Wildfire Risk Assessment and Detection for Remote Terrain

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***Abstract*— Many remote powerlines do not have enough wildfire surveillance to enable preventive or mitigation measures, resulting in massive destruction in the incidence of wildfires hitting powerlines. This project seeks to build a multi-sensor-based embedded system that monitors wildfire-related weather conditions to assess the risk and alert the appropriate fire management team, via a wireless data transfer protocol in case of outbreaks. The design of the system will prove useful at power stations where other safety features are incorporated to reduce the occurrences of fires. The embedded system works based on a HotDry-Windy index that monitors fire weather conditions that directly affect the spread of wildfires.**

Keywords—Wildfire, weather monitoring, embedded systems, sensor network, risk assessment.

I. Introduction

Wildfires have been a major source of destruction to property, human lives, and livelihoods; many wildfire cases are recorded yearly with varying forms of damage done. In 2018, California suffered a total of 8,527 fires covering a land area of 1.9 million acres (close to 2% of the entire land mass of the State; 7,700km^2 [1]. In the United States, the average number of fires recorded from 2001 to 2020 averaged 68,000 per year, covering a land size of 7 million acres [2]. The tendency or risk of wildfire outbreaks varies as the weather keeps changing. Generally, weather conditions such as surface windspeeds, relative humidity, and general fuel moisture all have direct impacts on the outbreak of wildfires and their spread across areas burned [3].

Decreasing fuel moisture and dry weather creates large areas of dry fuels that are more likely to ignite and carry fire over a longer period. The rising surface windspeeds also add to the frequency of the outbreak as they can carry fire long distances [4], [5]. These weather conditions are predominantly seen in the summer each year with the highest annual temperatures and lowest levels of precipitation annually.

Powerlines involved in wildfires are particularly devastating, either directly causing them or being caught up in the spread of the fires [6]. Powerlines belonging to Pacific Gas and Electric (PG&E) caused over 1,500 fires in six years, among the deadliest fires recorded devastating hundreds of thousands of acres, billions of dollars in financial impact, and impacting hundreds of thousands of people [7]. There is a need to mitigate the damage caused by these fires and by extension reduce the incidences of these fires. We propose to develop systems that monitor, prevent, and mitigate these wildfire outbreaks using sensor networks. The sensor nodes are designed and developed to prevent the occurrence of these fires but also to alert stakeholders to control and contain them once they break. The Wildfire Assessment Risk Management (WARM) System is a multi-sensor-based system that monitors a variety of fire weather conditions, assesses the risks, and provides prompt alerts in the case of an outbreak.

II. STATE-OF-THE-ART COMPARISON AND CHALLENGES

Wildfire monitoring has seen significant strides recently with real-time imaging and sensing [8-12]. The most notable techniques proposed include satellite surveillance, Unmanned Aerial Vehicles (UAVs), and ground-based watchtower detection systems.

Satellite Surveillance vs. Unmanned Aerial Vehicles vs. Groundbased Watchtower Detection

The imaging techniques used in satellite surveillance help detect fires and smoke in vast land areas, leading to its appeal to many research groups. The limitations, however, are the poor spatial resolution, high demand for data processing, and high deployment demands that make it costly to implement [8], [9]. Satellite detection faces a unique challenge during the winter due to the massive presence of clouds obscuring active fires on the land [10]. The challenge persists despite the efforts made to improve camera spatial resolution and artificial intelligence techniques in data processing.

UAVs by far seem to be the most viable solution to wildfire monitoring and mitigation. They do not experience the limitations of satellite-based detection systems but can still monitor vast terrain and detect fires [11]. They help reach areas that are dangerous and unreachable for humans, but in continuous landscape observation for the presence of fires, a challenge arises. Since UAVs only require remote operation by a ground-based human for task allocation, there is the problem of discontinuity in fire monitoring. This method introduces times when the system is not actively monitoring for the occurrence of fires when the human operator is not present [12].

Ground-based watchtower detection has been used for many years and continues to be used. They are constantly in operation and do not encounter the challenges of satellite detection systems or UAVs. Our WARM system cannot be used for firefighting directly like UAVs but can be used continuously for risk assessment and fire detection. Early detection is made

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possible by continuous surveillance and risk assessment. Our two-tiered approach, which we will discuss later in the paper allows us to achieve this easily and quickly.

III. THE WILDFIRE ASSESSMENT RISK MANAGEMENT SYSTEM

The WARM system is an embedded system that combines multiple sensors and data transfer protocols to monitor and evaluate the risk of fire outbreaks and send data to a base station for further action (Fig. 1A). The main components of the current system are the microcontroller unit and the sensors (Fig. 1B). The system is intended for remote terrains that generally do not have enough surveillance to detect fires rapidly. Hence, we have designed the system to be self-sustaining in terms of energy consumption by including a solar panel for energy harvesting. The design includes the HDW indexing system which allows for risk assessment.

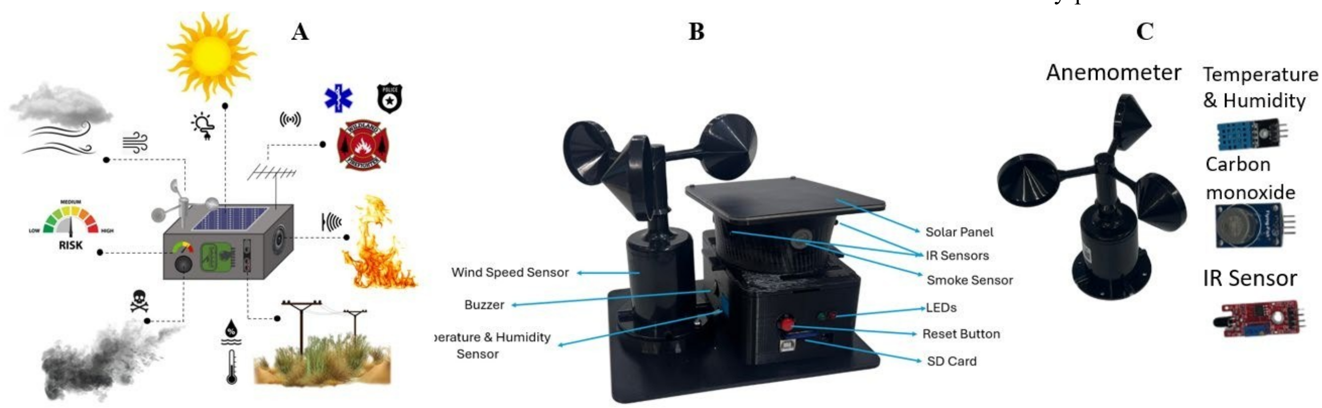

Figure 1: WARM sensor suite (A) concept design, highlighting all capabilities of the device (B) photograph of the current prototype with the included sensors and other components (C) sensors included in the prototype design.

We used multiple smoke and fire sensors to achieve fast detection and wide-angle coverage. Three fire sensors were placed 120º from each other while three smoke sensors were placed in-between them at 120º from each other. This ensures that each of the sensors is 60º apart.

The system uses a 16 MHz Arduino Mega Microcontroller Unit (MCU) with an ATMEL AT Mega 2560 chip which supports SPI and I2C communication protocols. The main parameters being monitored include temperature, relative humidity, and wind speed. In addition to these predictive parameters, smoke and fire sensors detect the presence of fires.

A. Multimodal Sensing

The MQ7 gas sensor from Winsen Electronics is primarily used for detecting carbon monoxide (Fig 1C). It operates using a heating and cooling cycle. In the heating phase, it operates at 5V and then cools down at 1.4V. The heating phase removes gas particles on the plates through evaporation and then during the cooling phase, it records data. The sensor is composed of a micro aluminum oxide (Al_2O_3) ceramic tube, a tin dioxide (SnO_2) sensitive layer, a measuring electrode, and a heater. The IR sensor, (Fig 1C) uses a photodiode with high resistance in the absence of radiation and reduces the resistance when infrared radiation is detected. The trim pot on top allows for simple modulation of the sensitivity.

A three-cupped CALT windspeed sensor is ideal for windspeed monitoring applications, (Fig 1C). It operates within the 0-45 m/s range with analog output for data recording.

The Digital Humidity and Temperature (DHT 11) sensor records both relative humidity and temperature data. It has a resistive humidity measurement component and connects to a highperformance 8-bit microcontroller. It has a humidity range of 20 – 90% RH, ±5% RH accuracy, and a temperature range of 0 - 50ºC ± 2ºC (32 – 122ºF) ± 3.6ºF.

B. Tiered Sensor Approach

For deployment of the WARM system to remote areas, we have integrated power harvesting capabilities using a solar panel to eliminate the need for wired or battery power. We used a Voltaic Systems waterproof, scratch-resistant, and UV-resistant panel with an output of 6 V and up to 2 W, which contains 12

high-efficiency cells with a nominal 0.5 V per cell. The available solar power is limited to daytime and may also be reduced due to weather conditions. Due to these limitations, we have implemented the system to reduce power using a tiered sensing system. This system uses low-power devices to determine the activation of the higher-tier sensors with greater power consumption. The multi-tiered sensing approach enables highprecision detection avoiding the higher power consumption associated with the higher tier sensing. In this implementation, we have divided the sensing into two groups—the Tier One and Tier Two sensors.

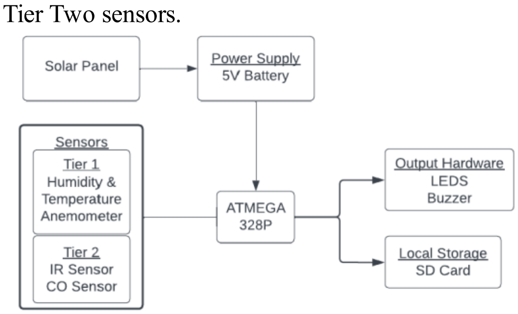

Figure 2: A block diagram showing the data flow within the system. The ATMega coordinates the data acquisition and a local SD Card stores data for redundancy and tracking data.

a) Tier 1 Sensors

This sensor group combines predictive sensors to ascertain the weather conditions that are most likely to enable the spread of fires; the temperature, relative humidity, and windspeed (Fig. 2). This data, when collected, is computed to determine the HDW, where a risk level is ascertained. This risk assessment metric then evaluates the risk level of current weather conditions. When the Tier 1 sensors indicate weather conditions are conducive to the spread of fires, the second level of sensing, Tier 2 should be activated (Fig. 3). The value obtained from the computation is compared against a threshold and once the threshold is reached, the Tier 2 sensors are called into action.

b) Tier 2 Sensors

This group of sensors determines the presence of actual fires. They include the IR and the carbon monoxide sensors (Fig. 1). This mode of operation enables fire detection along with wildfire risk by combining these two sensor Tiers to optimize power usage. Until the Tier 2 sensors are called, they operate in low-power sleep mode. Once the threshold is reached, they are activated and remain on until the risk level drops below the threshold. In this case, it means there are no recorded parameters that predict the presence of fires or danger of fire ignition and spread. Figure 3 is a logic diagram for the system indicating the activation and control of the Tier 1 and Tier 2 sensing modes.

C. Thresholding – HDW Indexing System

The HDW Index was developed to help determine conditions under which there is a high risk of fire incidence and the difficulty of managing it [13]. High values of the HDW index indicate that conditions are favorable for the rapid spread of fires, while low values indicate a lower risk of fire activity and spread. It is calculated by multiplying the windspeed (U) in meters per second (m/s) with the vapor pressure deficit (VPD) measured within 500 m above the ground.

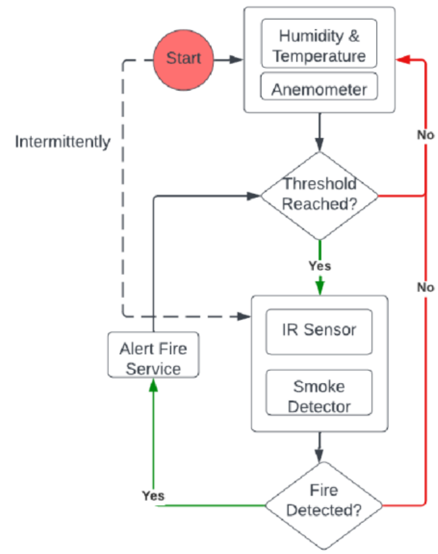

Figure 3: The logic diagram for the WARM system which uses a tiered sensing approach to enable fire detection with limited access to power. The thresholding approach helps to minimize power consumption while effectively monitoring weather conditions that foster the occurrence and spread of fires.

$$HDW = U \times VPD\ (T, q) \quad (1)$$

This model is unique because the vapor pressure deficit does not take into consideration the relative humidity, which is a ratio of the vapor pressure (e) to the saturation vapor pressure (e_s), but rather the difference between the two variables. This difference is believed to show practically how much water the atmosphere can hold before precipitation occurs. Hence, a true measure of whether there is enough moisture in the atmosphere to support or inhibit fires will be the vapor pressure deficit [14], [15] given by:

$$VPD = e_s(T) - e(q) \quad (2)$$

e_s = temperature-dependent vapor pressure (saturation vapor pressure) measured in hPa and e = moisture content-dependent vapor pressure measured in hPa.

The saturation vapor pressure is temperature dependent while the vapor pressure is moisture content dependent, hence, each variable is calculated for.

$$e_s(T) = 6.11 \times e^{\left(\frac{17.625T}{243.04+T}\right)} \quad (3)$$

$$e(q) = 6.11 \times e^{\left(\frac{17.625T_d}{243.04+T_d}\right)} \quad (4)$$

The temperature (T) in Celsius (C) is sampled from the sensor while the dew point temperature (Td) which is the temperature to which air must be cooled (at constant pressure) to achieve a relative humidity of 100% is calculated where RH is Relative Humidity.

Td = 17243.625.04− [IIIIIIII[$RRRR_{RRRR}$100100+−(1717.625.625xxxxxxxx243243.04.04++xxxx)]] (5)

D. Sensor Results

An acrylic chamber was built with dimensions 20” x 20” x 16” (Fig. 6). The temperature, humidity, and other sensor data in the box chamber were collected. Using a small tabletop fan, forced air was directed toward the anemometer to cause rotation. The speed of the anemometer was controlled by varying the speed of the tabletop fan. A portable pit fire is lit and introduced into the chamber and the fan speed alternated as shown in Fig. 4. Each time, sensor data was collected. As shown in Fig. 4, the IR sensor data alternates between 1 and 0, because the sensor operated in digital mode.

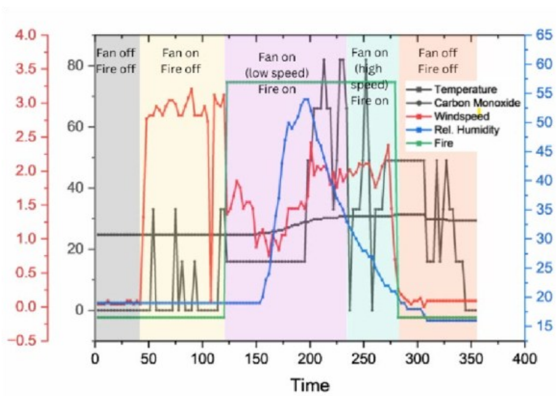

Figure 4: Various iterations to mimic weather conditions in the field. All parameters varied progressively.

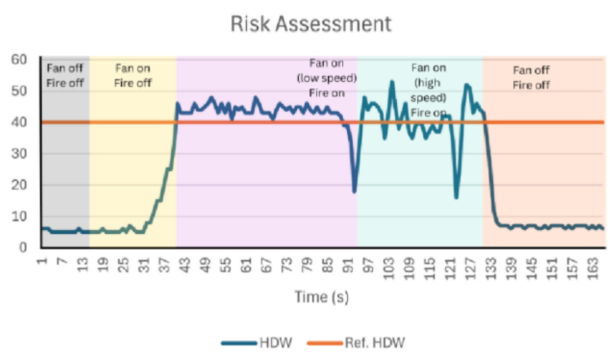

Figure 5: This shows the risk levels based on the HDW index. The HDW is compared against the reference HDW for the day. This allows the system to determine the need to engage the tier 2 sensors.

This HDW index becomes the reference index for the day. High-risk feedback is produced once we get a value that either equals or exceeds the reference index for the day (Fig 5).

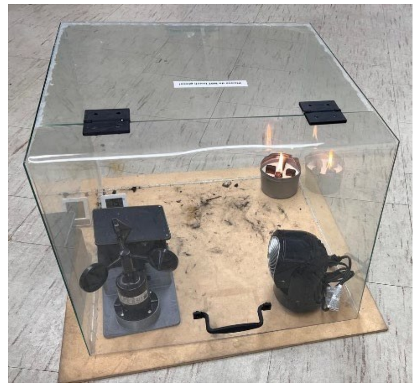

Figure 6: Photograph of the acrylic chamber with the sensors along with the small fire source, fan, and imaging. Suites implemented in actual fire detection will not be placed in the chamber; the system was used outdoors with the acrylic chamber was used to ensure the small fires were contained completely to maintain high safety standards.

The risk of fire occurrence depends on the moisture content in the air and the presence of winds to support combustion and carry fires along distances. The HDW indexing system allows us to determine the risks of fires happening daily (Fig. 5). The input data sampled from the sensor suite is fed into the model which uses a cascading effect to calculate the highest HDW for the day.

Wind speeds are often monitored by weather stations to inform the public about storms to maintain safety. Using the WARM system, once the windspeeds go beyond 47mph [16] threshold, a dust storm or gale is reported. When the temperatures go beyond the 100°F threshold, a heat wave is reported.

IV. Limitations/Challenges

The HDW index was tested against a dataset obtained through the Climate Forecast System Reanalysis (CFSR) from the National Centers for Environmental Prediction (NCEP) which covers 30 years [17]. This dataset shows that the indexing system worked well in predicting the days on which fires would be difficult to manage if they occurred. However, the testing of the indexing system was limited to just four notable wildfires that happened in the past in a few locations across the United States [13]. More testing must be done to cement its operational reliability.

The prototypical sensors and microcontrollers used do not allow for a broader range of testing which will then inform the spatial resolution of the system. The sensors, although functional, are prone to errors, hence, an important upgrade that will push the development of the system to the next level will be to move to a more industry-standard sensor suite.

V. Conclusion

Most fire mitigation systems either manage fires when they occur or perform continuous surveillance for early detection. By combining both ideas, fire mitigation would be more effective.

Although the project is designed to assess the risk of fires, we target deployment along powerlines to limit the coverage area; practically it would be very difficult to cover all uninhabited areas. The use also power lines also target the most impactful remote fire prevention and mitigation. Although the indexing system used in the project has been accessed and proven for a retrospective analysis, it needs to be tested on a large scale to gain trust and reliability. The sensor suites will need to have little to no maintenance required to demonstrate they are a viable monitoring technology.

VI. Future direction

The development of a broader dataset that contains fire outbreak data for a variety of locations and the prevailing weather conditions in those areas will be necessary to help us build a robust indexing system that will improve the accuracy of the system. The device will go through further benchmarking processes to improve reliability.

A camera module will be added to the tier 2 sensor suite to improve fire detection. These data samples will have to be transmitted across a wireless network to the fire response team to stay alert during high-risk seasons and provide a prompt response during the incidence of fires. To achieve this, a Long Range (LoRa) module will be incorporated into the design for data transmission from the power stations and powerlines to the base stations. A massive improvement in the sensor suite to a more robust and reliable suite will also need to be included.

VII. Acknowledgments

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VIII. References

[1] D. Wang *et al.*, "Economic footprint of California wildfires in 2018," *Nat Sustain*, vol. 4, no. 3, Art. no. 3, Mar. 2021, doi: 10.1038/s41893-020-00646-7.

[2] "Annual 2021 Wildfires Report | National Centers for Environmental Information (NCEI)." Accessed: Dec. 22, 2022. [Online]. Available: https://www.ncei.noaa.gov/access/monitoring/monthlyreport/fire/202113

[3] "Wildfires in the United States 101: Context and Consequences," Resources for the Future. Accessed: Dec. 22, 2022. [Online]. Available: https://www.rff.org/publications/explainers/wildfiresin-the-united-states-101-context-and-consequences/

[4] J. E. Halofsky, D. L. Peterson, and B. J. Harvey, "Changing wildfire, changing forests: the effects of climate change on fire regimes and vegetation in the Pacific Northwest, USA," *Fire Ecology*, vol. 16, no. 1, p. 4, Jan. 2020, doi: 10.1186/s42408-019-0062-8.

[5] J. S. Littell, D. McKenzie, H. Y. Wan, and S. A. Cushman, "Climate Change and Future Wildfire in the Western United States: An Ecological Approach to Nonstationarity," *Earth's Future*, vol. 6, no. 8, pp. 1097–1111, 2018, doi: 10.1029/2018EF000878.

[6] J. W. Mitchell, "Power line failures and catastrophic wildfires under extreme weather conditions," *Engineering Failure Analysis*, vol. 35, pp. 726–735, Dec. 2013, doi: 10.1016/j.engfailanal.2013.07.006.

[7] M. McFall-Johnsen, "Over 1,500 California fires in the past 6 years — including the deadliest ever — were caused by one company: PG&E. Here's what it could have done but didn't.," Business Insider. Accessed: Dec. 22, 2022. [Online]. Available: https://www.businessinsider.com/pge-causedcalifornia-wildfires-safety-measures-2019-10

[8] J. Chen *et al.*, "Overview of the performance of satellite fire products in China: Uncertainties and challenges," *Atmospheric Environment*, vol. 268, p. 118838, Jan. 2022, doi: 10.1016/j.atmosenv.2021.118838.

[9] G. Mazzeo *et al.*, "Integrated Satellite System for Fire Detection and Prioritization," *Remote Sensing*, vol. 14, no. 2, Art. no. 2, Jan. 2022, doi: 10.3390/rs14020335.

[10] F. Marchese *et al.*, "Issues and Possible Improvements in Winter Fires Detection by Satellite Radiances Analysis: Lesson Learned in Two Regions of Northern Italy," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 10, no. 7, pp. 3297–3313, Jul. 2017, doi: 10.1109/JSTARS.2017.2670059.

[11] A. Bouguettaya, H. Zarzour, A. M. Taberkit, and A. Kechida, "A review on early wildfire detection from unmanned aerial vehicles using deep learning-based computer vision algorithms," *Signal Processing*, vol. 190, p. 108309, Jan. 2022, doi: 10.1016/j.sigpro.2021.108309.

[12] S. Partheepan, F. Sanati, and J. Hassan, "Autonomous Unmanned Aerial Vehicles in Bushfire Management: Challenges and Opportunities," *Drones*, vol. 7, no. 1, Art. no. 1, Jan. 2023, doi: 10.3390/drones7010047.

[13] A. F. Srock, J. J. Charney, B. E. Potter, and S. L. Goodrick, "The Hot-Dry-Windy Index: A New Fire Weather Index," *Atmosphere*, vol. 9, no. 7, Art. no. 7, Jul. 2018, doi: 10.3390/atmos9070279.

[14] F. Sedano and J. T. Randerson, "Vapor pressure deficit controls on fire ignition and fire spread in boreal forest ecosystems," Earth System Science/Response to Global Change: Climate Change, preprint, Jan. 2014. doi: 10.5194/bgd-11-1309-2014.

[15] A. Jt and W. Ap, "Impact of anthropogenic climate change on wildfire across western US forests," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 113, no. 42, Oct. 2016, doi: 10.1073/pnas.1607171113.

[16] N. US Department of Commerce, "Estimating Wind." Accessed: Apr. 05, 2023. [Online]. Available: https://www.weather.gov/pqr/wind

[17] J. M. McDonald, A. F. Srock, and J. J. Charney, "Development and Application of a Hot-Dry-Windy Index (HDW) Climatology," *Atmosphere*, vol. 9, no. 7, Art. no. 7, Jul. 2018, doi: 10.3390/atmos9070285.