Wildfire Forecasting using AI-based DDDAS Propagation Prediction

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Abstract - *Wildfire annihilate thousands of hectares of global forestland annually. Predicting fire behavior is pivotal for coordinating mitigation resources and managing response efforts during such disasters. Fire spread forecasting systems require diverse data inputs plagued by uncertainties, such as meteorological forecasts and vegetation maps. The dynamic nature of wildfires demands adaptable prediction tools. This study applies two fire spread prediction systems based on the Dynamic Data-Driven Application System (DDDAS) framework and introduces a hybrid method that merges both approaches. The solution leverages high-performance computing to deliver rapid, real-time predictions.*

Keywords: Dynamic data-driven systems, parallel computation, uncertain data integration, predictive modeling, wildfire simulation.

1.INTRODUCTION

Ensuring reliable electrical power has become increasingly critical for utilities and consumers [1][2][3]. Voltage fluctuations, transients, and waveform distortions caused by grid or equipment disturbances can compromise power quality (PQ)—defined as maintaining stable voltage/current waveforms at specified frequencies and magnitudes with minimal distortion. The proliferation of power electronics in devices like industrial drives, renewable energy systems, and smart appliances has heightened grid vulnerability to PQ disruptions. Non-linear loads, including rectifiers and variable-speed motors, distort sinusoidal waveforms, leading to issues such as harmonics, voltage sags/swells, imbalances, and flicker. These disturbances threaten equipment reliability, operational efficiency, and system safety. For instance, voltage sags can trip sensitive machinery, while harmonics overheat transformers. Addressing PQ challenges is now essential to safeguarding modern power infrastructure and ensuring uninterrupted service in an era dominated by electronics-dependent technologies.

Innovations in power electronics have spurred transformative developments, particularly in power quality management through technologies like FACTS (Flexible AC Transmission Systems) and tailored power solutions. These advancements enable enhanced grid control, improving stability and efficiency. Modern power systems operate under deregulated frameworks, where generation, transmission, and distribution are decoupled to reduce costs. With escalating energy demands, optimizing existing power plants and operating transmission lines near thermal limits is essential for stability[7]. Reducing transmission losses remains a critical priority, necessitating tools like FACTS devices. These systems regulate power flow, maximize line capacity, and enhance operational resilience, ensuring reliable electricity delivery in evolving grids.

The integration of power electronic components in FACTS devices boosts control precision and increases power transfer capacity. By embedding FACTS into transmission networks, these systems can evolve into smarter, more adaptable infrastructures. Controllers like STATCOM, TCSC, SSSC, and SVC enable real-time adjustments to grid conditions, improving voltage stability and power quality. Reactive power deficits—often caused by faults, heavy loads, or voltage swings—are mitigated through FACTS devices, which dynamically inject or absorb reactive power to maintain equilibrium. FACTS devices enhance power flow management, suppress oscillations, reduce environmental footprint, and offer cost-effective alternatives to traditional grid upgrades. Among these, the Unified Power Flow Controller (UPFC) stands out. Its primary function is to adjust transmission line power distribution by modulating voltage magnitude and phase angle via a series voltage input[6][2]. This control over real and reactive power optimizes line usage, enabling operation closer to thermal limits while bolstering transient and small-signal stability. The UPFC combines impedance, voltage, and phase-angle compensation for comprehensive grid support (Figure 2). It employs two voltage source converters: a shunt converter (STATCOM) and a series converter (SSSC). The STATCOM supplies reactive power to the grid and maintains DC link voltage, while the SSSC injects a controlled series voltage into the transmission line. Both converters are linked via a shared DC capacitor, which acts as an energy buffer. The UPFC's shunt and series converters must balance active power exchange to ensure stability. The shunt converter draws active power to sustain the DC link, while the series converter injects it into the line[12][14]. This coordination, coupled with independent reactive power regulation in both converters, enables precise power flow control. A coupling transformer integrates the UPFC with the grid, ensuring seamless interaction.

1.1 Cardona Fire, Catalonia, Spain

The 2005 Cardona Fire in Catalonia, Spain (41°54' N, 1°40' E), which burned 1,439 hectares over five hours on July 8, underscores the challenges of predicting dynamic environmental events. The fire, ignited at 14:45 and contained by 19:45, exhibited a rapid acceleration from ~10 m/min to ~100 m/min two hours post-ignition, despite recorded wind conditions remaining relatively stable (4.8–2.2 m/s, 185°–190°). This acceleration highlights the critical influence of topography and fire-induced microclimates, particularly along south-facing slopes and valleys where solar exposure intensified fuel aridity (Fig. 1 a). Traditional models, designed to account for wind and slope, often fail to capture these complex, fire-driven atmospheric interactions.

To address these model limitations, Dynamic Data-Driven Application Systems (DDDAS) offer enhanced predictive accuracy by integrating real-time data streams. Techniques such as Kalman Filtering and Ensemble Kalman Filtering can dynamically adjust simulations based on sensor data, refining accuracy by up to 35%. Ensemble Forecasting, which combines outputs from multiple models, improves prediction reliability by accounting for parameter uncertainty. High-performance computing (HPC) facilitates parallel simulations, enabling rapid scenario testing during dynamic fire events. These adaptive strategies, which incorporate real-time data assimilation and hybrid modeling techniques, are crucial for managing complex and evolving systems effectively.

Unified Power Flow Controllers (UPFCs) in power grids mirror this adaptive approach. UPFCs, integrating Static Synchronous Compensators (STATCOMs) and Series Static Synchronous Compensators (SSSCs), enhance grid stability and efficiency through a variety of core functions: power flow control, harmonic suppression, and dynamic stability[16][5]. In power systems, as in wildfire management, there is an increasing need for real-time data integration and adaptive control. By leveraging real-time sensor measurements to refine predictive models and control actions, power grids can better respond to disturbances and maintain stability. The success of adaptive methodologies in these disparate domains underscores their potential to enhance resilience and efficiency in complex systems worldwide.

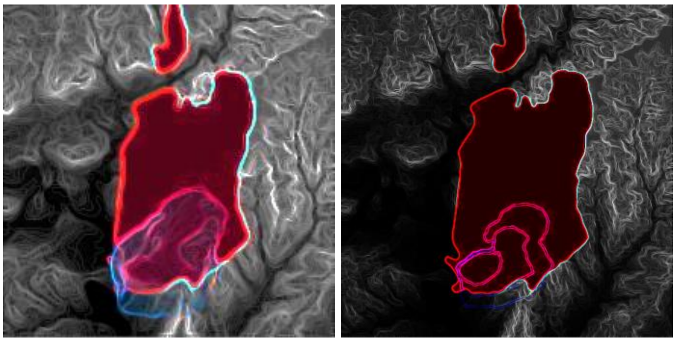
2. DDDAS FRAMEWORKS FOR FIRE PROPOGATION PREDICTION

As noted, prediction inaccuracies arise from the inability of simulators to fully account for fire-induced effects on environmental conditions. The microclimate created by the fire directly influences the local meteorological state, affecting data inputs. To address this, two DDDAS approaches are analyzed using the FARSITE and WildFire Analyst (WFA) simulators [4][10][1].

While both simulators implement Rothermel's equation, their methods for obtaining global prediction evolution differ, resulting in distinct predicted perimeters, as illustrated in Figure 2. In this example, both simulators provide a fire spread prediction using the initial recorded perimeter at 14:38 as the starting point and a simulation time of 5 hours. The meteorological conditions are set to those gathered at the ignition time and kept constant throughout the simulation[11].

3. Evaluating Fire Propagation with and without DDDAS

Neither basic prediction method accurately mirrors the observed fire progression. FARSITE (Fig. 2(a)) underestimates the actual fire spread, as does WFA (Fig. 2(b)). Therefore, Dynamic Data Driven strategies were employed to mitigate these limitations[3]. The methodology extracts relevant information about the observed fire spread to adjust parameters of the simulation process dynamically. These calibrated values are then fed into the simulation system to drive near-term evolution forecasts.



(a) (b)

Fig 1: Basic fire spread prediction obtained by applying FARSITE (a) and WFA (b) in the case of Cardona Fire

The way of extracting knowledge from observed fire behavior for the DDDAS strategy varies. However, the general scheme is illustrated in Figure 3. An adjustment stage requires access to two consecutive real fire perimeters or georeferenced points from the fire spread perimeter. The calibration process can be re-initiated each time the system is fed with new observed fire behavior. The goal is continuous system operation, providing fire evolution forecasts on preset time horizons. The input data set used for prediction is calibrated in the corresponding adjustment stage. This methodology is simulator-independent, allowing plug-and-play replacement.

In the next section, two DDDAS approaches for forecasting fire spread will be described: DDDAS-GA and DDDAS-ROS. Both use data from the fire propagation interval (14:38 to 17:13) to adjust input data. This data is then used to drive the fire evolution forecast dynamically until 19:40. Figure 4 shows initial, intermediate, and final perimeters used in the DDDAS forecast.

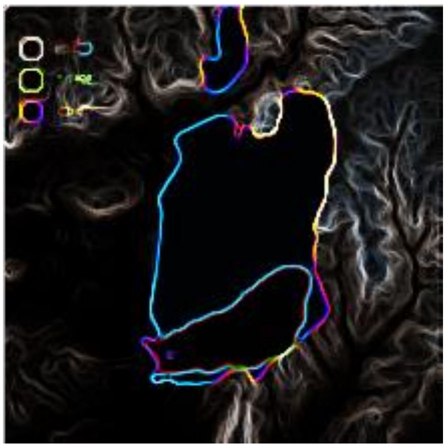


Figure 2: Real fire evolution of the Cardona Fire at three different time instants

3.1 DDDAS APPLYING GENETIC ALGORITHMS (DDDAS-GA)

DDDAS-GA is a dynamic data-driven prediction scheme hat employs a Genetic Algorithm (GA) for calibration. This strategy integrates field data to refine wildfire simulations by adjusting parameters like fuel moisture and wind speed. Although the fire simulator is FARSITE, the system is designed to be simulator-independent, allowing for flexibility in the choice of the underlying model.

The GA starts with a random population of individuals, each representing a simulation scenario. A scenario/individual comprises genes representing input variables (e.g., dead fuel moisture, live fuel moisture, wind speed, wind direction). Each individual is simulated, and the prediction results are compared to the most recently observed fire propagation. Fire spread is expressed using a cell map description, which shows whether a cell has been burned at a given time. This comparison assesses the symmetric difference between predicted and actual burned areas using equation:

Difference = (UnionCells - IntersectionCells) / (RealCells - InitCells)

In the above equation, UnionCells denotes the number of cells burned by either the predicted or real fire. IntersectionCells indicates the number of cells burned in both the predicted and real maps. RealCells represents the total number of cells burned in the real fire, and InitCells signifies the number of cells burned at the starting time. This difference accounts for both falsely burned and erroneously unburned cells. Based on this fitness function, the entire population is ranked, and genetic operators (selection, elitism, mutation, crossover) are applied, producing an evolved population retaining at least the best individual from the previous generation.

The new population is evaluated, and this iterative process identifies a suitable input parameter set. However, the substantial computational cost due to numerous simulations necessitates speeding up execution while maintaining prediction accuracy[5]. Therefore, a parallel implementation of this methodology has been developed using the Master/Worker paradigm with MPI, enabling efficient distribution of simulations across nodes. The master node generates a random initial population and distributes it among workers. Workers simulate each individual, evaluate the fitness function, and send errors back to the master. The master sorts individuals by their error, applies genetic operators, and generates a new population. This iterative process repeats a fixed number of times, with the final iteration providing a population from which the best individual is selected as the solution.

3.2 DDDAS WITH MAXIMUM RATE-OF-SPREAD (ROS) ADJUSTMENT

Wildfire Analyst (WFA), part of the Tecnosylva Incident Management suite, provides real-time analysis of wildfire spread, evacuation planning, and impact assessment for multi-agency incident management. WFA incorporates a data assimilation technique that tunes simulations based on observed fire behavior, seeking the best ROS adjustment factors to minimize the error between the simulated and real fire data. These factors are fuel model-specific and adjust the fire's rate of spread accordingly.

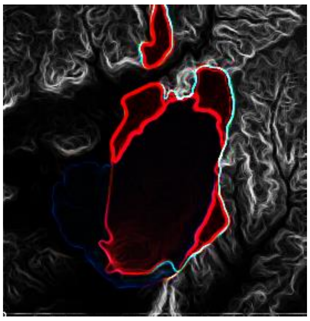
The method's strengths lie in its non-recursive nature, enabling near-instantaneous solutions, easy-to-interpret adjustments for fire managers, and minimal input data requirements. Unlike other methods, it doesn't analyze the root cause of observed errors (weather, fuel properties) but focuses on estimating future fire behavior regardless of the error source. While adjustments may be used for calibration, they can also guide recursive optimization or data assimilation schemes to determine the causes of observed errors.

The algorithm currently functions as an operational adjustment module, lacking automated data feeding for a fully operational data-driven application. It provides the best ROS factors fitting a fire and allows users to manually adjust them to instantly visualize the expected behavior without redoing the simulation. Users can also adjust the tuning strength to balance error minimization and the severity of adjustments. Mathematically, the method assumes simulated fire paths reaching the known fire location don't significantly change before and after adjustment, which typically holds unless adjustments are too drastic; a small recursive algorithm may be used otherwise

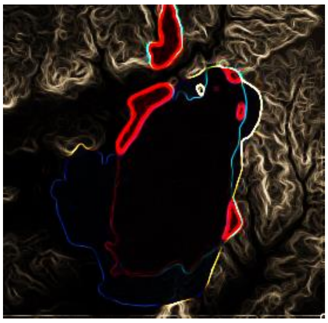
4. OVERLAPPING DDDAS FORECASTS

Two Dynamic Data-Driven Application Systems applied to forecast wildfire spread were described above. Both schemes adjust/calibrate unknown environmental data needed for fire spread simulations based on observed real fire evolution[6][12]. Figures 3(a) and 3(b) show the predicted spread for the Cardona Fire using DDDAS-GA and DDDAS-ROS, respectively. As expected, both approaches yielded slight differences compared to the actual final fire spread, though both predictions clearly match the main fire run direction despite not perfectly matching the shape. DDDAS-GA underestimates the real fire spread, while DDDAS-ROS overestimates the final burnt area. Therefore, overlapping DDDAS forecasts could take both prediction results into account. Figure 3a shows the prediction fire spread areas of both schemes and the final real burnt area. Analysis reveals that using data to drive the simulation system directly impacts fire spread direction. The overlapped DDDAS forecast can find the maximum rate of spread path, which depends on underlying topography and fuel.

Using the overlapped DDDAS forecast as a prediction approach, the area predicted to burn in all cases was destroyed by the fire, except the left flank where the overlapped DDDAS forecast overestimated the area. However, using the overlapped scheme reduces false alarms due to the compensating effect of using two DDDAS approaches, as could be observed in the back propagation.



(a)



(b)

Fig -3: Forest fire spread prediction applying both the DDDAS-GA scheme (a) the DDDASROS approach (b) (blue shapes) compared to the real fire burnt area (red shape).

5. CONCLUSIONS

Wildfires, a recurrent natural hazard, devastate vast forest areas worldwide annually. Computer simulation has become crucial in providing enhanced propagation information to decision support systems, aiding mitigation efforts. However, current forest fire simulators often lack the capacity to modify model behavior based on changing environmental conditions caused by the fire itself. To address this limitation, dynamic data-driven approaches have been developed, enabling model behavior updates based on observed real fire spread[2].

This paper describes two distinct DDDAS approaches: one based on Genetic Algorithms and the other on the maximum ROS path. Both approaches have demonstrated a strong ability to adapt to rapid changes in fire rate of spread resulting from micro-climates generated by the fire under specific topographic conditions. This adaptability was proven using the Cardona Fire, which occurred in 2005 in northeastern Spain, as a test case.

Fig- 4: Map overlap including the final fire predictions applying both DDDAS schemes and the real fire spread

Given the complementary strengths of both approaches, an overlapping DDDAS forecast is proposed to provide high-fidelity forest fire spread prediction (Figure 4), leveraging the advantages of both methods to improve accuracy and reliability.

Disclosure of conflict of interest
No conflict of interest to be disclosed.

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