Article

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

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3. Results

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