A Web-Based Simulation Interface for Fire Dynamics Analysis and Decision Support

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***Abstract*—Operational wildfire simulation remains challenging, particularly in Wildland–Urban Interface (WUI) areas characterized by complex spatial features and dynamic fuel conditions that cannot be estimated by conventional remote sensing approaches. This paper presents the design and implementation of a web-based platform for simulating wildfire spread in arbitrary geographic areas. The system employs an empirical Cellular Automata model, computationally efficient enough to be executed across a wide range of devices, including mobile phones and edge-computing systems. To address limitations of conventional fuel classification, especially in WUI environments, the platform incorporates human-reported inputs from in-field observations. These inputs are integrated directly into the simulation, enabling the representation of fine-grained and operationally relevant features. The proposed framework enhances accessibility, adaptability, and computational performance, supporting operational decision-making in civil protection and crisis management contexts.**

***Index Terms*—Web Interface, Wildfire Simulation, Cellular Automata, Wildland-Urban Interface, D2D.**

I. INTRODUCTION

Forest fires occur with increasing frequency, particularly around the Mediterranean. This trend is driven by multiple factors related to climate change (e.g., extreme temperatures) and increasing human activity in and around forest areas [1]. As city suburbs continue their expansion, they meet previously undeveloped, forestry areas, increasing the likelihood of fire ignition and spread. This contributes to an increase in *Wildland–Urban Interface* (WUI) fires which pose significant risks to civilian populations, as communities become exposed to rapidly spreading wildfires that are often difficult to contain or suppress. Proximity to forestry environments also constrains emergency response capacity, thus amplifying potential impacts on human life, property and infrastructure. Consequently, WUI fires represent a major challenge, necessitating integrated approaches to land-use planning, fire management, and climate adaptation strategies [2].

The accurate modeling of wildfires and the simulation of fire spread mechanics are essential for understanding fire behavior. The knowledge acquired from simulation-based analysis can support operational decision-making in civil protection and crisis management, improving their risk mitigation strategies. Over the past decades, numerous computational models have been developed to simulate fires, ranging from physics-based models to empirical approaches [3]. The applicability of each model must be aligned with the characteristics of the simulated area, as models proposed in the literature are typically designed to operate under very specific conditions, assumptions, and simplifications.

In general, empirical models exhibit lower accuracy, but they are more computationally efficiency, meaning that they can be applied to larger areas. In contrast, physics-based models, often formulated through *Partial Differential Equations* (PDEs), require detailed environmental representations and substantial computational costs. Although both categories of models have advanced considerably in terms of their predictive capabilities, their usability often remains constrained by complex implementation requirements, limited availability of up-to-date field observations, and restricted access to the platforms on which they are executed.

In our work, we have adopted an empirical model based on *Cellular Automata* (CA) [4]. CA models discretize both space and time, representing the simulation domain as a grid, in which local interactions among neighboring cells represent the spread of fire. CA are well-documented simulation approaches, and their computational efficiency has been widely demonstrated in the literature. As they require relatively low computational resources, they are particularly suitable for execution in constrained computing environments.

Conventional fire simulation tools are typically deployed as standalone desktop applications or research-oriented software frameworks, requiring specialized scientific computing environments (eg. MATLAB), technical expertise for proper use, familiarity with calibration procedures, and a solid background in fire dynamics. Such constraints limit their adoption by non experts, decision-makers, and civilians who may benefit from more intuitive simulations. As mobile phones and edge-computing devices continue to increase in processing capability, web-based platforms can serve as powerful tools for delivering computationally intensive simulations through accessible and user-friendly interfaces.

This paper presents the design and implementation of a web-based user interface for simulating wildfire spread processes in arbitrary geographic areas. The proposed platform aims to provide an interactive and extensible environment for conducting fire simulations, while maintaining computational efficiency and enabling execution across a wide range of devices, from desktop computers to mobile phones. The system architecture, interface design principles, and integration with the underlying CA-fire simulation engine are described, and its potential applications to decision support are discussed.

The remainder of this paper is structured as follows. In Section II we provide background on CA-based simulations for wildfire modeling, while Section III describes our crowdsourcing model for in-field data acquisition. Section IV describes the design and architecture of our simulation platform, while Section V compares our work with the state of the art in the area. Section VI describes its user interface of our tool. We present our conclusions in Section VII.

II. CELLULAR AUTOMATA FOR WILDFIRE MODELING

Cellular Automata (CA) based models for wildfire simulation constitute one of the most efficient and computationally economical methods for modeling wildfire spread. In the CA approach, the landscape is first rasterized into a discrete grid of cells, each representing a minimal spatial unit of the terrain that is (or, should be) relatively uniform in terms of vegetation and fuel characteristics. Each cell's state evolves over discrete time steps, according to a predefined set of transition rules. A cell can only take a limited number of discrete states, such as non flammable, unburned, burning, or burned. Fire propagation occurs only through local cell interactions that are deterministic (fixed rules) or probabilistic (introducing a burn probability). In probabilistic models, which are the most common, the probability that a cell ignites depends on the state of its neighboring cells, as well as on environmental factors. Neighborhood configurations commonly follow either the von Neumann (four adjacent cells) or Moore (eight surrounding cells) scheme, allowing the model to account for more realistic fire spread.

The burn probability p_{burn} of a cell is defined as the weighted product of environmental coupling (e.g., topographic effects), weather influences, and the composition and characteristics of forest fuels [4] (equation (1)).

$$p_{burn} = p_0(1 + p_{veg})(1 + p_{den})p_w p_s \tag{1}$$

where p_0 is a constant probability, p_{veg}, p_{den} are coefficients expressing fuel type and density, p_w a wind impact factor and p_s a factor expressing the influence of terrain slope. A comprehensive description of the calculation procedures for p_w and p_s can be found in [4].

III. OBTAINING FUEL CHARACTERISTICS

Forest fuel classification is a challenge as longstanding as wildfire simulation itself. Despite numerous proposed methods, achieving accurate classification is still hard. Most approaches rely on remote sensing, including satellite, aerial, or drone imagery. Images are typically preprocessed to extract fuel characteristics using point, edge, or region-based techniques [5]. Machine learning methods have also been applied to enhance classification accuracy, supporting more reliable feature extraction [6]. In areas where residential settlements intermix with forested land, forming WUI zones, fuel classification becomes even more challenging. Moreover, the imagery typically used to extract fuel characteristics is often outdated, as are global fuel maps. This issue is particularly pronounced during the spring and summer seasons, when rapid growth and drying of fuels lead to substantial temporal variability.

A promising alternative for capturing the temporal and spatial variability of fuels is presented in [7], in which users—typically firefighters and relevant authority stakeholders—report observations directly from the field during an event. These observations are then preprocessed to remove noise and distortions using simple, low-computational-intensity procedures, after which they can be incorporated into the simulation. We argue that this approach can significantly benefit wildfire modeling, particularly in WUI zones, as complex features can be added based on human judgment, independent of image resolution, age, or quality. Human-driven classification provides unmatched accuracy, even for intricate spatial features that play critical roles in wildfire dynamics. Examples include trees neighboring houses, tall trees susceptible to spotting, and fire-resistant materials that inhibit ignition of nearby structures.

IV. SIMULATION ENGINE FOR THE EDGE

The proposed platform utilizes a lightweight, browser-based hybrid architecture designed to facilitate *Volunteered Geographic Information* (VGI) collection and edge-computed simulations in WUI zones. To address the computational constraints of mobile edge devices while ensuring high-resolution data fidelity in complex WUI areas, the platform adopts a hybrid distributed architecture. Implemented as a cross-platform *Progressive Web Application* (PWA), the system leverages a thick-client model where the core CA-based simulation logic is executed locally within the client's browser environment using high-performance web technologies such as JavaScript and, potentially, WebAssembly.

The selection of a thick-client model allows the computational load of the CA-based wildfire propagation algorithm to be fully offloaded to the client device, accessing as much as possible data stored in the device's local storage to perform the simulation. This is achieved using optimized JavaScript to execute the simulation locally within the web browser, thereby minimizing and even eliminating the need for a central server, reducing latency and enabling offline functionality in remote areas. This is especially important when the communication infrastructure is limited (in remote areas), damaged (from the fire) or overloaded (from potential evacuees). A similar edge computing paradigm within the framework of *Information-Centric Networking* (ICN) has been proposed in [8].

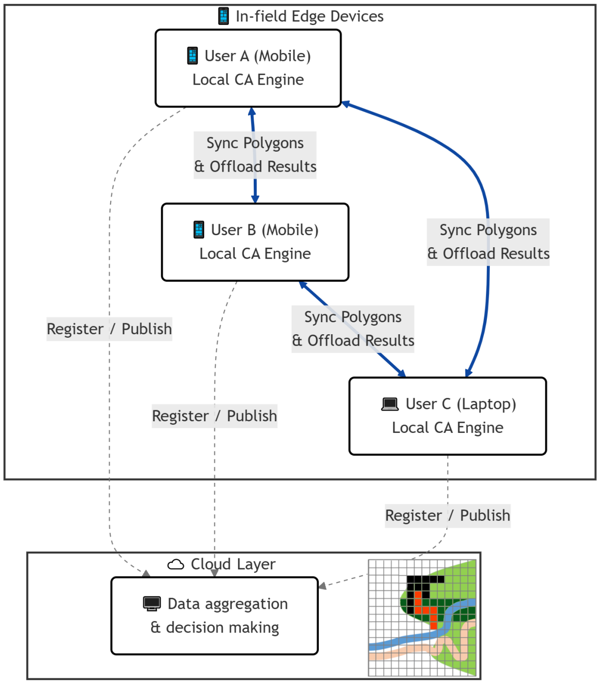


Fig. 1. High-level outline of the proposed hybrid distributed architecture. The system supplements the client–server paradigm with peer-to-peer communications to support operation in low or no network coverage scenarios.

Unlike traditional centralized systems, the proposed architecture integrates a *Peer-to-Peer* (P2P) communication layer to facilitate collaborative sensing and computational offloading. The user interface integrates an interactive mapping component based on Leaflet that allows users to manually digitize homogenous fuel zones as vector polygons overlaid on satellite-based tiles, if network connectivity is available. Each polygon is stored as a GeoJSON object, encapsulating its spatial geometry, alongside user-defined attributes from predefined categories, such as fuel density, canopy height, and moisture content. This allows firefighters to enter their own up-to-date observations from the field.

User-contributed data (that is, VGI) may be propagated directly between peers to fill data voids in the local simulation environment. For example, a user may be unsure about the fuel composition in a vegetation strip or be unable to identify it due to smoke cover. Once network connectivity is restored, even partially and by any individual user, the data can be uploaded to a backend server to disseminate the evolving situational knowledge to stakeholders outside the field.

To optimize energy consumption on battery-limited mobile devices, simulation generated outputs can also be shared across peers. This allows peers to retrieve pre-calculated propagation results, rather than repeatedly executing the CA algorithm, thus distributing the computational burden across the connected edge cluster.

The central backend server, accessible via a RESTful API, functions primarily as a synchronization hub rather than as a computing engine. It can aggregate the received crowdsourced fuel configurations and distribute corresponding updates to users that have access to the cellular network, allowing them to patch missing data in the WUI zone and share simulation outcomes in near real-time.

Given the volatile connectivity users exhibit in wildfire environments, the platform implements a *Delay Tolerant Networking* (DTN) application layer [9] to ensure data persistence and support offline operation (Fig. 1). Unlike traditional synchronous web applications that require continuous connectivity, a DTN-based system adopts a store-and-forward paradigm, allowing edge devices to operate offline, cache data locally, and forward messages (called DTN bundles) opportunistically whenever connectivity becomes available.

Our application employs the WebRTC API for the opportunistic transport of DTN bundles between peers. Whenever a nearby peer is discovered, devices establish a transient WebRTC data channel through localized offline signaling mechanisms. Once connected, nodes exchange their simulation state to identify divergent or missing simulation components (fuel, weather) and transfer only the required bundles. The connection is short-lived, aligning with store-and-forward DTN semantics, rather than striving to achieve complete synchronization between the peers.

All spatial data updates (e.g., fuel polygon modifications) and simulation progress are encapsulated into lightweight GeoJSON FeatureCollections in each application's local storage. These messages are stored in the browser's IndexedDB until a new transmission path is established. In remote areas where the cellular infrastructure is unavailable or unreliable, the platform transitions into an opportunistic *Device to Device* D2D operating mode [10]. It employs local peer discovery mechanisms—such as *multicast DNS* (mDNS) or *Bluetooth Low Energy* (BLE) advertisements, accessed via native wrappers where required—to identify nearby devices within physical proximity. Upon discovery, the DTN agent initiates a synchronization handshake during which peers exchange their current knowledge about the state of the simulation environment. As a result, WUI fuel data propagates virally across the loosely connected mesh cluster, ensuring eventual consistency among isolated user groups.

V. STATE OF THE ART

Recent advancements in wildfire monitoring and management have increasingly leveraged mobile technologies and crowdsourced data collection paradigms. In particular, research has focused on optimizing user-centered data input mechanisms, designing scalable and efficient computational architectures, and enhancing system resilience under conditions of network instability and intermittent connectivity.

The *CITISENS* [11] mobile application utilizes smartphone orientation sensors and the device camera to georeference wildfire hotspots via "view-rays" intersecting with *Digital Elevation Models* (DEMs). The system supports the reporting of hotspot coordinates and provides burn probability estimates through a web-based simulator operating in a separate module (FLogA). However, it depends on server-side processing and stable network connectivity. In contrast, the proposed approach relocates the simulation entirely to the client side, thereby reducing reliance on continuous connectivity. Furthermore, it enhances data granularity by enabling users to delineate complex polygons representing fuel types and burned areas, rather than relying exclusively on point-based inputs.

FireLoc [12] represents a similar approach to rapid wildfire geolocation, integrating monocular depth estimation and cross-camera methodologies with DEMs to derive spatial information from smartphone imagery. While the system is effective in reducing mapping latency, its principal contribution lies in the localization of fire hotspots and associated features (e.g., wildfire perimeters) through a modular architectural design. However, as a cloud-based service, it remains dependent on reliable network connectivity, which poses a significant limitation for image-based localization in remote, densely vegetated regions where connectivity is often intermittent or unavailable.

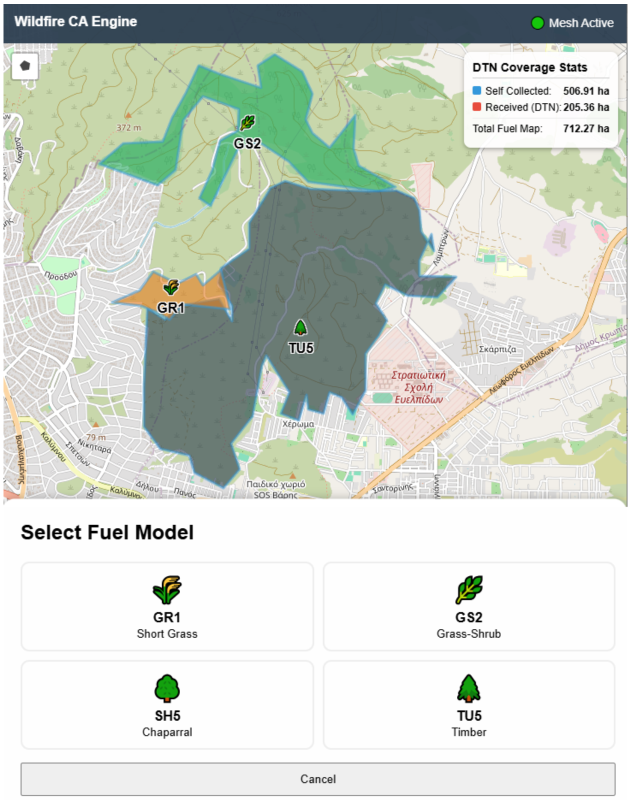
The framework proposed in [13] addresses wildfire monitoring at WUI locations by integrating heterogeneous data sources—including social media streams, remote sensing products and meteorological data—into a centralized Knowledge Base Service, formalized through the *WUIFire ontology*. While this approach enables a high level of situational awareness, and employs ontology-driven reasoning in a manner comparable to our previous work [14], it presupposes reliable network connectivity for the continuous ingestion of external data sources. In contrast, the proposed method operates independently of centralized infrastructures, relying instead on direct user input (e.g., fuel characteristics and fire perimeters) to generate localized fire spread models that remain functional under zero-connectivity conditions. Furthermore, ontology-based knowledge representation and querying typically introduce dependencies on external frameworks (e.g., GraphDB, SPARQL), which may be ill-suited to deployment on resource and power constrained edge devices.

A promising study in [15] investigates the use of smartphone sensors to estimate wildfire hazard by deriving *Vapor Pressure Deficit* (VPD) from ambient temperature and humidity measurements. While this approach offers a valuable crowdsourced indicator of fire potential, it does not support real-time tracking or the simulation of active fire dynamics.

VI. USER INTERFACE

A. VGI Interface

The graphical user interface of the VGI component (Fig. 2), aims to guide in-field users to actively map their environment by collecting and categorizing local fuel data across their designated sectors. They select specific fuel models and assign critical physical properties, such as tree height or canopy density, to ensure accurate fuel inputs. Additionally, operators may mark areas that have already been burned and zones of non-flammable materials—like rocks or water bodies—which act as natural firebreaks. Once these local observations are logged, the application leverages the DTN to broadcast this information, while simultaneously receiving synchronized updates from other peers operating in the field. As new, distributed data arrives to fill in geospatial gaps, it is continuously fed into the local simulation engine. This allows the system to generate highly localized fire simulations, enabling teams to dynamically examine how the fire's behavior and predicted frontline evolve, as fresh situational awareness propagates across the mesh network.



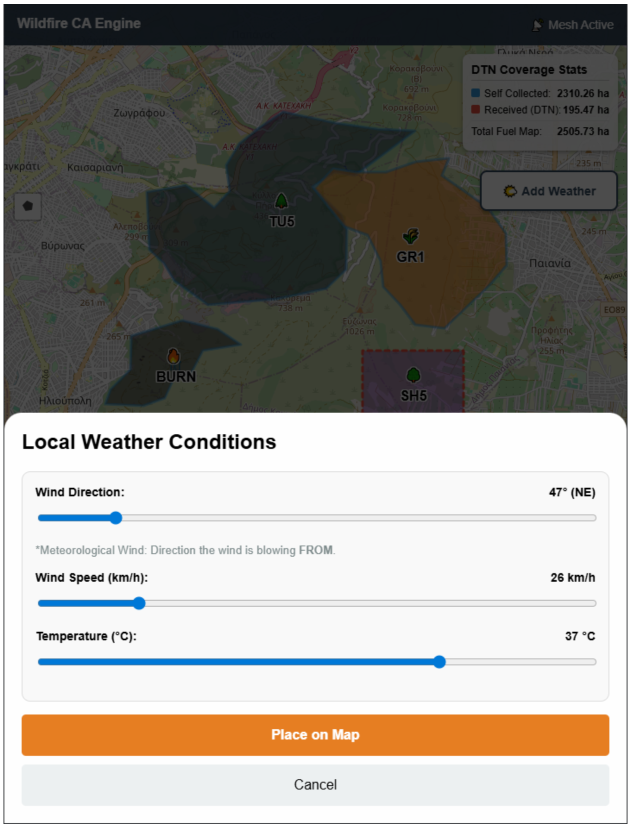
DTN Coverage Stats
🟦 Self Collected: 506.91 ha
🟥 Received (DTN): 205.36 ha
Total Fuel Map: 712.27 ha

Fig. 2. User-assigned fuels and wildfire updates propagate through the DTN.

B. Burned Area Simulation

The final CA simulation is projected in a similar interface, where the affected area is discretized into a grid; the visibility of the grid is toggled according to user preference. The spatial extent of the fuels is visualized with color-coded polygons, indicating differences in fuel types, while areas with active flaming are shown in red and burned areas in black.

Weather information is another critical input for accurate wildfire simulation. When network connectivity via the cellular infrastructure is available, weather data can be retrieved automatically through external web APIs, ensuring that the simulation is up-to-date. However, in environments with limited or no coverage, the web interface of the VGI system provides users with the capability to manually input weather conditions at any known location on the map. Through this interface, users can specify relevant meteorological parameters (e.g., wind speed) associated with a known geographic point. This manual input enables the system to maintain its functionality even in disconnected scenarios, allowing simulations to proceed using locally provided observations. Once entered, the weather information can be propagated to other peers in the network using the DTN mechanism described previously. Fig. 3 shows an example of a user providing weather information through the system's interface.



DTN Coverage Stats
Self Collected: 2310.26 ha
Received (DTN): 195.47 ha
Total Fuel Map: 2505.73 ha

Local Weather Conditions

Wind Direction: 47° (NE)

*Meteorological Wind: Direction the wind is blowing FROM.

Wind Speed (km/h): 26 km/h

Temperature (°C): 37 °C

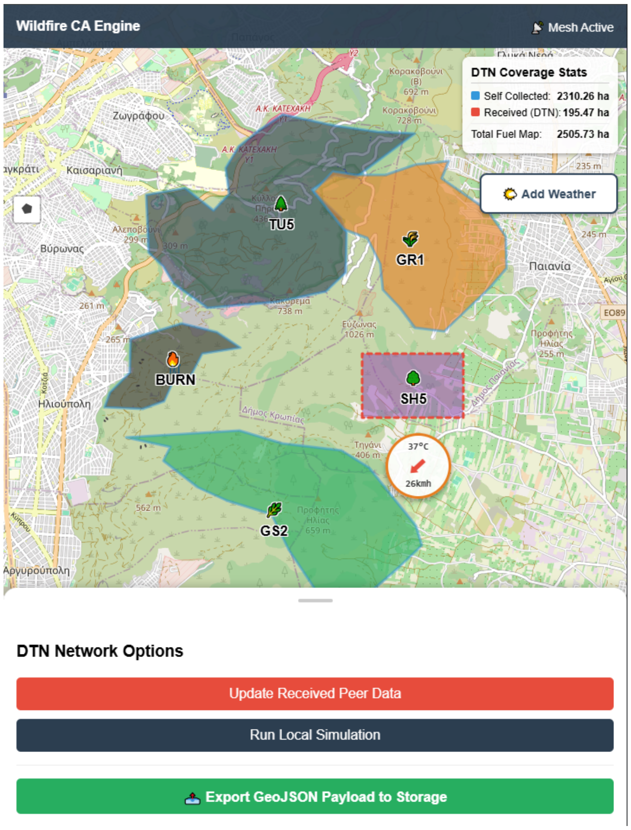
Place on Map

Cancel

Fig. 3. Manual entry of weather conditions by a user.

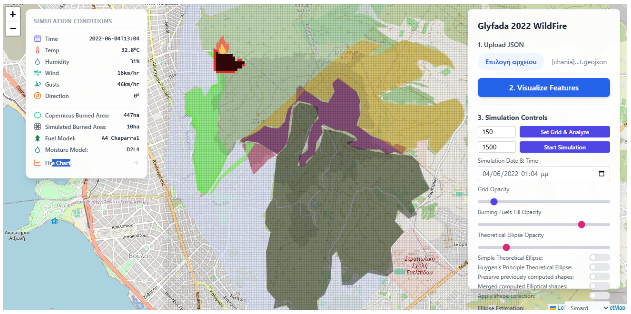
An overview of the VGI interface is illustrated in Fig. 4. The interface displays user-provided weather inputs alongside fuel polygons containing the fuel characteristics entered by the user. The gray polygon denotes an area that has already marked as burned; consequently, fire propagation is constrained from spreading into this region when a simulation is executed. On the other hand, the polygon outlined with a red dashed boundary represents fuel data that has been received from another peer within the network.

A typical CA run is depicted in Fig. 5. Each user runs a local simulation; therefore, fire spread may differ between users due to variations in the available fuel data or user-defined meteorological parameters, in case no weather APIs are available due to limited connectivity. As user-submitted data are spread via the DTN or the server infrastructure, the individual simulations become more accurate, but they are unlikely to fully converge, as new user inputs are added at each local simulation instance.



DTN Coverage Stats
Self Collected: 2310.26 ha
Received (DTN): 195.47 ha
Total Fuel Map: 2505.73 ha

Fig. 4. Overview of the VGI interface as viewed from a user's mobile device, showing weather inputs and fuel data collected from the area.



SIMULATION CONDITIONS
Time 2022-06-04T13:04
Temp 32.8°C
Humidity 31%
Wind 16km/hr
Gusts 46km/hr
Direction 0°
Copernicus Burned Area: 447ha
Simulated Burned Area: 10ha
Fuel Model: A4 Chaparral
Moisture Model: D2L4

1. Upload JSON: [chania]...t.geojson
150 Set Grid & Analyze
1500 Start Simulation
Simulation Date & Time: 04/06/2022 01:04 μμ
Simple Theoretical Ellipse: ○
Huygen's Principle Theoretical Ellipse: ○
Preserve previously computed shapes: ○
Merged computed Elliptical shapes: ○
Apply shape corection: ○
Ellipse Estimation: Simard

Fig. 5. Typical CA simulation for a forestry area located in Glyfada, Greece.

The simulator also provides a Fire Characteristics Chart as a visual analytics component for interpreting predicted fire behavior [16]. The chart graphically represents the relationship between *Rate of Spread* (ROS) and *Heat per Unit Area* (HPUA) at a given point of the simulated fire front, using Rothermel's fire spread model [17]. From the position of the plotted point within the chart, additional fire behavior indicators—such as flame length and fireline intensity—can be inferred. This visualization enables users to quickly assess the potential severity of a fire under the current fuel, terrain, and weather conditions. The chart also serves as a decision-support aid, by indicating the expected difficulty of fire suppression and whether direct attack by firefighting personnel may be considered safe or operationally feasible. The curved lines shown in the chart represent constant flame length levels, which are commonly used as operational thresholds to classify fire behavior and assess the potential effectiveness and safety of different suppression tactics. By integrating this analytical visualization into the web interface, the simulator facilitates the interpretation of model outputs and supports situational awareness during wildfire analysis. An example of a Fire Characteristics Chart is shown in Fig. 6.

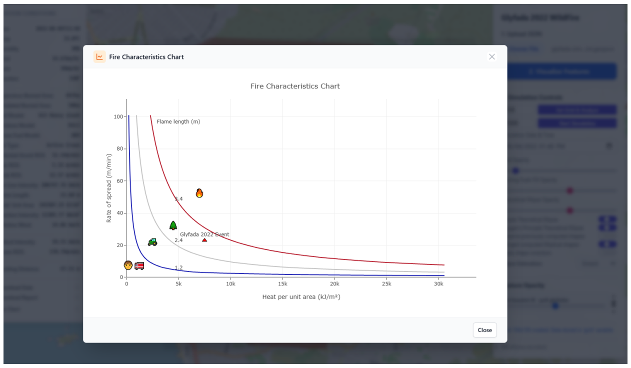


Fig. 6. Example of a typical Fire Characteristics Chart for the simulated incident in Glyfada, Greece.

VII. CONCLUSIONS

The proposed simulator application demonstrates a practical approach for enabling offline, peer-to-peer data exchange among mobile devices in remote forest environments, leveraging D2D communications. The adoption of web technologies for the core components of the simulation engine facilitates cross-platform portability, allowing deployment even on resource-constrained systems. By operating under the DTN paradigm, the system allows wildfire-related geospatial data, such as fuel types and frontline propagation, to be propagated reliably between users, even in the absence of cellular coverage. Moreover, the use of real-time information provided directly by users in the field offers significant advantages over traditional approaches, which rely on data from databases that may remain outdated for extended periods.

Preliminary simulation results indicate that the continuous reception of updates from other users significantly improves the accuracy and timeliness of the local wildfire model [18], allowing each device to maintain an up-to-date representation of fuels and fire progression. This collaborative approach ensures that the wildfire simulation remains robust and useful even during limited or unreliable network connectivity, which is typically encountered in remote forest areas. This enhances situational awareness and supports quick decision-making during fire management operations. Overall, the framework highlights the potential of offline, user-assisted data sharing to overcome connectivity challenges while maintaining an adaptive, lightweight, resilient wildfire prediction engine.

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