

Predicting the damage of urban fires with Grammatical Evolution.

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Abstract: Fire, whether it is a wildfire or urban fire, is sustained by the triad of oxygen, fuel, and heat. Although urban fires may cover a smaller area compared to wildfires, they are equally hazardous to human life and the socio-economic stability of a community. A dark chapter in the modern history of Greece is the wildfire of July 23, 2018, in Mati, Attica, when the forest fire spread into the urban area, resulting in 104 fatalities. In this context, when dealing with an urban fire, the most at-risk groups for fatality and injury, are the elderly and young children, as they often lack the necessary awareness of how to respond and face mobility limitations when attempting to evacuate. Consequently, predicting the impacts of an urban fire is of critical and vital importance for firefighting forces and civil protection authorities, to ensure that such a tragedy is never repeated. The current work proposes the application of a method that is based on Grammatical Evolution which produces classification rules in a human readable form. The rules produced are largely successful in distinguishing between urban fires that have caused a small number of or a large number of disasters.

Keywords: Urban fires; Machine learning; Neural networks; Genetic Programming; Grammatical Evolution.

1. Introduction

Whereas, fires can be triggered by various causes significant fires are frequently outcome from the following disasters: storms, transportation accidents, criminal activity / terrorism, droughts, hazardous materials spills [1] and forest fires. Also, Urban fires are predominantly attributed to negligent cooking practices, whereas rural fires often stem from faulty electrical installations, malfunctions in heating systems, or even natural causes such as lightning strikes [2]. Small scale urban fires often do not have a significant impact on an area, nevertheless on the other hand they still are equally hazardous to human life, in the socio-economic stability of a community, or even they contribute to increased insurance premiums [1].

Referring to human lives, let us examine the numerical data provided by the Hellenic Fire Service, which is available as open data in accordance with the European Union Directive (2013/37/EE) aimed at enhancing transparency [3]. Consequently, as presented in Figure 1, an increase in fatalities associated with urban fires, has been observed since 2020, with a slight decline in this trend, in 2023.

Received:

Revised:

Accepted:

Published:

Citation: Kopitsa, C.; Tsoulos, I.G.; Miltiadous, A.; Charilogis, V. Predicting the damage of urban fires with Grammatical Evolution. *Journal Not Specified* **2025**, *1*, 0. <https://doi.org/>

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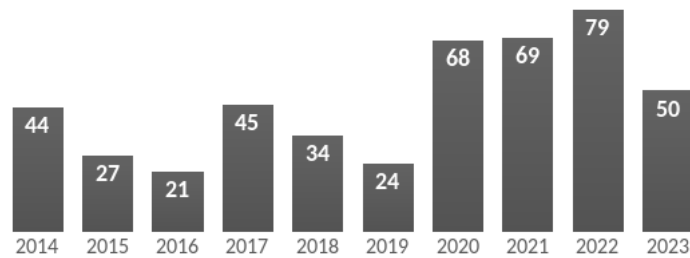


Figure 1. A graph presenting the deaths from fires in Greece for a period from 2014 to 2023.

Beyond this, it is observed that in 2018, the human casualties from the devastating fire in Mati, Attica, have not been accounted for, as previously mentioned in the Abstract [4,5]. This is likely due to the classification of this particular fire as a wildfire rather than an urban fire.

According to a study conducted, in America, by the National Fire Protection Association (NFPA), there was an approximate 4% rise in residential fires and a 13% increase in deliberately ignited structural fires in 2018 [2]. Thus, based on the official fire situation report, *Fire Loss in the United States During 2017*, published by the National Fire Protection Association, fire departments across the United States responded to an estimated 1,319,500 fire incidents in 2017. These incidents led to approximately 3,400 civilian fatalities, 14,670 civilian injuries, and an estimated \$23 billion in direct property damage [2].

Additionally, the World Health Organization (WHO), an estimated three million fires occur globally each year, resulting in approximately 180,000 fatalities [6]. Moreover, the majority of these disasters take place in major urban centers, within low - income countries, where various economic, social, and environmental factors contribute to an increased risk of fire incidents.

Nevertheless, the data demonstrate that wildfires are not solely an issue confined to low socio-economic status countries. Notably, the Black Summer of Australia in 2019–2020 remains a significant historical event. Tragically, the fires claimed 33 lives and impacted thousands through smoke inhalation and other effects. By the end of the season, they had burned a record 19 million hectares, destroyed over 3,000 homes, displaced tens of thousands, and caused the loss of billions of animals [7,8]. Furthermore, in July 2024, wildfires occurred in the Arctic plains of Russia's Far East, posing significant challenges to containment efforts [9,10]. That summer, wildfires had already devastated nearly 5 million hectares of forest in Russia. Wildfires in Russia's Siberian and Far East regions, which occur annually during the summer, have become more severe in recent years due to climate change, which has intensified the hot and dry conditions that fuel these fires [11]. Climate change projections, indicate that urban environments may face increasing, fire hazards [12]. A stark example of the interconnectedness between climate change, and wildfires, is evident in the fires that occurred in Los Angeles in January 2025, and in Japan in February of the same year. In this connection, Climate scientists are working to identify the impact of climate change on wildfires. However, the most substantial human influence may lie in the ignition sources, as no lightning storms were present at the time, in L.A, to naturally trigger the fires [13]. As the relentless wildfire advanced into urban areas, driven by wind speeds exceeding 80 miles per hour, it destroyed over 16,000 homes and buildings [13]. By February 4, a total of 29 fatalities had been reported [14]. Another technologically and socioeconomically advanced nation, Japan, was struck by an uncontrolled wildfire on February 26, 2025 [15]. The fire scorched over 2,100 hectares and destroyed more than 80 buildings. Determining whether climate change has directly caused or intensified specific wildfires is challenging, as other factors, such as land-use changes, also play a

role. However, the IPCC asserts that climate change is increasing the likelihood of weather conditions that facilitate the spread of wildfires [16].

From these real events, it is inferred that an unpredictable natural disaster, such as a wildfire, does not discriminate between low and high-socioeconomic areas. Furthermore, it highlights the precarious balance (sword of Damocles) between climate change, and urban expansion into forested regions. This underscores the critical importance of our research in predicting the impacts damages of an urban fire. Next, we will refer to relevant studies focused on the field of urban fire prediction. A team of researchers, used data from Ankara region, of Turkey, for analysis of the spatial and temporal patterns of residential fires, can enable decision-makers to strategically allocate resources for fire management, based on the intensity of fire clustering over time and across different locations [17]. Next, we proceed with an article that examines existing research on the social, economic, and building stock characteristics associated with residential fire risk in urban neighborhoods [18]. From Australia in 2010, we have the first study utilizing the Bayesian approach, to produce detailed spatial forecasts of residential household fires, across metropolitan South-East Queensland [19]. Also, from Australia, a study employs a Markov chain approach to estimate the likelihood of residential fire occurrences based on historical fire data. Utilizing fire incident records collected over a decade in Melbourne, Australia, the spatially integrated fire risk model forecasts potential fire events by incorporating spatial and temporal variables as key predictive factors [20]. Subsequently, the following study builds upon the methodology and effectiveness of a firefighter-led public education campaign on fire prevention, which successfully decreased both the frequency, and severity, of residential structure fires in high-risk areas of Surrey, British Columbia [21]. In the sequel, some studies have used GIS methods, to analyze the fire risk in urban areas. In Turkey, a study examines fires that have occurred in various locations across Turkey, including cold storage facilities, factories, and manufacturing plants. The case data was utilized to calculate risk scores using Geographic Information System (GIS), Analytical Hierarchy Process (AHP), and Inverse Distance Weight (IDW) methods [22]. In China, in order to select the best suitable fire brigade zone, they analyze: fire-risk areas, traffic congestion, land cover, and location. They employ various methods, including Geographic Information Systems (GIS), Multi-Criteria Decision Making (MCDM), and Location-Allocation (L-A) techniques, along with multi-source geospatial data such as land cover, points of interest, drive time, and statistical yearbooks. Additionally, they used Analytic Hierarchy Processes (AHP) to thoroughly assess undeveloped areas based on factors such as location, topography, and potential fire-risk zones [23]. The next study conducted in Greece, to develop a fire risk estimation model that integrates recent land cover changes alongside other critical risk factors. They implemented a Support Vector Machine (SVM) algorithm combined with the Analytic Hierarchy Process (AHP), within a Geographic Information System (GIS) platform. This approach allowed for a more precise assessment of fire-prone areas. As a case study, they applied this methodology to the Dadia-Lefkimi - Soufli National Forest Park, ensuring a comprehensive evaluation of fire risk in the region [24].

Afterwards, a study seeks to assess fire risk in urban areas by analyzing 19 factors related to economic, social, and built environment aspects, as well as past fire incidents. It employs Multi-Criteria Decision Making (MCDM) techniques, specifically the Analytic Hierarchy Process (AHP) to determine the significance and weighting of each criterion. To illustrate the method's effectiveness, the research develops an urban vulnerability index map for Ardabil, Iran, using the Fuzzy-VIKOR approach within a Geographic Information System (GIS) framework [25]. Building upon, Analytic Hierarchy Process, the paper from Taiwan, evaluated the severity of building fires across 17 villages in Taishan District, New Taipei City. A comprehensive literature review was conducted to examine the influence of

fire severity assessment criteria, which served as the foundation for identifying key factors, and developing evaluation items, within the (AHP) framework [26].

(TEXT ABOUT THE PROPOSED METHODS...)

The rest of this article is divided as follows: in section 2 the proposed methods are presented in detail, in section 3 the experiments are illustrated and discussed and finally, in section 4 some conclusions are presented.

2. Materials and Methods

This section initiates with a detailed description of the used datasets and it continues with a brief presentation of the Grammatical Evolution technique and concludes with the full description of the used techniques.

2.1. The used datasets

The dataset utilized in this research was sourced from the Hellenic Fire Service in compliance with open data guidelines established by the European Union Directive (2013/37/EU), aiming to promote transparency and open access to governmental records. The dataset contains comprehensive records detailing urban fire incidents specifically for the calendar years 2014-2023.

For each urban fire event documented, detailed information was systematically collected, including the date and precise time of occurrence, allowing for temporal analysis and identification of patterns over various time intervals. The geographic location for each incident was also reported with a municipality code. In addition, specific characteristics relevant to each fire event were captured, including the probable cause or origin of the fire, which helps in identifying common fire risk factors within urban settings. Data regarding the structural properties involved, such as building type or property classification, was also documented, contributing to a comprehensive risk profile for urban infrastructure.

Furthermore, human casualty data detailing the number of fatalities and injuries associated with each incident were recorded. The dataset indicated an average of 0.002 fatalities per incident, with a maximum of 2 fatalities observed in a single event. Injuries averaged at approximately 0.0008 per incident, with a maximum of 1 injury recorded per event. Additionally, instances of burn injuries were relatively infrequent, averaging around 0.002 per incident, with a maximum count of 2 burn cases reported.

Information on the resources deployed was also comprehensively documented. On average, each incident involved approximately 1.65 firefighting vehicles, with a maximum of 24 vehicles responding to the most severe incidents. Personnel deployment averaged about 4.18 firefighters per incident, with an interquartile range from 2 to 5 firefighters, and up to 67 personnel attending a single event in extreme cases.

The dataset underwent thorough preprocessing procedures to ensure high-quality data for analysis. These procedures included validation checks for data accuracy, consistency, completeness, and the removal or correction of any identified errors or inconsistencies. Such rigorous preprocessing steps were critical for enhancing the reliability and validity of the analytical processes that followed.

2.2. Grammatical Evolution

(TO BE CHANGED)

Grammatical evolution is a genetic algorithm where the chromosomes stand for the production rules of any given BNF (Backus–Naur form) grammar[27]. Grammatical Evolution has been used successfully in a variety of cases, such as function approximation[28,29], solution of trigonometric equations [30], automatic music composition of music [31], neural network construction [32,33], creating numeric constraints[34], video games [35,36], esti-

mation of energy demand[37], combinatorial optimization [38], cryptography [39] etc. The BNF grammar can be used to describe the syntax of programming languages and usually it is defined as the set $G = (N, T, S, P)$ where

- N is the set of the so - called non-terminal symbols. Every non - terminal symbol is associated with a series of production rules used to produce terminal symbols.
- T is the set of terminal symbols.
- S is a the start symbol of the grammar and $S \in N$.
- P is a set of production rules, used to produce terminal symbols from non - terminal symbols. These rules are in the form $A \rightarrow a$ or $A \rightarrow aB$, $A, B \in N$, $a \in T$.

The algorithm starts from the symbol S and gradually creates terminal symbols by replacing non-terminal symbols with the right hand of the selected production rule. The rule is selected through the following procedure:

- Read the next element V from the current chromosome.
- The production rule is selected as: Rule = $V \bmod R$, where R is the total number of production rules for the current non – terminal symbol.

2.3. Neural Network Construction using Grammatical Evolution

2.4. Feature construction using Grammatical Evolution

2.5. Create classification rules using Grammatical Evolution

3. Results

Table 1. Experimental results using various machine learning techniques. Numbers in cells represent average classification error as measured on the corresponding test set.

YEAR	BAYES NET	MLP(BP)	RBF	NNC	FC2	GENCLASS
2014	9.01%	8.34%	11.97%	7.82%	7.35%	7.03%
2015	8.75%	7.63%	10.79%	7.13%	6.78%	6.65%
2016	8.99%	8.13%	10.73%	7.48%	7.10%	7.05%
2017	8.43%	8.29%	10.78%	7.68%	7.24%	7.13%
2018	8.38%	7.99%	9.33%	7.30%	7.11%	6.74%
2019	7.31%	7.78%	24.81%	7.33%	7.15%	6.26%
2020	8.70%	7.86%	10.03%	6.99%	6.66%	
2021	8.58%	7.88%	10.37%	6.87%	6.55%	
2022	8.80%	7.29%	8.45%	6.86%	6.52%	
2023	8.46%	7.50%	10.56%	6.87%	6.58%	
AVERAGE	8.54%	7.87%	11.78%	7.23%	6.90%	

Table 2. Experiments with the Feature Construction method.

YEAR	FC2MLP	FC2RBF	FC3MLP	FC3RBF	FC4MLP	FC4RBF
2014	7.70%	7.35%	7.77%	7.37%	7.69%	7.50%
2015	7.21%	6.78%	7.13%	6.70%	7.21%	6.69%
2016	7.46%	7.10%	7.52%	7.14%	7.41%	7.04%
2017	7.68%	7.24%	7.67%	7.19%	8.01%	7.20%
2018	7.21%	7.11%	7.19%	7.06%	7.52%	7.04%
2019	6.59%	7.15%	6.89%	6.76%	6.59%	7.31%
2020	6.84%	6.66%	6.84%	6.60%	7.18%	6.67%
2021	6.88%	6.55%	6.81%	6.57%	6.76%	6.55%
2022	6.77%	6.52%	6.81%	6.54%	7.10%	6.52%
2023	6.73%	6.58%	6.69%	6.40%	7.09%	6.53%
AVERAGE	7.11%	6.90%	7.13%	6.83%	7.26%	6.91%

4. Conclusions

Author Contributions: C.K., V.C. and I.G.T. conceived of the idea and the methodology, and C.K. and V.C. implemented the corresponding software. C.K. conducted the experiments, employing objective functions as test cases, and provided the comparative experiments. A.M. performed the necessary statistical tests. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Acknowledgments: This research has been financed by the European Union : Next Generation EU through the Program Greece 2.0 National Recovery and Resilience Plan , under the call RESEARCH – CREATE – INNOVATE, project name “iCREW: Intelligent small craft simulator for advanced crew training using Virtual Reality techniques” (project code:TAEDK-06195).

Conflicts of Interest: The authors declare no conflicts of interest.

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