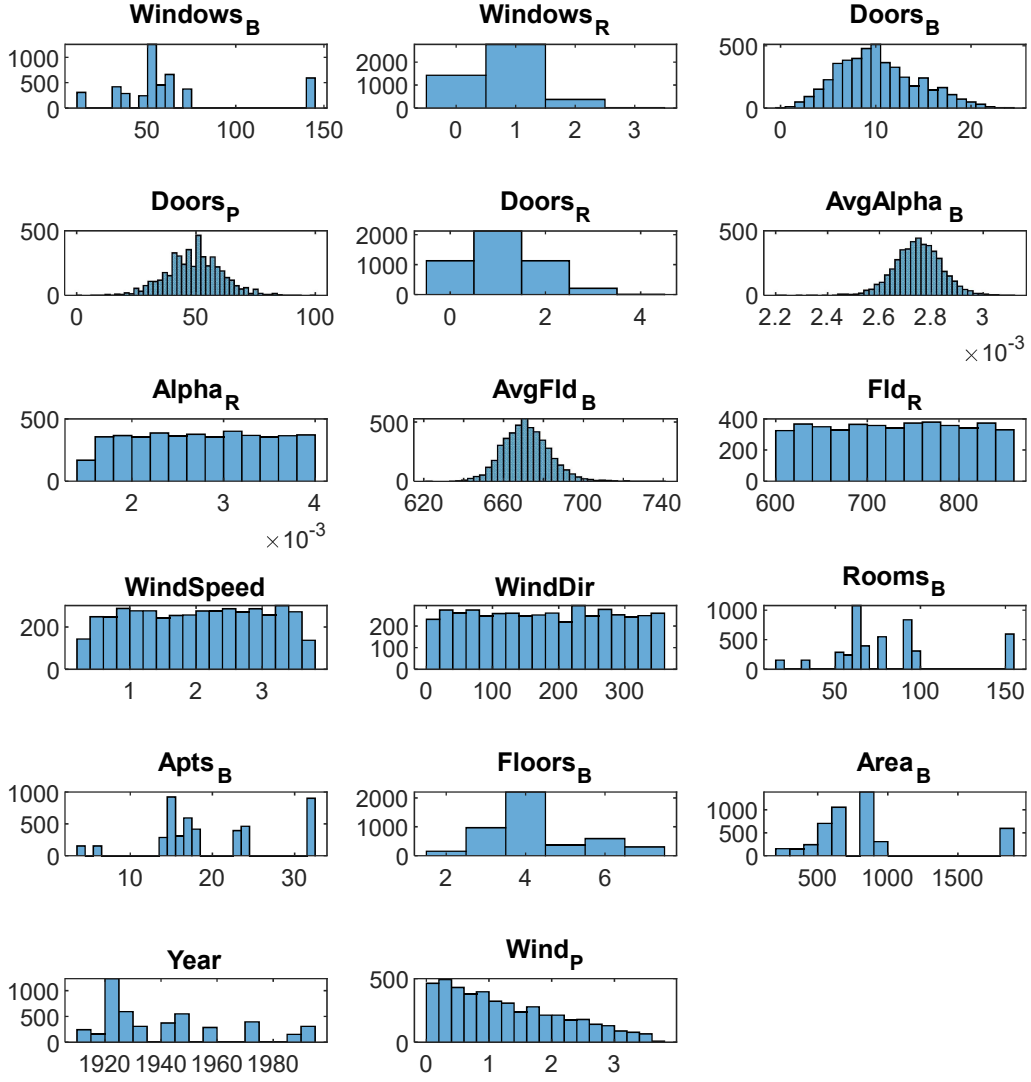


Figure 24. Histograms of independent variables.

Different distributions can be observed from the histograms. Variables such as $Alpha_R$, Fld_R , $WindSpeed$ and $WindDir$ have a distribution that can be considered uniform or rectangular and may pose issues with the homoscedasticity assumption. This is understandable, as these values were randomized within a range for the simulations. Other variables have a distribution with a normal tendency, such as $AvgAlpha_B$ and $AvgFld_B$, which, due to their nature of being an average of random values, is something that could be expected and should not require adjustments.

Doors and windows ($Doors_B$, $Doors_R$, $Windows_B$, $Windows_R$) have a positive asymmetry, as do the variables related to size. Furthermore, some variables ($Rooms_B$, $Apts_B$, $Area_B$) have a multimodal distribution, which could indicate the presence of subgroups. Nevertheless, because these variables are related to the

buildings and cannot be modified, the only possible solution would be to disregard the data related to the higher values. To quantify the asymmetry that some of these variables have, the skewness values are obtained in Table 9.

<i>Variable</i>	<i>Skewness</i>
<i>Windows_B</i>	1.412
<i>Windows_R</i>	0.270
<i>Doors_B</i>	0.510
<i>Doors_R</i>	0.382
<i>Doors_P</i>	0.045
<i>AvgAlpha_B</i>	-0.177
<i>Alpha_R</i>	-0.004
<i>AvgFld_B</i>	0.640
<i>Fld_R</i>	-0.019
<i>WindSpeed</i>	-0.030
<i>WindDir</i>	0.012
<i>Rooms_B</i>	0.913
<i>Apts_B</i>	0.256
<i>Floors_B</i>	0.571
<i>Area_B</i>	1.401
<i>Year</i>	0.995
<i>Wind_P</i>	0.602

Table 9. Skewness of independent variables.

Typically, skewness values greater than +1 or less than -1 indicate a highly skewed distribution that may require correction. For moderately skewed distributions (skewness between +0.5 and +1 or between -0.5 and -1), a transformation can be considered but might not be as critical. When skewness is close to 0 (between -0.5 and +0.5), the distribution is approximately symmetric, and no transformation is usually necessary. The variables with a skewness value over 0.5 are indicated in blue for their potential correction when building the model.

When referring to possible transformations for highly positive skewed variables, the most common are logarithmic and squared. The logarithmic transformation consists of taking the logarithm of the dataset to obtain a new one. By doing this, a more symmetrical distribution can be obtained. Depending on the skewness degree, there exist different options, such as the natural logarithm (for moderate to high skewness) or the base 10 logarithm in the case that skewness is higher. The square root transformation consists of adding the square of the variable as an additional variable (the unsquared variable would remain in the model). This is useful when there is

moderate skewness or when a quadratic relationship between the independent and the dependent variable is observed. The latter will be explained in a later section.

10.1.3 Correlation Matrix and Multicollinearity

Analyzing the correlation matrix of the independent variables before creating a linear model is crucial to detect multicollinearity, which occurs when two or more predictors are highly correlated. Multicollinearity can inflate the variance of the coefficient estimates, making the model unstable and the estimates unreliable. This complicates the interpretation of the model, as it becomes difficult to determine the individual effect of each variable. A correlation coefficient value above 0.8 is typically considered too high, indicating that one of the correlated variables should be disregarded or combined to maintain the integrity and interpretability of the model. The correlation matrix of all the independent variables considered is presented as a heatmap in Figure 25.

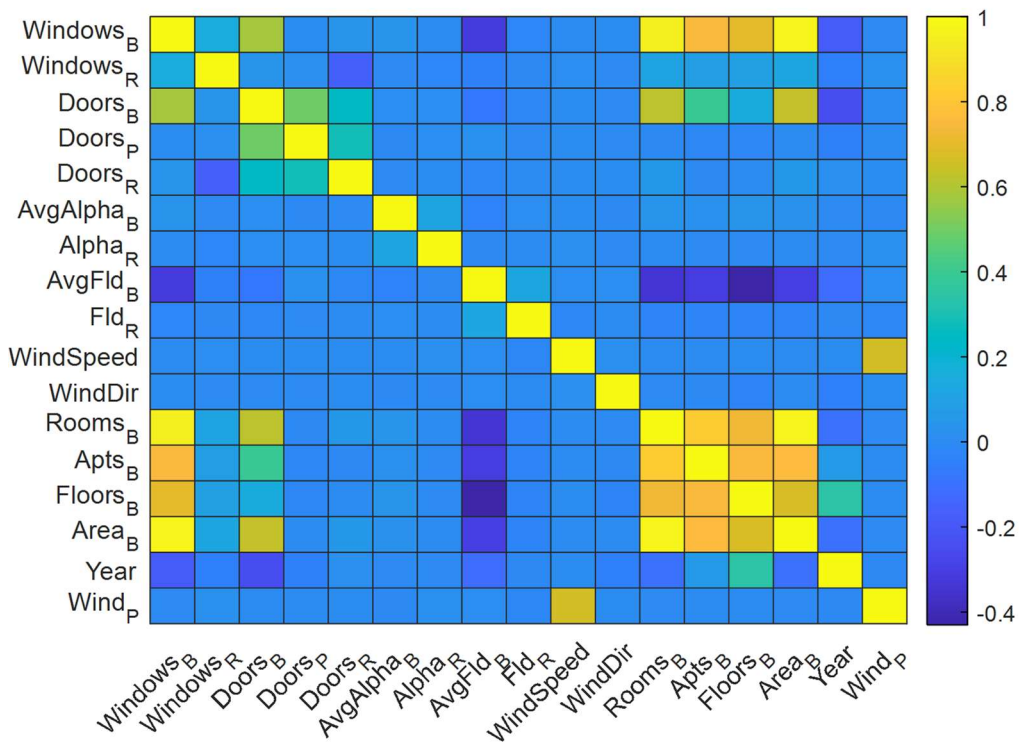


Figure 25. Correlation heatmap of independent variables.

From the point of view of the independent variables, several observations can be made. The variable $Windows_B$ which quantifies the number in the ignited room has a high correlation (greater than 0.95) with $Area_B$ and $Rooms_B$. These last two variables, related to the size of the building also have a high correlation between each other,

reaching a value of 0.975. This correlation makes sense, as the variables $Area_B$ and $Rooms_B$ measure a similar parameter, which is the size of the building. Furthermore, from the correlation of these two variables with $Windows_B$, it can be concluded that bigger buildings have a higher number of windows, which is a logical and expected outcome. Because of their multicollinearity, two of these variables will be disregarded for the model. The variable $Area_B$ is selected in the end because it is thought to be more representative of the size of the building. Eliminating variables may cause problems of endogeneity if the missing variables are important. Nevertheless, it is considered that the variable $Rooms_B$ and $Area_B$ measure the same variable, as rooms are uniform in size, so endogeneity is not expected to be introduced through this change. In addition to this, if multicollinearity is not solved, the model cannot be used for explanatory purposes.

The final correlation matrix heatmap, disregarding the discussed related variables is displayed in Figure 26. In this case, the correlation values are all lower than 0.8, so the multicollinearity problem is corrected.

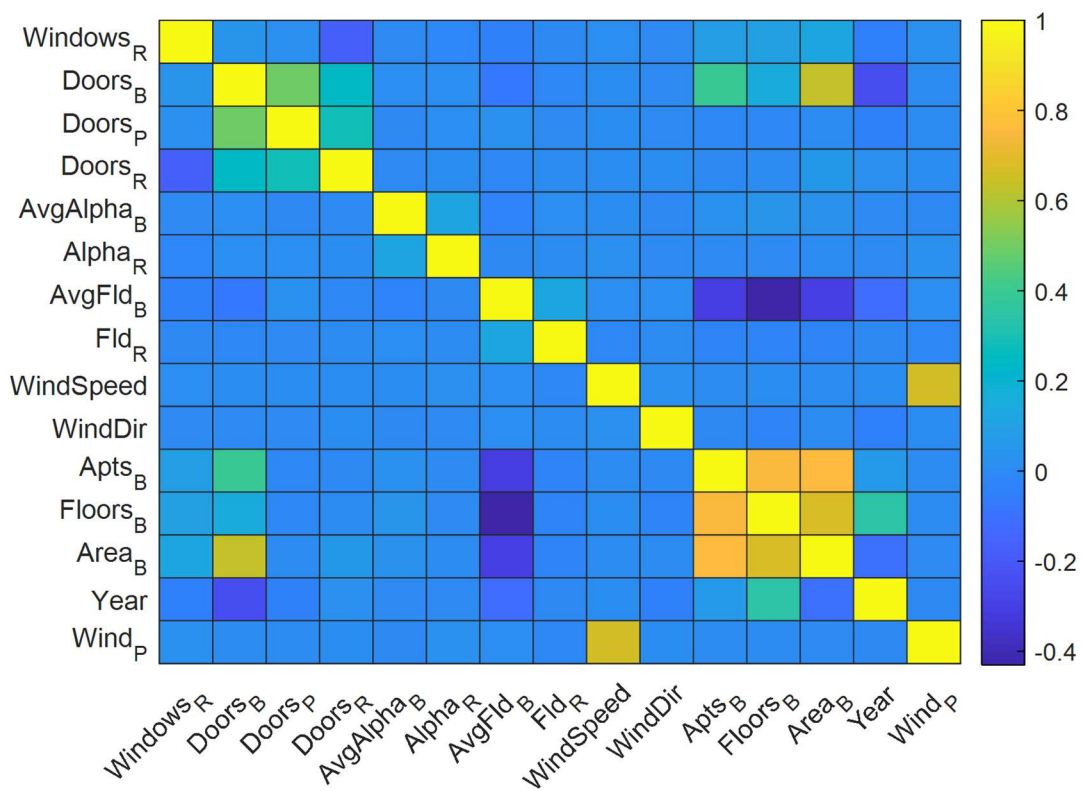


Figure 26. Correlation heatmap of independent variables after adjustment.

10.1.4 Analysis and selection of dependent variable

There are three potential dependent variables to analyze, being *AffApts*, *AffFloors*, and *AffArea*. Importance should be placed on the three variables as, for example, the number of affected apartments signifies the number of affected households or families. The number of affected floors influences the possible evacuation plans as well as accessibility of the building. Furthermore, the affected area quantifies the extent of the damage caused by fire. Because of this, a combination of the three variables is considered to have potential to obtain a variable representative of all.

The distributions of *AffApts*, *AffFloors*, and *AffArea* are analyzed to make the correct adjustments before combining. In addition to this, their correlation is assessed to find the best tool to combine the variables.

Histograms of the data distributions for the three variables can be observed in Figure 27. Furthermore, their skewness is presented in Table 10.

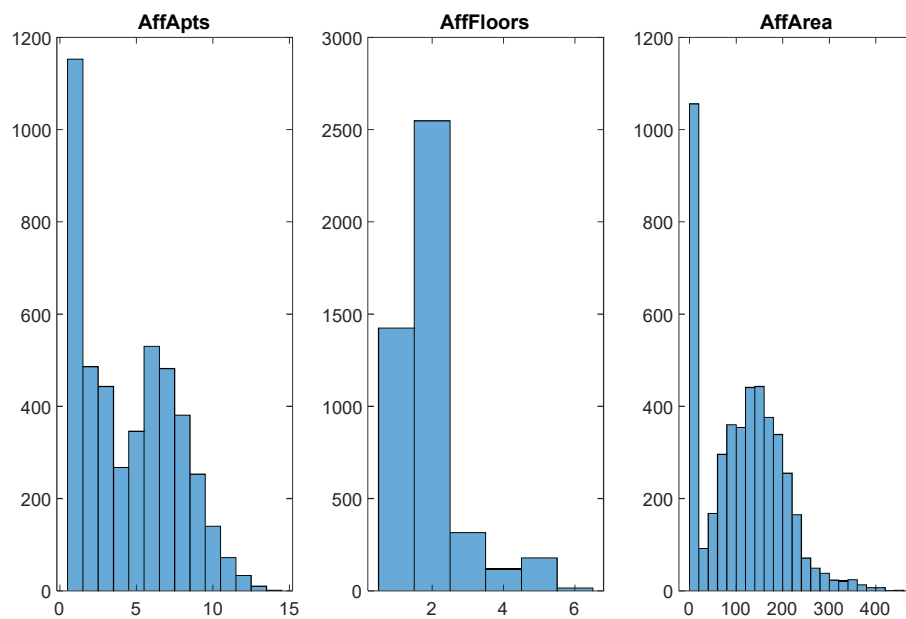


Figure 27. Histograms of dependent variables.

It is interesting to note, from Figure 27 that all three measured variables present asymmetry. Meaning that there is a higher concentration of simulations with low values for the three variables. Furthermore, the distributions for affected area and apartments are bimodal, as there are a lot of data in the first interval but there is a second peak in an interval placed towards the middle. This could be due to fact that, in a scenario where

there are no openings, the fire does not spread. Because of the randomness in door distributions, this event may be frequent.

Variable	Skewness
<i>AffApts</i>	0.385
<i>AffFloors</i>	1.676
<i>AffArea</i>	0.431

Table 10. Skewness of dependent variables.

Positive skewness can be observed for all three variables, although *AffFloors* is the only with a high level of skewness, according to standards. Because of this, skewness is corrected by taking the logarithm of every value. Calculating the skewness again, the value is reduced to 0.2312. The variable $\ln(AffFloors)$ is considered instead of *AffFloors* from now on.

Figure 28 contains a heatmap of the correlations between the variables.

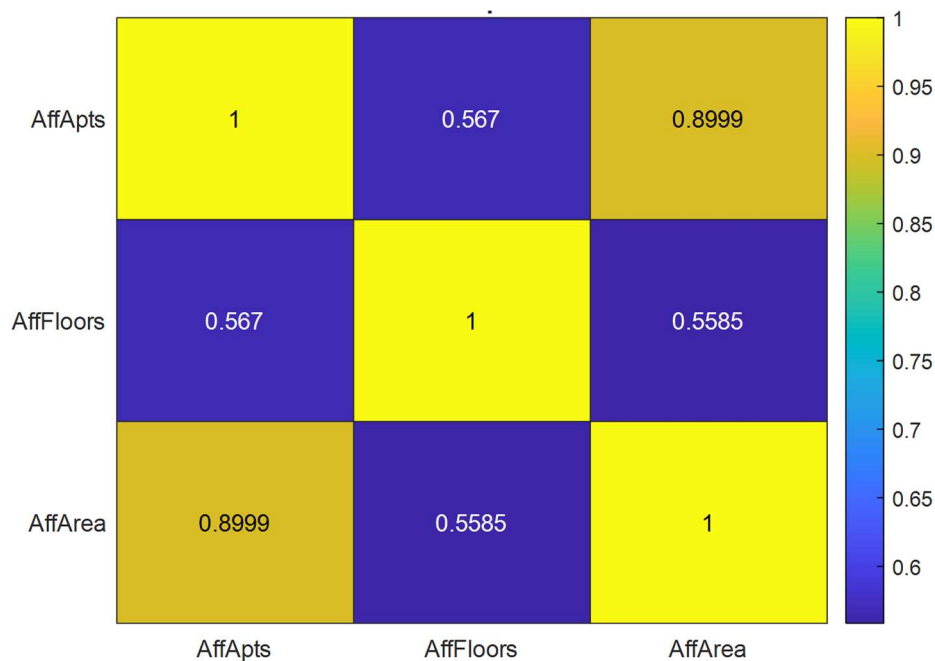


Figure 28. Correlation heatmap of dependent variables.

A high correlation can be observed between the affected area and affected apartments, almost reaching a value of 0.9, which indicates that these variables may contain redundant information. Furthermore, the correlation of both these variables with the logarithm of affected floors remains lower, at a value of approximately 0.56.

Principal Component Analysis (PCA) arises as an option to reduce the dimensionality of data, while preserving the essential characteristics. It is particularly useful for

datasets with highly correlated variables such as this because it identifies patterns and relationships among them, allowing for a more compact representation of the data while minimizing information loss.

A new variable is obtained by performing PCA with the dependent variables (*AffApts*, $\ln(AffFloors)$, and *AffArea*) and extracting the first principal component as the combined value because it captures the highest variance from the transformed data. This variable is normalized to maintain a range between 0 and 1 by subtracting the minimum value and dividing by the maximum range. This new variable is named *RiskFactor* since it is a combination of the three variables that measure the damages and risk that the fire poses, and it is the dependent variable selected. Its histogram is displayed in Figure 29.

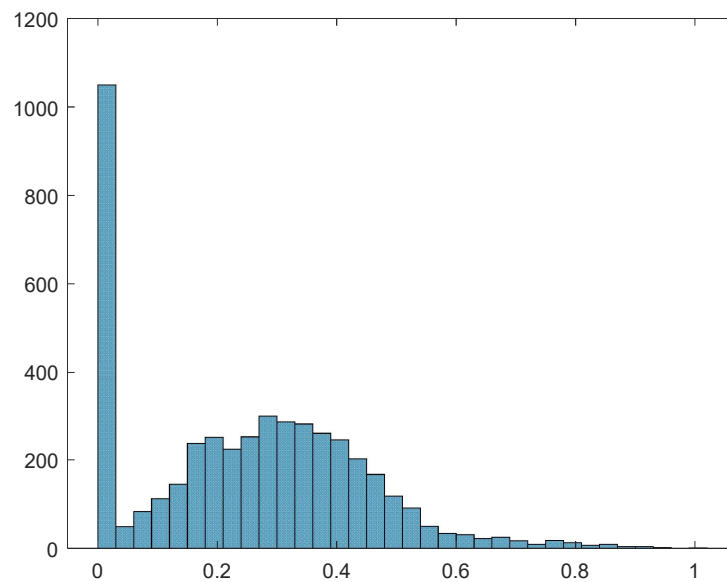


Figure 29. Histogram of Risk Factor.

This new variable has a similar distribution to the variables related to affected area, apartments, and floors. With a mean of 0.2521 and a standard deviation of 0.1858, the distribution is normal if the lowest interval is disregarded. There is a high number of cases with an extremely low level of risk, which, as explained before, may be because of the scenarios where all doors in the room are closed and there are no windows. Because of this, a logarithmic transformation is considered to reduce the level of skewness and potentially improving the fit of the model.

10.1.5 Relationship between the dependent and independent variables

Analyzing the relationship between independent variables and the dependent variable using scatter plots is crucial in linear modeling, as it provides visual insights into the nature of their associations. Scatter plots can reveal patterns such as linearity, curvature, and the presence of outliers, guiding the need for variable transformations. For instance, if the relationship between an independent variable and the dependent variable appears to be quadratic rather than linear, adding the square of the independent variable to the model can significantly improve its fit. Such adjustments help in accurately capturing the underlying data structure, therefore enhancing the reliability of the linear model. Scatterplots displaying the relationships between each of the independent variables and the dependent variable (*RiskFactor*) are shown in Figure 30.

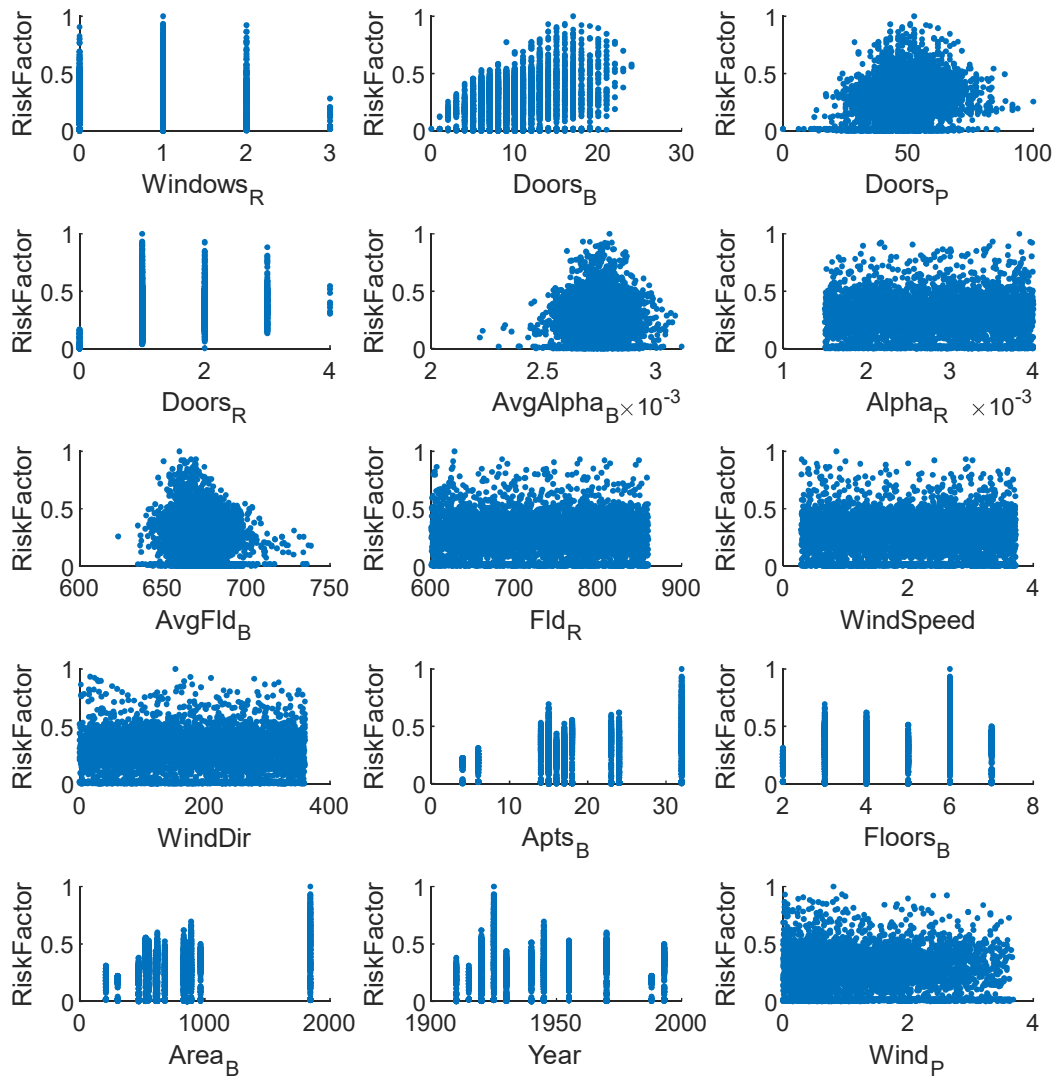


Figure 30. Independent variables vs. Risk factor scatter plots.

Several observations can be made about these graphs. No clear direct relationship can be observed between the variables for any of the plots. This indicates that the dependent variable cannot be explained by a single independent variable. Furthermore, there exist different relationships between the variables. In the case of the year of construction, for example, the risk factor is low for older buildings (early 1900s), later grows for some medium-aged buildings, and has another growth towards the end. This might indicate that this variable has a quadratic relationship with the risk factor. Adding a square might be interesting to verify this hypothesis. Other variables such as the average alpha and the fire load density might have a similar occurrence.

10.1.6 Summary of the behavior of the independent variables

In this section, a summary of the independent variables available for the model is presented. Information regarding possible adjustments that may further optimize the model is also displayed in Table 11, as discussed in the previous section. An X in the “Logarithmic Adjustment” or “Square Adjustment” columns represents the fact that an adjustment may be beneficial for the model.

<i>Independent Variables</i>	Logarithmic Adjustment	Square Adjustment
<i>Windows_R</i>		
<i>Doors_B</i>	X	X
<i>Doors_R</i>		X
<i>Doors_P</i>		X
<i>AvgAlpha_B</i>		X
<i>Alpha_R</i>		
<i>AvgFld_B</i>	X	X
<i>Fld_R</i>		
<i>WindSpeed</i>		
<i>WindDir</i>		
<i>Wind_P</i>		
<i>Apts_B</i>		
<i>Floors_B</i>	X	
<i>Area_B</i>	X	
<i>Year</i>	X	X

Table 11. Potential logarithmic and square adjustments.

10.2 Model Building

Two linear models will be built: one with an explanatory purpose, and the other with a predictive purpose. Variables are progressively added individually or in groups while experimenting with transformations such as taking logarithms or squares to improve the model's fit. After each adjustment or variable addition, model performance is evaluated using statistical metrics such as R-squared, adjusted R-squared, and residual analysis to ensure the model adequately fits the data and meets underlying assumptions like linearity and homoscedasticity. In addition to this, in the case of the explanatory model, the p-values of the X-variable coefficients are analyzed to disregard the variables with a high value and guarantee the significance of the model. This iterative approach allows for refining the model until a satisfactory balance between model complexity and predictive accuracy is achieved.

Interactions between independent variables are also considered, as they can significantly impact the outcome of the model and enhance the explanatory and predictive power. When two variables interact, the effect of one independent variable on the dependent variable may depend on the value of another independent variable. This interaction can be captured by including an interaction term, which is the product of the two interacting variables. Possible interactions within the same group of variables shown in Figure 31 will be checked with each addition.

The groups of variables and the order of addition into the model are shown below:

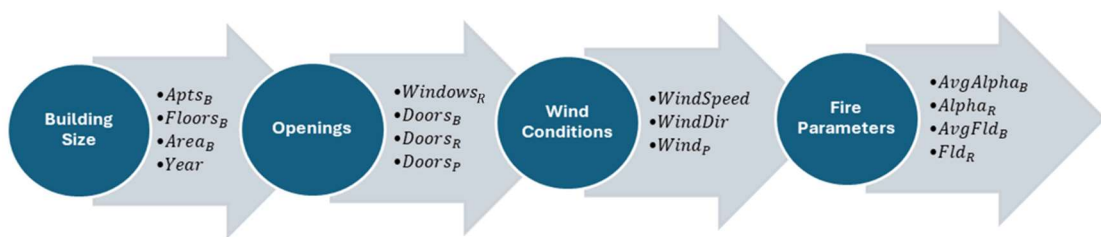


Figure 31. Groups of variables and order of addition.

The variables are added to the model in the groups shown Figure 31. Beginning with the building size and ending with the fire parameters. The squares are to be included in addition to the variable without the square, while the logarithms replace the variable without logarithm. For the explanatory model, if any of the coefficients of the variables have a p-value higher than 0.1, the variable is considered not significant enough for the

model. In the predictive model, the variables that cause a reduction in the adjusted R-squared may be discarded.

Data scaling is performed before inputting the variables into the model to facilitate the interpretation of coefficients and avoid the dominance of certain variables. The independent variables are normalized by subtracting the mean and dividing by the standard deviation each value. This also aids in the interpretation of the coefficients and variables, as now they are on the same scale and can be compared. After following the building process, the model shown in Table 12 is obtained. A +5 is added to the $Floors_B$ to ensure that the values within the logarithm are always larger than 0. The standardization process is repeated after the logarithmic addition to ensure that all variables (except squares and interactions) are standardized.

<i>Variable</i>	<i>Coefficient</i>
<i>(Intercept)</i>	0.043479
<i>Apts_B</i>	0.04655
<i>ln(Floors_B+5)</i>	-0.020012
<i>Area_B</i>	0.015801
<i>Year</i>	0.020341
<i>Year²</i>	-0.012881
<i>Windows_R</i>	0.0069043
<i>Doors_B</i>	0.017588
<i>Doors_R</i>	0.36842
<i>Alpha_R</i>	0.0070549
<i>Root Mean Squared Error (RMSE): 0.123</i>	
<i>R-squared: 0.661, Adjusted R-Squared: 0.661</i>	
<i>F-statistic vs. constant model: 995, p-value = 0</i>	
<i>All coefficients significant at the 1% level</i>	

Table 12. Coefficients and parameters of the final explanatory model.

The final explanatory model obtained, rounding the decimal points, is the following:

$$\begin{aligned} \ln(RiskFactor) = & 0.043 + 0.046 \cdot Apts_B - 0.02 \cdot \ln(Floors_B + 5) + 0.016 \cdot Area_B \\ & + 0.02 \cdot Year - 0.013 \cdot Year^2 + 0.0069 \cdot Windows_R + 0.018 \cdot Doors_B \\ & + 0.368 \cdot Doors_R + 0.0071 \cdot Alpha_R \end{aligned}$$

The same process is followed for the predictive model, shown in Table 13. Nevertheless, as explained before, an increasing adjusted R-squared is the main objective when adding new variables. Furthermore, overfitting should be looked at, as it may be an issue in this case. To check for this, the data is divided into two: a training

set (70%) and a test set (30%). The root mean squared error (RMSE) is calculated for both sets. If the RMSE is significantly higher for the test set, the model is likely overfitted.

<i>Variable</i>	<i>Coefficient</i>
<i>(Intercept)</i>	0.030105
<i>Apts_B</i>	0.057379
<i>ln(Floors_B+5)</i>	0.0021439
<i>Area_B</i>	-0.063554
<i>Year</i>	0.046229
<i>Year²</i>	-0.024692
<i>Windows_R</i>	0.0030641
<i>Doors_B</i>	0.045295
<i>Doors_R</i>	0.36929
<i>Doors_P</i>	-0.012186
<i>Alpha_R</i>	0.0081005
<i>AvgAlpha_B</i>	0.0031529
<i>Fld_R</i>	-0.0010812
<i>AvgFld_B</i>	-0.0047343
<i>Apts_B · ln(Floors_B+5)</i>	-0.022703
<i>Area_B · ln(Floors_B+5)</i>	0.062874
<i>Root Mean Squared Error (RMSE) Training: 0.119</i>	
<i>Root Mean Squared Error (RMSE) Test: 0.120</i>	
<i>R-squared: 0.688, Adjusted R-Squared: 0.689</i>	
<i>F-statistic vs. constant model: 537, p-value = 0</i>	

Table 13. Coefficients and parameters of the final predictive model.

The final predictive model obtained, rounding the decimal points, is the following:

$$\begin{aligned}
 \ln(RiskFactor) = & 0.03 + 0.057 \cdot Apts_B - 0.0021 \cdot \ln(Floors_B + 5) - 0.063 \cdot Area_B \\
 & + 0.046 \cdot Year - 0.025 \cdot Year^2 + 0.0031 \cdot Windows_R + 0.045 \cdot Doors_B \\
 & + 0.369 \cdot Doors_R - 0.012186 \cdot Doors_P + 0.0081 \cdot Alpha_R + 0.0032 \cdot AvgAlpha_B \\
 & - 0.0011 \cdot Fld_R - 0.0047 \cdot AvgFld_B - 0.0227 \cdot Apts_B \cdot \ln(Floors_B + 5) \\
 & + 0.0629 \cdot Area_B \cdot \ln(Floors_B + 5)
 \end{aligned}$$

10.3 Explanatory Model Analysis

An analysis of the significant variables and their coefficients, as well as the model in general will be conducted. It should be noted that the independent variables are standardized, while the dependent is the logarithm of the risk factor, normalized to have values between 0 and 1. This makes the coefficients comparable to determine the level

of impact that each independent variable has on the risk factor. Nevertheless, the measurement of the unitary impact that each parameter has on the dependent variable cannot be directly measured.

Firstly, it should be noted that some of the variables initially considered for the model were found to be not significant at the 10% level. Because of this, they are not present in the final model. All variables related to the building parameters are significant in the model. In the case of variables related to openings, the ratio of open doors was considered not significant when explaining the risk of fire. Wind conditions were not found to be important when analyzing the fire risk. It should be noted that more extreme wind conditions could render a different result and may have a more noticeable effect on risk. In addition to this, it is complex to capture the interaction of wind conditions in the case of fire. Numerical models such as the ones used tend to make simplifications in this sense. From the point of view of fire parameters, only the fire growth rate in the room resulted significant. It is understandable that, in this case, fire load density is not significant because it only affects the fire curve after flashover, which does not influence the fire spread. This would mean that the fire load that is present in the room affects the duration of the fire, but not its expansion. No interactions between variables were determined significant.

The analysis of coefficients is key in understanding the effects of each of the independent variables on the dependent variable. Table 14 displays variables and coefficients related to building parameters and characteristics. It should be noted that, since there are 12 buildings in the model, there are 12 sets of “building parameters” variables. Because of the low quantity, it may be difficult to draw conclusions that can be extrapolated to other cases.

<i>Variable</i>	<i>Coefficient</i>
$Apts_B$	0.04655
$\ln(Floors_B + 5)$	-0.020012
$Area_B$	0.015801
$Year$	0.020341
$Year^2$	-0.012881

Table 14. Building parameter coefficients.

The year of construction has a negative quadratic relationship with the fire risk. First, risk increases with increasing year of construction; afterwards, it decreases. This

variable ranges from 1910 to 1993 in the case study. This relationship may be due to changes in design trends of the buildings, as safety technologies and materials are not considered to be different among buildings. The number of apartments and area have a positive coefficient, while the number of floors has a negative relationship. This demonstrates that larger buildings when it comes to floor area have a higher risk factor than smaller, which is a reasonable conclusion. As the risk factor also evaluates the number of affected apartments, it is also acceptable that, if a building has more apartments, more of them may be burned. Regarding the floors, as there is a variable that accounts for the size of the building, having more floors for the same area reduces the risk of fire. This would mean that spread within the same floor can be more probable than vertical spread.

Coefficients of variables related to openings, as well as fire characteristics are presented in Table 15.

<i>Variable</i>	<i>Coefficient</i>
<i>Windows_R</i>	0.0069043
<i>Doors_B</i>	0.017588
<i>Doors_R</i>	0.36842
<i>Alpha_R</i>	0.0070549

Table 15. Opening variable and fire characteristic coefficients

All coefficients are positive, meaning that a higher number of windows in a room, or doors in a room or building, in addition to a higher fire growth rate result in a higher level of damage in the event of a fire. The presence of open doors in the room where the fire originates has the highest impact on the model. This is because it has a direct effect on the expansion of fire into contiguous rooms. If all doors in the room are closed, the fire is not able to expand horizontally within the floor. Comparing the coefficients, the presence of doors in the room increases the risk of fire up to 60 times more than the presence of windows. Windows may have a lower effect than doors on fire risk because of their smaller size, adding to the fact that they contribute to vertical spread, while doors act on horizontal spread. Thus, it can be concluded that horizontal fire spread is more prominent than vertical in the case of the ignited room. This conclusion could be valid, as horizontal spread might cause more damage since the spread can be towards 1 to 4 rooms at the same time, while vertical spread only happens from one room to another. The number of doors within the building is also important, as it provides insight

into how easily the fire can spread. It is interesting to notice that fire growth rate, even within ranges that are considered usual for residential fires, significantly impacts the risk of fire.

Explanatory Model Characteristics
Root Mean Squared Error (RMSE): 0.123 R-squared: 0.661, Adjusted R-Squared: 0.661 F-statistic vs. constant model: 995, p-value = 0 All coefficients significant at the 1% level

Figure 32. Explanatory model characteristics.

From Figure 32 a general analysis of the model can be carried out. The normalized linear model is based on 4598 observations and exhibits a moderate fit to the data, as indicated by an R-squared value of 0.661 and an adjusted R-squared value of 0.661, suggesting that approximately 66.1% of the variance in the dependent variable is explained by the model. The root mean squared error (RMSE) measures the accuracy of the model by presenting the square root of the average squared differences between the predicted and actual values. In this case, it is 0.123 indicating a moderately low average error in predictions. Knowing that the dependent variable takes values between 0 and 1, suggests that the model is moderately accurate for its purpose. With 4587 degrees of freedom for the error term, the model's F-statistic of 995 is highly significant (p-value = 0), strongly rejecting the null hypothesis that the model with no predictors (constant model) fits the data just as well as the proposed model. This demonstrates the model's overall efficacy in capturing the relationship between the independent variables considered for the model and the *RiskFactor*.

Summarizing, the model characteristics suggest that, even though the model could be used for explanatory purposes, some limitations should be regarded. Because approximately 45% of the variance remains unexplained, there may be other important variables or factors not captured by the model or the dependent variable could have inherent unpredictability.

10.4 Predictive Model Analysis

The predictive model presents an increase in the adjusted R-squared, as well as an improvement of the Root Mean Squared Error (RMSE), as seen in Figure 33. Its R-squared value of 0.69 suggests that approximately 68.9% of the variance in the risk factor is explained by the model. The model remains significant, with a high F value

(537) and a p-value close to 0. As explained before, the data is divided into two sets, one for training (70% of the data) and another for testing (30%). By comparing the RMSE, a possible overfitting issue in the model can be identified. In this case, the RMSE for the test data is only 0.001 higher than for the training data, thus, a potential overfitting is discarded.

Model Characteristics
Root Mean Squared Error (RMSE) Training: 0.119
Root Mean Squared Error (RMSE) Test: 0.120
R-squared: 0.688, Adjusted R-Squared: 0.689
F-statistic vs. constant model: 537, p-value = 0

Figure 33. Predictive model characteristics.

The actual versus the predicted values for the test set (30% of the data available) are graphed in Figure 34. Two separate groups of variables may be seen: one with a risk factor close to zero and another with a higher risk factor. The separation of these two groups to make two stronger models was considered. Nevertheless, the outcome of the models was not improved. Because of this and the fact that the aim of the tool is to be able to predict both high and low risk factors, the model with both groups is preferred. As can be seen, the values with an actual value close to zero, which represent extremely low risk, are below 0.2 in predicted value. Furthermore, high actual risk factor values (over 0.8) have a predicted value over approximately 0.5. The underestimation of the values with a high risk factor should be taken into account when using the model, knowing that a predicted value over 0.5 may be related to a high risk scenario. Values that are extreme can thus, be identified in this way.

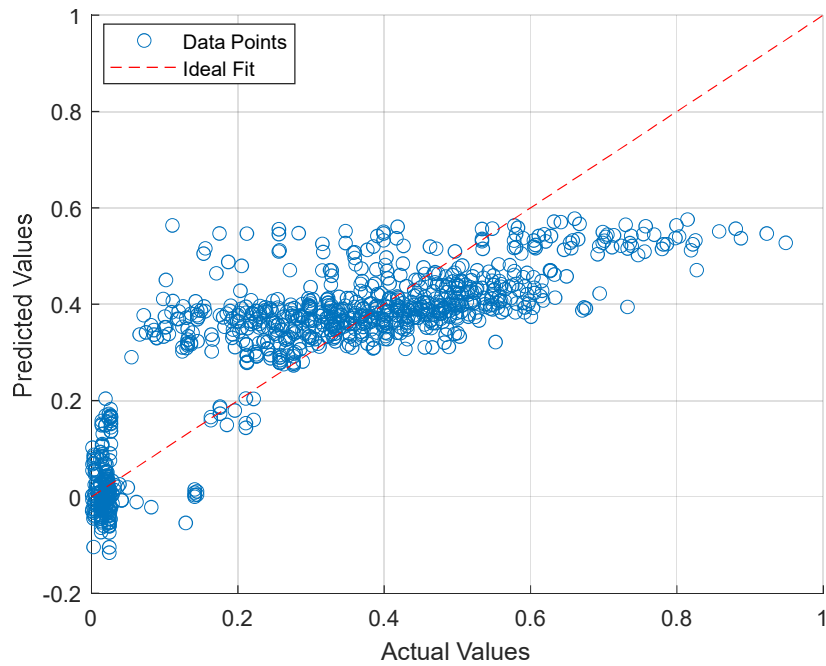


Figure 34. Actual vs. Predicted value of test set.

The residuals (difference between the observed and predicted values) plot for the training set is presented in Figure 35. Analyzing this plot is important, as it is a valuable diagnostic tool that could reveal issues about the fit and assumptions of the model. An optimal residuals plot should show residuals scattered randomly around the horizontal zero line.

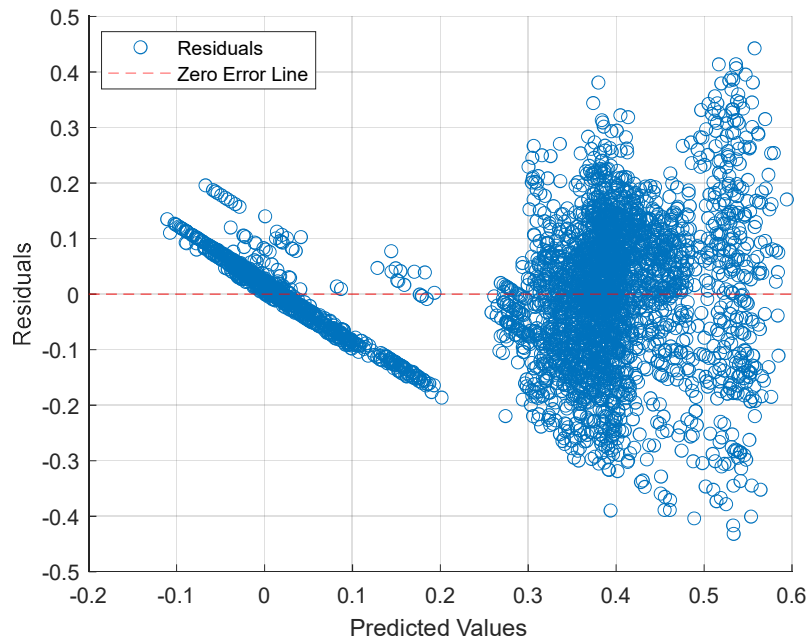


Figure 35. Residuals plot of training set.

In this case, a linear pattern can be seen with predicted values between -0.1 and 0.2. This is due to the fact that, since there exist a lot of scenarios with a low risk factor

(actual values close to 0), these tend to be predicted in a range of -0.1 and 0.2. Because of this, the residuals are positive with negative predicted values and negative with positive predicted values, with a linear tendency. Additionally, there are both positive and negative residuals, meaning that the model overestimates for some cases and underestimates for others. Furthermore, for predicted values higher than 0.2, the residuals are randomly scattered through the plot, without any apparent pattern, providing a positive outcome for this analysis.

11. Conclusions

To conclude, the main objective was to assess fire resilience in vulnerable dwellings. This has been done through two steps. The first one being the modification and refinement of a tool to simulate fire spread through a GIS model and numerical models for compartment temperature. The second step is the creation of a linear regression model that calculates a risk factor depending on several parameters related to the building, room where the fire originates, and fire characteristics. The risk factor is defined by the damage that a potential fire would cause, represented by the area that is affected, the floors and the number of apartments and defined in a 0 to 1 scale. An additional model is created with a predictive purpose. The explanatory model is used as a tool to understand the impact of each variable on the risk factor, while the predictive model serves as a potential tool to calculate risk factors of other scenarios.

When it comes to the analysis of the effects of the independent variables on the risk factor, several observations can be made. The variables that have a more notable impact on the risk are related to the openings and the building characteristics. Regarding the openings, the number of open doors within a room has the highest impact out of all variables on the risk factor. The fire growth rate (related to the nature of the materials burned in the fire) does have an impact on the risk factor, although lower than other variables considered for the explanatory model. The fire load density present in the rooms is found to affect the duration of the fire but not the expansion and damage, thus not being significant for the model. The wind characteristics (both speed and directions) were found to have an insignificant impact on the risk.

The explanatory model presents an adjusted R-squared of 0.66, determining that its explanatory power is moderate. The reason why it is not higher could be due to an inherent unpredictability of the model or additional factors that are not included.

Furthermore, in the case of the predictive model, the R-squared (0.69) also determines a moderate predictive power. analyzing the RMSE (0.119) with relation to the range of Y values (0-1), the model is found to be reasonably accurate for its purpose, which would be to identify cases with a high risk factor.

The limitations of both the simulation tool and the model should be addressed. Several assumptions are made when building the simulation tool:

- Flashover temperature is set to 500°C, and the windows are set to break at 239°C: it is known that this is not always the case. Furthermore, the simulation time, which would translate to the time it would take to extinguish the fire, is set to 1 hour but could vary.
- The fire is assumed to spread vertically the moment that the flame from the opening reaches the top window: flame temperatures would need to be calculated, which are complex and models for them are inaccurate.
- The use of temperature curves is introduced as a simplification to model the expansion of the fire. These are assumed to be continuous; nevertheless, this is not realistic as, for example, when a window breaks, there is an increase in ambient oxygen and a temperature peak, which would be difficult to characterize.
- In the case of wind, the difficulty to model its effect on compartment fires is noteworthy. This is due to its possible effect on the quantity of oxygen that reaches the inside of the compartment and the hot and cold gas interaction.

As for the models, a few limitations should be considered:

- The explanatory and predictor power of the models is moderate (with an adjusted R-squared of 0.66-0.69 and a RMSE of 0.12, with a 0-1 dependent variable scale). The model should not be used to make precise predictions or specific assumptions about the explainability of independent variables in other scenarios.
- Even though there is a large sample of data used for the model (4589 simulations), this data comes from a reduced number of buildings (only 12 buildings are considered), meaning that the variables related to building characteristics do not have a great number of variations.
- The data used from the model is obtained from simulations and not real data (because of the unavailability of it). Interpretations and the analysis of the outcome of the model should be done taking this into account.

Future research may be divided into several points:

- Validation of the temperature curves, as well as the linear model. This could be done through simulations in other buildings or with data from real fires. Specific data regarding real fires and their development remains difficult to find. Nevertheless, doing so would aid in understanding if the simulations and the linear model portray a realistic outcome. This would also provide information on the possible extrapolation to other types of buildings (different sizes and geometries).

- Refining the model with the use of new data: 12 buildings were utilized for this model. Using more buildings with different sets of characteristics (number of floors, area, year of construction...) could help obtain a more efficient model. In addition to this, if a higher computational power were available, utilizing a more accurate technique to simulate the fire spread, such as FDS, would render more realistic data to improve and refine the model.
- Finding additional variables that could aid in increasing the R-squared of the models so their explanatory and predictive powers may increase. Materials used in the construction of the building in addition to the fire safety measures are some possibilities.

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Appendix 1. Sustainable Development Goals

The Sustainable Development Goals (SDGs) are the 17 goals at center of the 2030 Agenda for Sustainable Development. This agenda was implemented by all United Nations Member States in 2015 as a call for global partnership in sustainability issues. These strategies aim to end poverty, improve education, improve economic growth, reduce inequality, as well as fight climate change and preserve biodiversity. Because of the United Nation's commitment to these goals, projects should work towards reaching SDGs. [46] In the case of this project, the goal number 11- Sustainable cities and communities is at the core. Nevertheless, other goals, such as 9- Industry, innovation, and infrastructure and 3- Good health and well-being, were also considered when conducting the project. A more detailed explanation of the three goals will be made next.

11- Sustainable cities and communities

The aim of this goal is to “make cities and human settlements inclusive, safe, resilient and sustainable.” A specific target (11.5) mentioned in the SDGs document is: “By 2030, significantly reduce the number of deaths and the number of people affected and substantially decrease the direct economic losses relative to global gross domestic product caused by disasters, including waterrelated disasters, with a focus on protecting the poor and people in vulnerable situations”. As the main objective of this project is to assess the resilience of vulnerable dwellings, it aligns perfectly with the target 11.5. Assessing the safety and dangers that vulnerable buildings suffer with relation to others takes a step into identifying for further improvement of settlements.

9- Industry, innovation, and infrastructure

The objective of this goal is to “build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation.” Resilience in infrastructure and promotion of inclusivity are topics that this project touches upon in a significant way. Technological innovation and advancements are also mentioned, as further research and investigation is a necessity.

3- Good health and well-being

This goal promotes healthy lives and prevention of needless suffering and premature death. Although this project does not directly relate to disease, it does have to do with unnecessary

deaths. Healthier and safer lives for vulnerable groups are the focus of this sustainable development goal, which complies with this project's objectives.

Appendix 2. GAMA Software Code

The part of the code that was altered to include the temperature models described in Section 7 is shown below (other changes were made, although less significant):

```
ask room {
//setting room draft conditions and fire parmeters

    if int(my_windows count each.upwind)>=1 and
int(my_windows count each.downwind)>=1 {draft<-true;}

    //    write"draft"+draft;
    if floor=1{
        Ad1<- sum (my_doors accumulate (each.Ad));}
    if floor>1{
        Ad1<-sum (my_doors_t accumulate (each.Ad));}
    if name ="room933"{
        Ad1<- sum (my_doors accumulate (each.Ad));}

    Ad2 <- sum (my_windows accumulate (each.Ad));
    Ad<-Ad1+Ad2;
    ArT<-(wr*2+dr*2)*floor_height+wr*dr*2-Ad;
    if (Ad1>0){my_hd<-2.0;}
    if (Ad2>0){my_hd<-1.0;}

    if (Ad1=0 and Ad2=0){my_hd<-0;}
    if(Ad>0 and my_hd>0){
        eta<-ArT/(Ad*my_hd^0.5);

    }else{eta<-0;}
    if floor=1{

        Fld<-730;

    }else{Fld<-650;}

    if UNIQ_ID=0 and apt=0{Fld<-200;}
    if aleatorio=true and floor=1{Fld<-rnd(600.0,860.0);}
    if aleatorio=true and floor>1{Fld<-rnd(500.0,800.0);}
    if aleatorio=true and UNIQ_ID=0 and apt=0{Fld<-
rnd(150.0,250.0);}

    }
    if draft{
        mr<-L/1200;}
    if !draft{
        mr<-0.18*(1-#e^(-
0.036*eta))*Ad*(my_hd^0.5)*((dr/wr)^(-0.5));}
    //the room has open doors
    if Ad1>0{
        A1<-
sqrt(g)*cp*rho_inf*normal_temperature*Ad*sqrt(my_hd);
        B1<-(hk*ArT/(sqrt(g)*cp*rho_inf*Ad*sqrt(my_hd)));
        t1 <- (A1/alpha)^(1/2)*((523-
normal_temperature)/480)^(3/4)*B1^(1/4);
        if Ad2>0{
            my_hd<-(2+Ad2)/Ad2;
        }
    }
```

```

A2<-
sqrt(g)*cp*rho_inf*normal_temperature*Ad*sqrt(my_hd);
B2<-(hk*ArT/(sqrt(g)*cp*rho_inf*Ad*sqrt(my_hd)));
t21 <- (A2/alpha)^(1/2)*((523-
normal_temperature)/480)^(3/4)*B2^(1/4);
t22 <- (A2/alpha)^(1/2)*((773-
normal_temperature)/480)^(3/4)*B2^(1/4);
Afuel <- 0.26*Fld^(1/3)*Arf;
X <- Ad*sqrt(my_hd)/Afuel;
if X <= 0.081{
  Q<-Afuel*1.6*X;}
else if X > 0.1{
  Q <- Afuel*2.5*X*exp(-11*X)+0.048;}
else {
  Q <- Afuel*0.13;}
C3<-
1280*(Q/(sqrt(ArT*sqrt(k*rho*c))*sqrt(Ad*sqrt(my_hd))))^(2/3);
t3<-((773-normal_temperature)/C3)^6;
t3<-t3*60;
tf <- Fld*Arf/(Q);
if tf<t3{
  tf<-t3+tf;
}
}
//the room has windows but no open doors
if Ad1=0 and Ad>0{

  K1<-2*0.4*sqrt(k*rho*c)*ArT/(2.5*Arf*rho_inf*cp);
  K2<-1/(2.5*Arf*rho_inf*cp);

  iteration <- 0;
  a <- 0;
  b <- 1200;

  if ((2*alpha*a^2*K2/K1^2)*(K1*sqrt(a)-1+e^(-
K1*sqrt(a)))-523+normal_temperature)*((2*alpha*b^2*K2/K1^2)*(K1*sqrt(b) -
1+e^(-K1*sqrt(b)))-523+normal_temperature)>0{
    write ("error");

    t1<-100;
  }else{
    loop while:true{

      if (b-a)/2 < tolerance or iteration >
max_iterations{

        break;

      }

      A<-(2*alpha*a^2*K2/K1^2)*(K1*sqrt(a)-1+e^(-
K1*sqrt(a)))-523+normal_temperature;

      midpoint <- (a + b) / 2;
      if
(2*alpha*midpoint^2*K2/K1^2)*(K1*sqrt(midpoint)-1+e^(-K1*sqrt(midpoint)))-
523+normal_temperature = 0{

        t1<- midpoint;
        break;}

```

```

else if
((2*alpha*midpoint^2*K2/K1^2)*(K1*sqrt(midpoint)-1+e^(-K1*sqrt(midpoint)))-
523+normal_temperature) * A < 0{
    b <- midpoint;}
else{
    a <- midpoint;}
iteration <- iteration + 1;

}
t1<-(a+b)/2;

}

}
if Ad2>0{
    my_hd<-Ad2;

    A2<-
sqrt(g)*cp*rho_inf*normal_temperature*Ad*sqrt(my_hd);
    B2<-(hk*ArT/(sqrt(g)*cp*rho_inf*Ad*sqrt(my_hd)));
    t21 <- (A2/alpha)^(1/2)*((523-
normal_temperature)/480)^(3/4)*B2^(1/4);
    t22 <- (A2/alpha)^(1/2)*((773-
normal_temperature)/480)^(3/4)*B2^(1/4);
    Afuel <- 0.26*Fld^(1/3)*Arf;
    X <- Ad*sqrt(my_hd)/Afuel;
    if X <= 0.081{
        Q<-Afuel*1.6*X;}
    else if X > 0.1{
        Q <- Afuel*2.5*X*exp(-11*X)+0.048;}
    else {
        Q <- Afuel*0.13;}
    C3<-
1280*(Q/(sqrt(ArT*sqrt(k*rho*c))*sqrt(Ad*sqrt(my_hd))))^(2/3);
    t3<-((773-normal_temperature)/C3)^6;
    t3<-t3*60;
    tf <- Fld*Arf/(Q);
    if tf<t3{
        tf<-t3+tf;
    }
}
//the room does not have windows or open doors
if Ad=0{
    K1<-2*0.4*sqrt(k*rho*c)*ArT/(2.5*Arf*rho_inf*cp);
    K2<-1/(2.5*Arf*rho_inf*cp);

    iteration <- 0;
    a <- 0;
    b <- 1200;

    if ((2*alpha*a^2*K2/K1^2)*(K1*sqrt(a)-1+e^(-
K1*sqrt(a)))-773+normal_temperature)*((2*alpha*b^2*K2/K1^2)*(K1*sqrt(b)-
1+e^(-K1*sqrt(b)))-773+normal_temperature)>0{
        write ("error");

        t1<-100;
    }else{
        loop while:true{
            if (b-a)/2 < tolerance or iteration >
max_iterations{
                break;

```

```

    }

    A<- (2*alpha*a^2*K2/K1^2)*(K1*sqrt(a)-1+e^(-
K1*sqrt(a)))-773+normal_temperature;

    midpoint <- (a + b) / 2;
    if
(2*alpha*midpoint^2*K2/K1^2)*(K1*sqrt(midpoint)-1+e^(-K1*sqrt(midpoint)))-
773+normal_temperature = 0{

        t1<- midpoint;
        break;}
    else if
((2*alpha*midpoint^2*K2/K1^2)*(K1*sqrt(midpoint)-1+e^(-K1*sqrt(midpoint)))-
773+normal_temperature) * A < 0{
        b <- midpoint;}
    else{
        a <- midpoint;}
    iteration <- iteration + 1;
}
t1<-(a+b)/2;
}
//if there are no open doors / windows, the fire
ends

tf<-t1+100;

}
}

```

The calculation of the flame tip, based on the formulas explained in section 7.2 is shown below:

```

action calculate{
    if cos(360-wind+90-heading)<0{
        fact<- (-cos(360-wind+90-heading));
    }else{
        fact<- cos(360-wind+90-heading);
    }

    flame_tip<-(-
0.049)*(wind_speed*fact)+9.8*(one_of(my_room).mr/(width))^(2/3)-height;
    flame_impigment_range<-
0.043*(wind_speed*fact)+0.55*height*((1.175/height)^(1/3));
}

```

Appendix 3. MATLAB Code

Exploratory Data Analysis

```
% Initialize arrays to store the statistics

data=FINALESS2;

%%Statistics
means = zeros(1, width(data));
medians = zeros(1, width(data));
stdDevs = zeros(1, width(data));
maxValues = zeros(1, width(data));
minValues = zeros(1, width(data));

% Calculate the statistics for each column
for i = 1:width(data)
    columnData = data(:, i);
    means(i) = mean(columnData);
    medians(i) = median(columnData);
    stdDevs(i) = std(columnData);
    maxValues(i) = max(columnData);
    minValues(i) = min(columnData);
end

% Create a table to display the statistics
statsTable = table(data.Properties.VariableNames', means', medians', stdDevs',
    maxValues', minValues', ...
    'VariableNames', {'Variable', 'Mean', 'Median', 'StandardDeviation',
    'Maximum', 'Minimum'});

% Display the table
d1isp(statsTable);

%% Histograms
figure;
data3 = data;
data3(:, [1,2,3]) = [];
for i = 1:width(data3)
    subplot(6, 3, i);
    histogram(data3(:, i));
    title(data3.Properties.VariableNames{i});
end
figure;
for i = 1:3
    subplot(1,3, i);
    histogram(data(:, i));
    title(data.Properties.VariableNames{i});
end

%% Correlation
corrMatrix1 = corr(data(:, 1:3));
figure;
heatmap(data.Properties.VariableNames(1:3), data.Properties.VariableNames(1:3),
    corrMatrix1, 'Colormap', parula, 'ColorbarVisible', 'on');
title('Correlation Matrix Dependent Variables');

corrMatrix2 = corr(data(:, 4:width(data)));
```

```

figure;
heatmap(data.Properties.VariableNames(4:width(data)),
data.Properties.VariableNames(4:width(data)), corrMatrix2, 'Colormap', parula,
'ColorbarVisible', 'on');
%title('Correlation Matrix Independent Variables');

data2 = data
data2(:, [4, 15]) = [];
corrMatrix3 = corr(data2{:,4:width(data2) });
%figure;
heatmap(data2.Properties.VariableNames(4:width(data2)),
data2.Properties.VariableNames(4:width(data2)), corrMatrix3, 'Colormap', parula,
'ColorbarVisible', 'on');
%title('Correlation Matrix Independent Variables');

%% Skewness
%columnData = log(data{:, 2});
skewnessValues = skewness(data);

% Initialize an array to store skewness values
skewnessValues = zeros(1, width(data));

% Calculate skewness for each column
for i = 1:width(data)
    columnData = data{:, i};
    skewnessValues(i) = skewness(columnData);
end

% Display skewness values
skewnessTable = table(data.Properties.VariableNames', skewnessValues',
'VariableNames', {'Variable', 'Skewness'});
disp(skewnessTable);

%% Scatter Plots
data_s=FINALESS2;
Y = data1(:,20);
X_columns = 1:15;
data_s(:,[1,2,3,4,15])=[];
Y_variable_name = 'RiskFactor';

% Create a figure for the subplots
figure;
y_min = min(Y{:, 1});
y_max = max(Y{:, 1});

for i = 1:width(data_s)
    X_variable_name = data_s.Properties.VariableNames{X_columns(i)};
    subplot(5, 3, i); % Create a 3x5 grid of subplots
    scatter(data_s{:, i}, ((Y{:, 1}-y_min)/(y_max-y_min)), 4,'filled'); % Plot the
x data and single y data
    xlabel(X_variable_name);
    ylabel(Y_variable_name);
    ylim([y_min y_max])
end

```

PCA Transformation

```
%pca
data2=FINALESS2
data1=FINALESS2

data1{:,2}=log(data2{:,2});
datapca=table2array(data1(:,1:3));
[coeff, score, ~, ~, explained] = pca(datapca);
data1{:,20}=(score(:,1)-min(score(:,1)))/(max(score(:,1))-min(score(:,1)));
figure;
data1{:,21}=log(data1{:,20}+1);
```

Data Standardization

```
data=table2array(FINALESS2);
% Initialize a matrix to hold the standardized values
standardizedData = zeros(size(data));

% Loop through each column to standardize it
for col = 1:size(data, 2)
    % Extract the column
    columnData = data(:, col);

    % Calculate the mean and standard deviation of the column
    meanCol = mean(columnData);
    A=columnData';
    stdCol = sqrt((var(A)));

    % Standardize the column
    standardizedData(:,col) = (columnData - meanCol) / stdCol;
end

% Display the first few rows of the standardized data for verification
disp(standardizedData(1:10, :));
```

Model Building

```
% Split data into 70% training and 30% validation
cv = cvpartition(size(X,1), 'HoldOut', 0.3);
x_train = X(training(cv), :);
y_train = y(training(cv), :);
x_test = X(test(cv), :);
y_test = y(test(cv), :);

% Create and train the linear regression model
mdl = fitlm(x_train, y_train);

% Display the model summary
disp(mdl);

% Predict the response for the test set
y_pred = predict(mdl, x_test);

% Calculate the mean squared error for the test set
```

```

mse = sqrt(mean((y_test - y_pred).^2));
fprintf('Mean Squared Error on the test set: %.4f\n', mse);

%% Plot the actual vs predicted values for the test and training set
figure;
scatter mdl.Variables.y, mdl.Fitted);
scatter(y_test, y_pred);
hold on;
plot([0,1], [0,1], 'r--');
xlabel('Actual Values');
ylabel('Predicted Values');
title('Actual vs Predicted Values');
legend('Data Points', 'Ideal Fit');
grid on;

%% Plot the residuals
figure;
scatter(mdl.Fitted, mdl.Residuals.Raw);
scatter(y_pred, y_test-y_pred);
hold on;
yline(0, 'r--');
xlabel('Predicted Values');
ylabel('Residuals');
title('Residuals Plot');
legend('Residuals', 'Zero Error Line');
grid on;

```