System for Monitoring Forests with Context-Aware Capabilities

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Abstract

A forest fire protection system exemplifies context-aware and proactive responsiveness to potential threats during routine monitoring of forested areas and firefighting operations. We advocate for the development of a context-driven system, which entails deploying a network of sensors across the different sectors of forests. Additionally, we incorporate context-driven and automated negotiation techniques to mitigate forest fire threats. The intelligent decisions facilitated by the system, aimed at supporting users, are the outcome of the proposed context processing.

Keywords: Forest protection, context-aware system, smart decision.

1. Introduction

Forest fire protection is a crucial issue within sophisticated, intelligent, and proactive systems. Our research aims to develop a context-aware and proactive system that integrates pervasive computing, proactive, and ambient intelligence principles.

In order to achieve this, we have developed a multi-agent system architecture to process contextual data and we have introduced context-driven, automated negotiation techniques to address forest fire threats effectively. This system supports forest patrols and firefighting crews by generating intelligent, context-based decisions.

Simulation experiments demonstrate that our system enhances environmental self-awareness and automates decision-making in intelligent environments, marking a significant advancement in forest fire management.

2. Preliminaries

The following parameters are collected during forest area monitoring: temperature (°C), air humidity (%), litter moisture (%), wind speed (km/h), wind direction (N, NE, E, SE, S, SW, W, NW), carbon dioxide (CO2) concentration (ppm) and the concentration of atmospheric aerosols with a diameter $\leq 2.5\ \mu$m (PM2.5) (μg/m^3).

Table 1. Risk scale for fire threats and fire classification

	Risk scale	FDDI	PM2.5 [μg/m3]
1	low	<5	<50
2	moderate	5-12	50-90
3	high	12-24	91-150
4	very high	24-50	151-250
5	extreme	>50	>250

	Fire classification
0	non-combusted
1	early fire
2	medium fire
3	full fire
4	extreme fire
5	completely combusted

Fire classification considers combustibility, wind, temperature, humidity, and other factors, leading to the following scale: 0 – non-combusted, 1 – early fire (manageable by one fire engine), 2 – medium fire (manageable by local fire station crews), 3 – full fire (requires maximum available crews), 4 – extreme fire (exceeds local fire station capabilities), 5 – completely extinguished or combusted.

3. Multi-agent system for context modelling

We consider the following categories of agents: MA (Managing Agent): Initiates the system and other agents; SA (Sensor Agent): Reads and sends measurement data from sensors, assigned with a unique number and GPS location, and transmits data at regular intervals; AA (Analyst Agent): Analyses measurements, determines threat levels and fire stages; NA (Negotiating Agent): Allocates Firefighting Agents (FAs) to sectors based on a fire status in collaboration with the Fire Command Authority Agent (FCA); PA (Patrol Agent): Conducts ground patrols, monitors fires, and confirms fire risks; OCA (Overseer Controller Agent): Acts as a forester, assigns tasks to PAs, and decides on activities in at-risk sectors not covered by fire; FA (Firefighter Agent): Extinguishes fires in designated sectors, assigned by the system; FCA (Fire Command Authority Agent): Acts as the firefighting operation commander, sends fire brigade units to affected sectors. Table 2 illustrates agent behaviours during forest monitoring phases.

Table 2. Agents behaviours towards particular sectors when calculating a fire risk (top) and agents behaviours towards particular sectors when fighting with fire (bottom)

<table>
<tr><th rowspan="2">Fire risk</th><th colspan="7">Agents</th></tr>
<tr><th>SA</th><th>AA</th><th>NA</th><th>PA</th><th>OCA</th><th>FA</th><th>FCA</th></tr>
<tr><td>1</td><td rowspan="5">Gathering data from sensors and transferring it to AA</td><td rowspan="3">Calc. risk; sending it to OCA</td><td rowspan="5">Idle</td><td rowspan="5">Observing, sending messages to AA & OCA</td><td rowspan="5">Disp-atching PAs</td><td rowspan="5">Idle</td><td rowspan="5">Idle</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td></tr>
<tr><td>4</td><td rowspan="2">Calc. risk; sending it to OCA & FCA</td></tr>
<tr><td>5</td></tr>
</table>

<table>
<tr><th rowspan="2">Fire threat</th><th colspan="7">Agents</th></tr>
<tr><th>SA</th><th>AA</th><th>NA</th><th>PA</th><th>OCA</th><th>FA</th><th>FCA</th></tr>
<tr><td>0</td><td colspan="7">See the table above</td></tr>
<tr><td>1</td><td rowspan="5">Idle</td><td rowspan="5">Determines a fire scale, sending it to FCA</td><td rowspan="5">Negotiating strategies for FAs, sending it to FCA</td><td rowspan="5">Idle</td><td rowspan="5">Idle</td><td rowspan="5">Fightings in the sector until extinguished or recalled, sending messages to AA & FCA</td><td rowspan="5">Disp-atching FAs</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td></tr>
<tr><td>4</td></tr>
<tr><td>5</td></tr>
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4. Context-driven automated negotiation

Our next objective is to develop an intelligent mechanism for the automated negotiation of firefighting resource allocation in wildfire-affected forest sectors, especially during rapid fire spread. Inspired by [8], our approach is adapted to our domain with a more intricate hierarchical agent-based system and specific contextual variables.

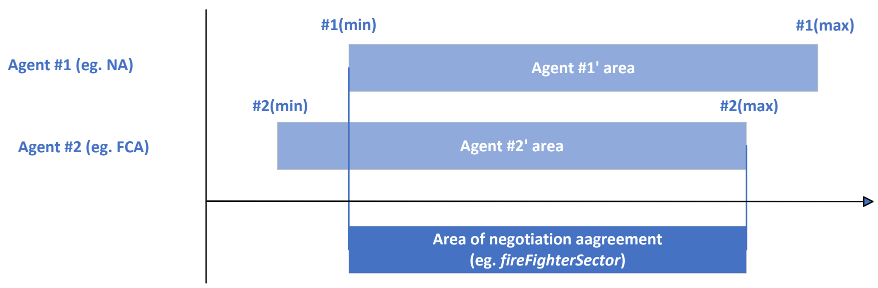

Fig. 1. The space of bilateral negotiation agreement, in terms of $fireFighterSector$, i.e. the number of fire crews assigned to a sector

Our goal is to develop a smart decision-making method for the FCA agent, managing firefighting crews, and the NA agent, overseeing a forest and a fire status. They negotiate decisions, modeling interactions between firefighters and the spreading fire, using a simplified model and Q-learning.

The contextual variable for each sector is $fuel$, representing the combustible material present. The NA agent knows the $fuel$ level for each sector, which ranges from 0 (no fire) to 5 (completely burnt). If a sector is on fire (levels 1-4), it progresses to a higher level unless extinguished by FAs, which can reduce it to 0. Fuel decreases in each simulation step depending on the fire level (0.5 for level 1, 1 for level 2, 2 for level 3, 4 for level 4). If fuel runs out, the sector reaches level 5. Fire can spread to adjacent sectors, and firefighter crews can reduce the level.

The FCA agent deploys FA agents to sectors based on a fire size and extinguishing likelihood. The Q-learning algorithm with reinforcement learning is used, enabling adaptation through experience. The reward function is $r = f - e$, where f is the remaining fuel in a sector and e is the total exposure of firefighters to risks. Higher fire levels and more firefighters increase exposure. Specific experimental values are omitted

The Q-learning simulation considers the following parameters: episodes: Number of training episodes; ε – Probability of taking a random action, ranging from 0 to 1; ε_{decay} – Rate at which ε decreases per episode, ranging from 0 to 1; α – Learning rate, indicating how quickly Q-values adjust, ranging from 0 to 1; γ – Discount factor for the influence of future rewards, ranging from 0 to 1.

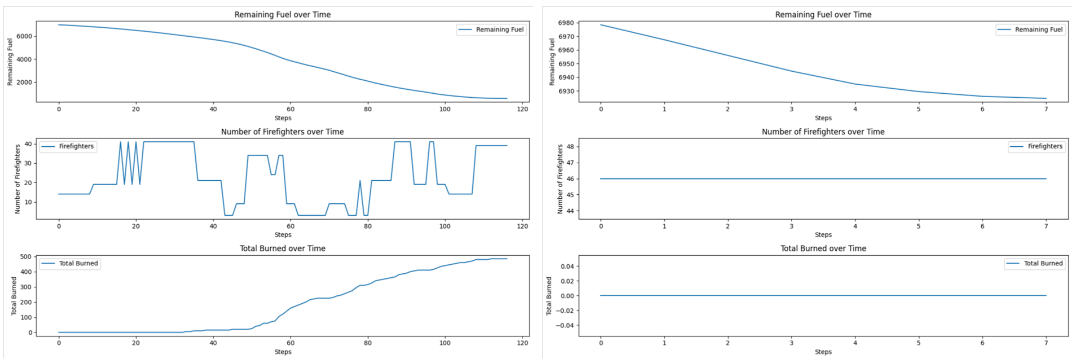

Fig. 2. The simulation results for $\varepsilon = 0.65$, $\varepsilon_{decay} = 0.98$, $\alpha = 0.4$, and $\gamma = 0.9$ (left) and $\varepsilon = 0.6$, $\varepsilon_{decay} = 0.9$, $\alpha = 0.55$, and $\gamma = 0.9$ (right)

The experiments utilised the Mesa framework[1] for modeling agent-based systems. All experiments[2], initialised with identical fire levels and numbers of FA agents in each sector, are presented in Figure 2.

The learning model's quality depends on approximately 1000 training iterations, leading to quicker fire containment, reduced firefighter risk, and a smaller forest area which is burnt. Proper parameter selection is crucial; abrupt changes in firefighter allocation are unfavourable, while more firefighters improve outcomes. More experiments are needed to include additional variables, but the results are promising.

5. Related works

The concept of context and contextual data was introduced by Dey and Abowd [5]. Augusto et al. [2] provide a historical development, while Zimmermann et al. [12, 7] propose context categories to address data complexity. Cheng et al. [4] analyse research efforts in understanding context, and Bettini et al. [3] discuss context modeling techniques and requirements. Alegre et al. [1] offer insights on designing context-aware systems. Perera et al. [11] survey context awareness from an IoT perspective. Liang and Cao [10] discuss social context for applications,

[1]https://mesa.readthedocs.io/en/stable/

[2]Special thanks to Adrianna Pączek and Wojciech Żyła for their technical support in the simulations

and Li et al. [9] cover context-aware middleware solutions. This follows work [6], introducing agents and a negotiation mechanism.

6. Conclusions

We proposed a framework for contextual data modeling to create reliable context-aware systems, enabling smart decision-making for forest workers and firefighters. We also introduced context-driven automatic negotiation to optimise firefighting crew operations.

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