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Complex Battery Storage Fire Propagation Translational Forensic Study Using Cellular Automata

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Abstract: The surge in lithium-ion battery (LIB) use, essential for mass-scale renewable energy storage, raises concerns about fire hazards. However, to date, there is a lack of industry-wide understanding of large-scale LIB fire propagation. This paper suggests a translational forensic approach to promote fire safety awareness and introduces the cellular automata (CA) model coupled with the Monte Carlo (MC) approach to address the complex fire propagation simulation within an energy storage system (ESS). The objective is to demonstrate that the CA-MC model can provide a flexible and scalable connection for all levels of battery fire studies. The numerical model is coupled with experimental tests which have been performed to establish the actual timing of fire propagation from a single source. Cellular automata simulation, conducted through hybrid modeling and an applied risk analysis approach to evaluate fire hazards associated with LIBs, offers crucial insights into potential risks. The results demonstrate that, with fire incident initiation at a probability of 0.1 (10%), 33% of batteries will burn, and at a probability of 0.6 (60%) and beyond, the entire battery module will face complete burndown. Achieving full combustion of the entire module will take only approximately 42 timesteps on average, indicating rapid fire propagation. The actual time for a complete fire to occur in the battery module has been estimated to be 304 s per timestep, or 3.5 h total. Using this example, it is shown that the CA-MC approach can be extended to many other aspects of battery fire studies and is ideal as a translational tool, spanning all domains of the LIB industry.

Keywords: lithium-ion battery (LIB); cellular automata (CA); Monte Carlo (MC) approach; fire propagation; risk analysis; energy storage system (ESS)

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1. Introduction

Lithium-ion batteries (LIBs) have seen a significant rise in adoption as a key technology for supporting the energy transition and mitigating climate change. They are widely utilized in electric vehicles (EVs) and energy storage systems (ESSs). High-capacity LIB units, ranging from 20–30 kWh for EVs to MWh or even GWh scales for utility storage, have become integral to various large-scale applications. Figure 1 shows the projected LIB global sales growth and the shares between EV and ES usage.

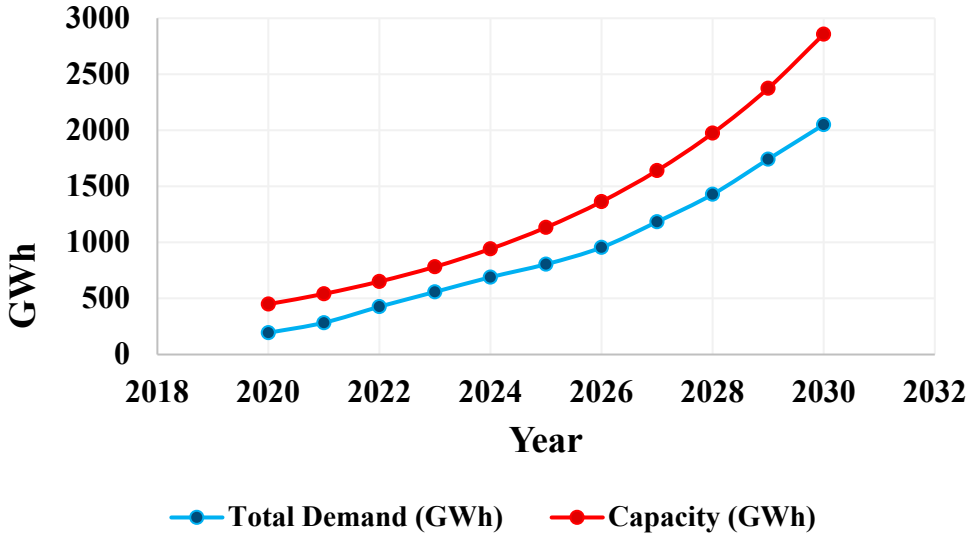


Figure 1. Global LIB demand and supply projections from 2020 to 2030 [1,2].

A major concern with large-scale LIB installations is the risk of battery fires, with several significant incidents reported globally to date [3–6]. LIB fires involve the thermal runaway phenomenon, which can result in a unique fire propagation problem (Figure 2). It is recognized widely that LIB fire would require much more water to extinguish than other fossil-fuel-associated fires [7]. Another critical issue associated with LIB fire is that the design of the battery pack can be a predominant factor in fire propagation: LIB batteries are fabricated at the cell level and then packaged at the module level; hence, the packaging technique and design can dictate the propagation of a battery fire.

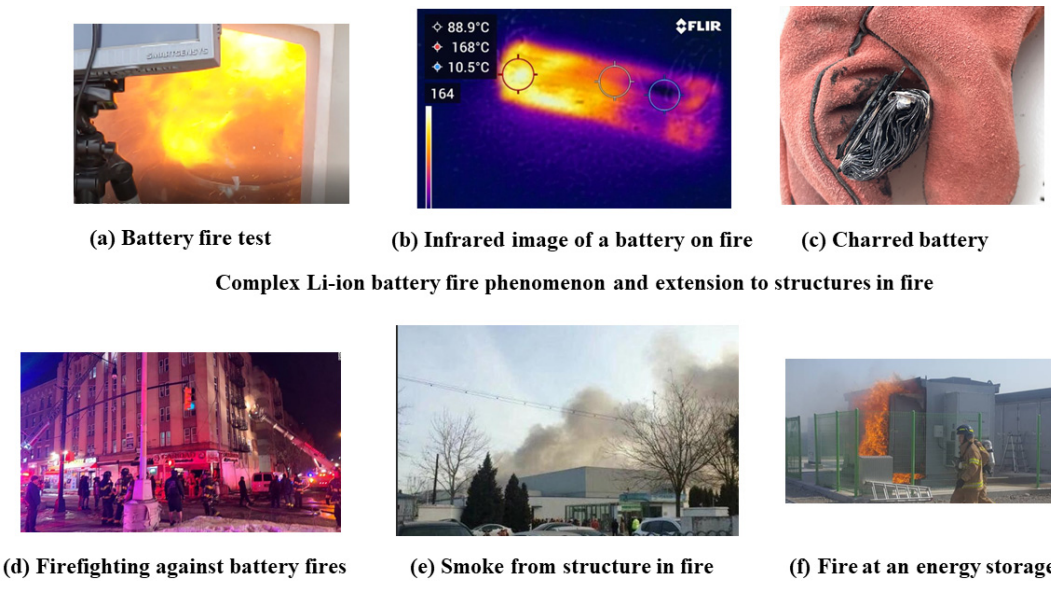


Figure 2. Diverse scales of LIB fire: (**a**) Experimental evaluation of battery ignition scenarios; (**b**) thermal imaging of a battery fire test; (**c**) post-combustion charred battery; (**d**) suppression measures during fire events; (**e**) battery fire in a commercial building; and (**f**) energy storage facility fire [8].

Because LIB technology implementation is occurring at such a rapid pace, the biggest challenge is to bring awareness of battery fire issues and research outcomes to industry applications and the public. Herein, the accelerated transfer of technical knowledge to practitioners, also referred to as translational forensics, is suggested for the LIB technology industry. Translational research in an industry aids in sharing technical knowledge across

all sectors, which the medical field calls a "bench-to-bedside" transfer [9,10]; this can be equally beneficial to the battery fire management field, coined "cells-to-infrastructure".

Braxtan et al. [8] first introduced the concept of translational research for LIB fire, described as translational forensics. They proposed some general rules and stages for integrated studies of Li-ion battery hazards (hence, forensic science); these are based on goals for practitioners, research, and education and their connections and outcomes. These are presented in Figure 3.

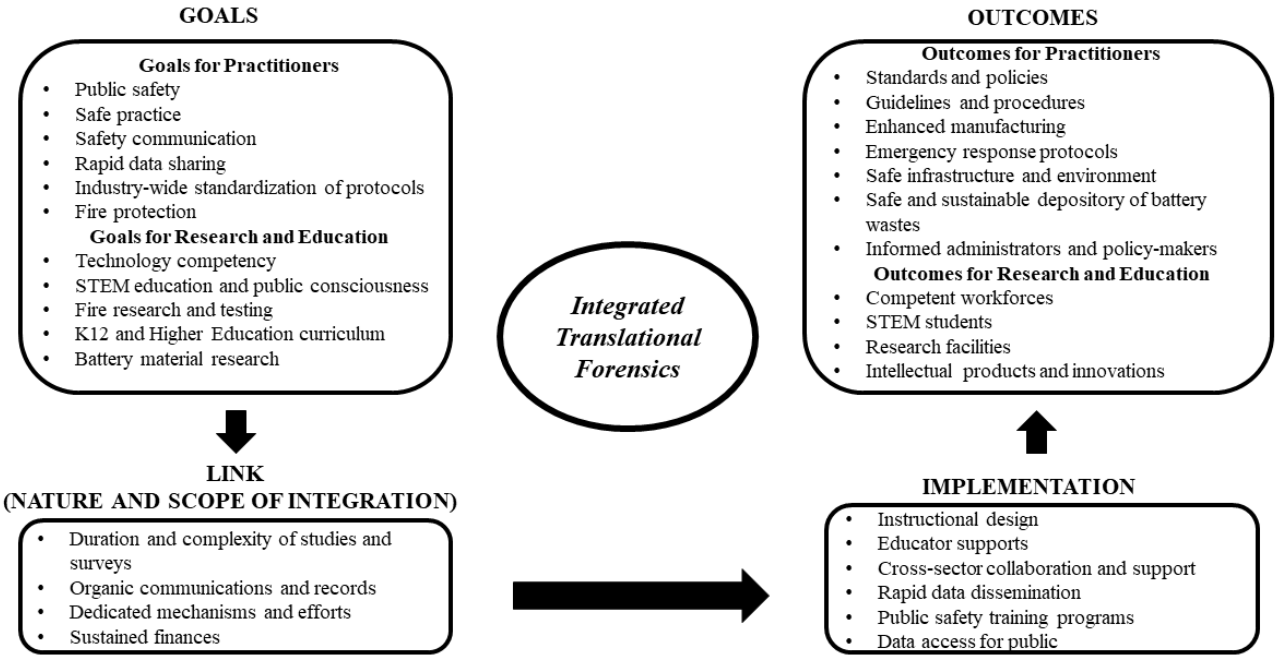


Figure 3. Translational forensics framework for battery safety.

Figure 4 further outlines the necessary research endeavors and the knowledge advancement process to produce valuable insights into LIB fire safety. These research endeavors can be cleaved into basic, applied, and advanced measures for research. There is also a potential to introduce hybrid methods that combine different research stages, which could yield greater benefits earlier in the process. For instance, integrating numerical modeling (basic research) with risk assessment (applied research) in a collaborative study may be an effective way to accelerate translational work. There are several examples in system design that involve combining various tasks to create concurrent outcomes. Figure 5 illustrates the diverse steps in translational research and the levels of development regarding battery behavior. These levels should account for varying structural complexities, from individual cells to modules and complete battery racks.

The high energy density and chemical composition of LIBs make them susceptible to thermal runaway, which can result in overheating and fires or explosions. Thermal runaway may occur due to overcharging, thermal abuse, physical and structural damage, or manufacturing defects. The specific characteristics of different battery cell types (such as cylindrical, pouch, or hard-cased) can significantly influence the spread of fire, thereby affecting the fire's intensity and the strategies implemented for suppression. Most existing studies concentrate on the cell level and the analysis of the thermal runaway (TR) phenomenon in LIB, with limited studies examining the impacts of battery fire at the pack level. Chen et al. [11] showed that the TR propagation hazard associated with a LIB pack can exceed that of a single battery due to the increased heat generated during TR in a pack. Zhang et al. [12] investigated LIB fires in enclosed spaces, revealing that the heightened fire hazards are primarily due to increased heat flux. However, there is no universally accepted testing protocol for these scenarios, leading several researchers to create their

own experimental setups to gather data on fire characteristics during thermal runaway [13]. Furthermore, there are few published safety design guidelines, highlighting a significant gap in standard practice for battery storage facility design [14].

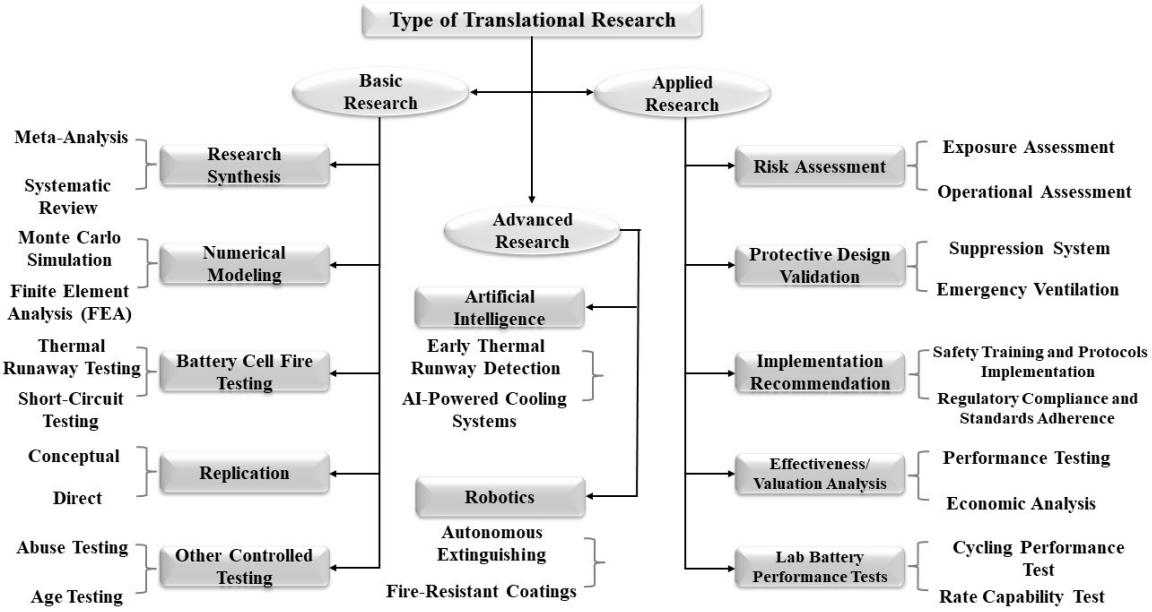


Figure 4. Advancing knowledge and implementation via the translational forensic platform.

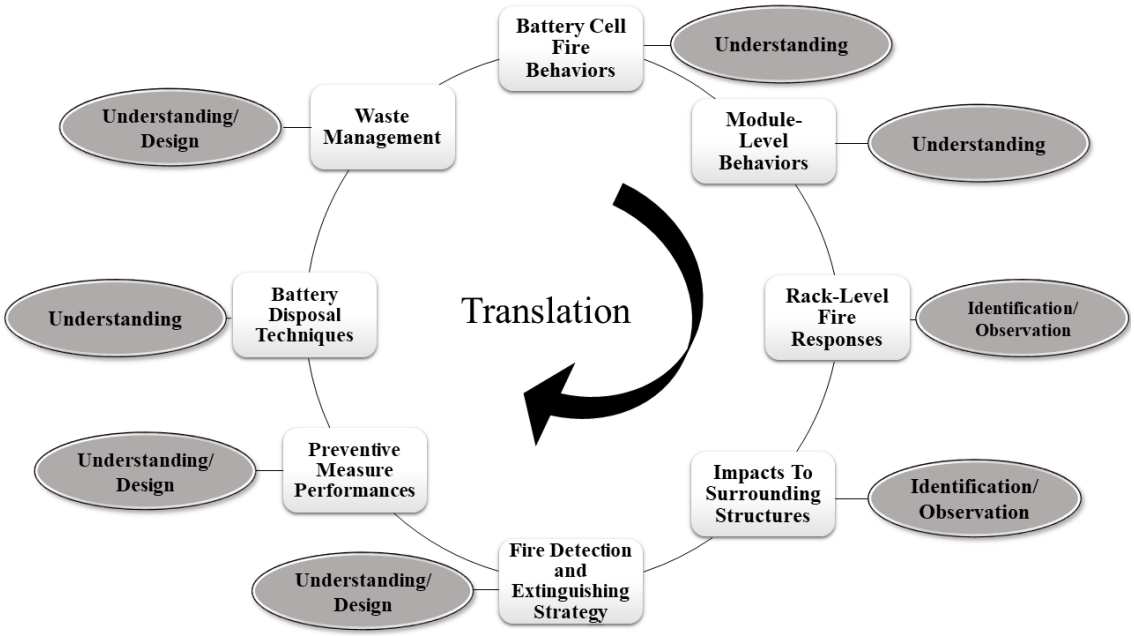


Figure 5. Technical processes supporting the establishment of reliable insights into battery fire structures.

Assessing battery rack fires typically involves real-time power flow monitoring via battery management systems (BMSs) or the use of fire, gas, or smoke detection systems [15–18]. These systems may also incorporate thermal sensors such as thermocouples and infrared thermography. Unfortunately, extensive tests specifically designed for large-scale battery fires are not conducted frequently. As mentioned earlier, most test results are kept confidential. Consequently, research on LIB thermal runaway is still predominantly focused at

the cell level, and there is a limited body of literature available on modular to full-scale fire propagation studies. This is especially true regarding the impacts of battery fire propagation on existing infrastructure.

Fire propagation research related to fire spread in built environments has been extensively conducted and applied. This field encompasses a range of focus areas including the estimation of fire emissions, the dynamics of wildfire spread, and the impact of external structures on fire behavior. Studies have examined several factors, such as enhancing the fire resistance of structures in wildland–urban interfaces by analyzing fire pathways and the separation distance to ornamental vegetation [19]. Furthermore, research has employed GIS-based models to simulate wildfire propagation while taking into account spatial and temporal factors [20]. There is also an emphasis on forecasting fire propagation using methods like cellular automata, which effectively visualize fire spread [21–24].

As early as the 1980s, the automata method has been proposed for 2D fire propagation simulation [25]. Researchers, including Muttulakshmi and Wee [26] and Wang and Chang [27], have further demonstrated the effectiveness of the CA technique in modeling forest fires. CA models simulate highly complex phenomena using computer algorithms. Von Neumann outlined five general principles governing cellular automata: (1) the algorithms follow a universal set of logical operations; (2) the automaton (or element) functions based on the principle of constructability; (3) the construction process is universal; (4) the construction process is self-generating (self-reproductive); and (5) self-reproduction should facilitate the spread of fire by incorporating dynamic neighborhood structures and spatial data, thus enabling the prediction of fire states with quantified uncertainty [28]. These methodologies enhance our understanding of fire propagation, which is crucial for emergency planning and informed decision-making. For instance, Green et al. [29] utilized cellular automata to model forest fires using actual terrain data, thereby improving the precision of their forecasts. De-Castro et al. [30] implemented a physics-based parametrization of fire-spotting, called RandomFront, into the operational wildfire spread simulator PROPAGATOR, a CA-based fire study software. Hou et al. [31] improved the accuracy of conventional forest fire spread models by optimizing the CA structures and rules. They created a CA-based forest fire simulation system featuring dynamic displays and 3D visualization. Furthermore, the integration of CA with genetic programming has shown potential in predicting wildfire fronts, presenting a promising alternative to traditional physics-based models.

Given the extensive use of cellular automata in studying wildfire propagation, it is essential to recognize the potential to apply this methodology to large-scale safety and risk analysis of Li-ion batteries. In this study, we developed a reductive CA model coupled with MC simulation to investigate the fire propagation behavior of LIBs at a large scale, specifically at the rack and module levels. In addition to formulating and validating the actual time of fire spread, we conducted experimental tests. The subsequent sections outline the principles of the cellular automata with Monte Carlo methods, the experimental approach, and the results and discussion pertaining to the risk assessment.

2. Materials and Methods

2.1. Battery Module Arrangement

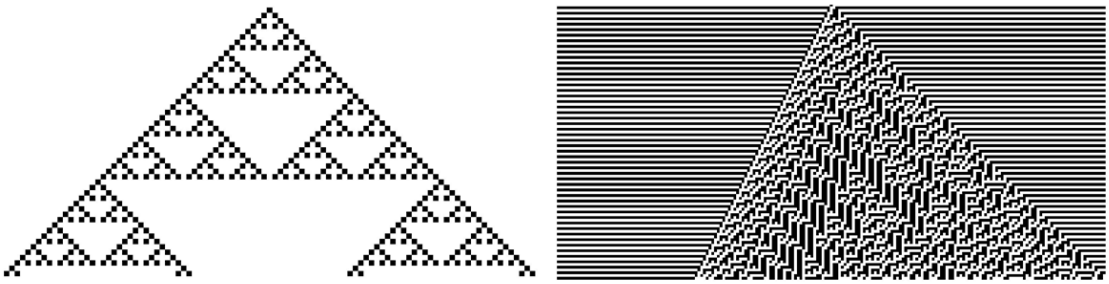
The fire propagation model within the battery facility involves a two-dimensional representation of a battery stack in a 16×54 rectangular grid. These battery modules are positioned closely together.

2.2. Cellular Automata and Monte Carlo Approach

Cellular automata, initially conceptualized by von Neumann [32], represent extensive discrete dynamical systems characterized by their simple structure, yet capable of exhibiting complex and varied behaviors. These models consist of cells organized in a grid that evolves according to rules based on the states of neighboring cells. They reveal how intricate patterns can emerge from simple local rules and have found applications in various

fields such as physics, biology, and computer science, particularly for simulating patterns and processing information [33]. The complete structure of state transition diagrams is formulated using algebraic and theoretical principles. In its simplest form, a cellular automaton consists of a linear arrangement of sites, each assigned a binary value of 0 or 1. These values progress through synchronous evolution across discrete time intervals, influenced by the states of neighboring sites. For example, a common rule of evolution dictates that a site's value at a given timestep is computed as the sum of its nearest neighbors' values from the previous timestep, with the rule applied simultaneously at each site [34].

Figure 6 depicts a series of nodes aligned in a row, with each node assigned a binary value of either 0 or 1. The resulting pattern of nonzero sites generated by this rule emerges from an initial condition that features a single nonzero site. Such illustrations elucidate the dynamics and emergent properties inherent in CA systems, offering valuable insights into their behavior and potential applications [35].



(a) Evolution based on rule 90 **(b) Evolution based on rule 75**

Figure 6. A primary demonstration of cellular automata basic configuration and site's time evolution [36].

The fire propagation risk assessment is conducted through a constrained Monte Carlo-driven dynamic model. This model, derived from CA principles, simulates the distinct state, space, and temporal characteristics of fire propagation. Within this simulation, each unit cell is presumed to possess identical properties and fire behaviors. The fire initiation is modeled as commencing from a single battery cell, with the spread occurring randomly, based on a designated probability, to adjacent cells. The progression of fire at each time interval depends on the condition of the cell and its neighboring cell. The fire spread probabilities in the CA model are specifically designed to reflect the stochastic nature of thermal runaway propagation in densely packed battery modules. When a battery undergoes thermal runaway, the heat or flames emitted from one cell may or may not trigger similar events in adjacent cells, influenced by factors such as thermal resistance and the unique characteristics of each cell. This randomness, unlike traditional fire spread, arises from the variability in cell interactions and the likelihood of ignition. The model is further enhanced by employing the Monte Carlo approach, which simulates a range of random scenarios to assess fire spread probabilities under various conditions, thereby capturing real-world uncertainties. It is noteworthy that this study involved 100,000 randomly generated simulations. This extensive number of simulations not only refines prior research but also significantly improves the accuracy in determining the probability of fire spread. Figure 7 illustrates the correlation between individual cells and their neighboring counterparts as follows:

- Cell Identification: Each cell is identified by its (i, j) index and possesses a specific state influenced by neighboring cells.
- Fire Propagation: The spread of fire is contingent upon assessing neighboring cell states at each timestep.
- Diagonal Cells: Diagonally positioned cells do not affect the state of the focal cell.
- Boundary Assumption: The module periphery is assumed to contain empty cells.
- Matrix Configuration: The computational matrix size is (n + 2, n + 2).

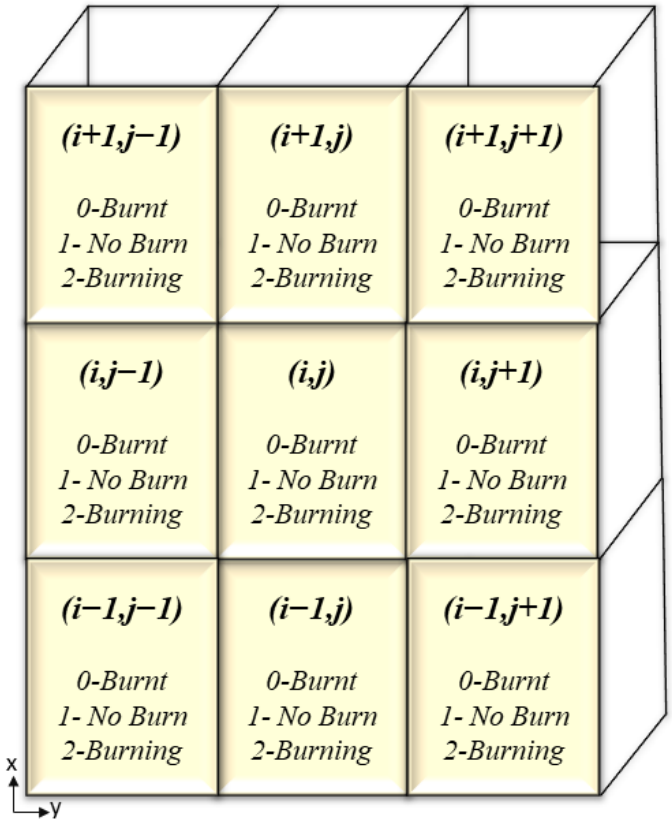


Figure 7. A grid framework for a battery pack utilizing cellular automata.

The complete process flow is depicted in Figure 8, categorizing the cell states into three types: 0 for empty or burnt battery cells, 1 for non-burning battery cells, and 2 for burning battery cells. Once ignited, a cell transitions to a burning state and subsequently becomes empty in the following timestep, as battery burnout occurs within a single timestep. During each iteration, the state of a cell is influenced by its neighboring cells, with a certain probability determining ignition from adjacent burning cells. Burnt cells serve as barriers to the spread of fire, influencing its direction. Fire spread is based on a comparison between a generated random number and the probability of ignition, P_{ignite}. Fire propagates from burning cells to neighboring unburnt cells with a defined probability, P_{spread}. For each unburnt cell, the number of burning neighbors is calculated, with the likelihood of ignition increasing as the number of burning neighbors rises. The probability that an unburnt cell will catch fire is expressed as follows:

$$P_{ignite} = 1 - \left(1 - P_{spread}\right)^{(n_{burning})} \quad (1)$$

where $n_{burning}$ represents the number of burning neighbors.

It is important to highlight that the program ensures grid updates by referencing the previous state, thereby preventing any interference. Additionally, the incorporation of random numbers introduces an element of unpredictability, mimicking the uncertainty inherent in real-world fire propagation. Equation (1) presents a simplified model of fire ignition that is commonly employed in fire simulations. More sophisticated models have been developed in other domains such as market pricing modeling [37]. The underlying principle governing fire propagation is outlined in the algorithm depicted in Figure 9.

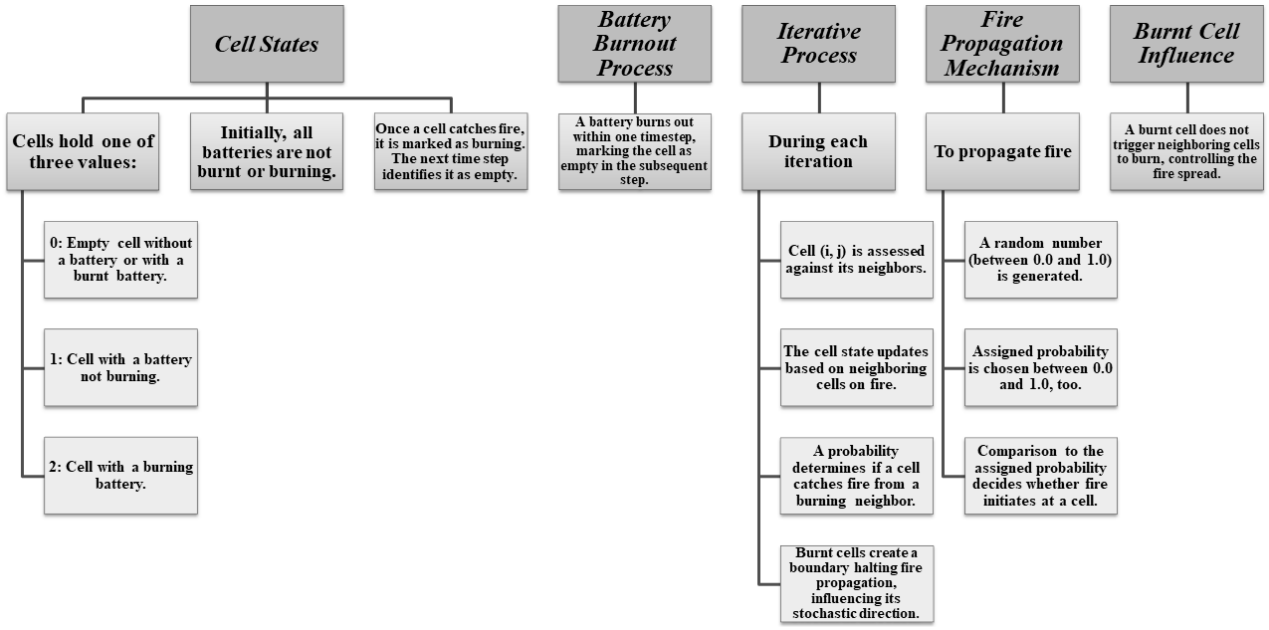


Figure 8. Simulation mechanism and rules.

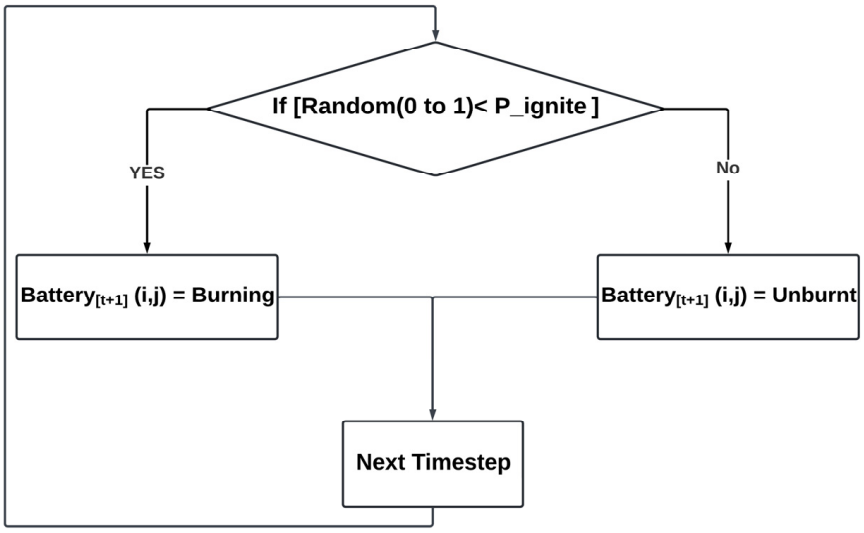


Figure 9. Principle governing fire propagation.

2.3. Experimental Test

An experimental study was performed to calibrate the battery fire propagation with actual battery fire scenarios. Three cylindrical INR (Lithium Nickel Cobalt Manganese Oxide, NMC) 18650 battery cells (Samsung SDI, Yongin-si, Republic of Korea), each at 100% state of charge (SOC), were tested in series with positive-to-negative end alignment. The cells were placed in direct contact, with no spacing between them, to simulate a worst-case scenario that maximizes thermal interaction between the cells. This configuration mirrors real-world applications, particularly the fire propagation in compact battery arrangements found in consumer electronics such as laptops. The cells were secured together with tape wound around the circuit board strips acting as supports along the edges of the cells. An Oster electric hotplate was used to induce thermal abuse, facilitating and simulating a real-world LIB failure mode during the experimental tests. The bottom cell was in contact with the hot plate through its negative end cap, directing any potential positive end-fire event upward into the cell above. Type-K thermocouples were affixed at mid-height positions

along the length of each cell. The thermocouples were connected to an Omega signal conditioner, which converted the signal for the node device. The node transmitted data to a gateway located at a safe distance, connecting via USB to the monitoring computer. Data were logged and displayed in real time using SmartConnect and National Instruments Compact Data Acquisition (DAQ). The experimental setup is shown in Figure 10.



Figure 10. 18650 multi-cell test setups.

Using the recorded time from the experiment as an estimation for each timestep in the simulation, the actual time of burn at the module level is formulated for different fire propagation probabilities:

$$Actualestimationtimepertimestep = t_{fire2} - t_{fire1} \quad (2)$$

$$Estimatedfirepropagationtime = Fire\ spread\ timesteps \times \left(t_{fire2} - t_{fire1}\right) \quad (3)$$

where t_{fire} is the discrete time at a particular fire state.

3. Results

In this section, the probabilistic assessment of fire propagation based on CA and MC simulations is introduced. Subsequently, the experimental test results and the modular simulation are provided.

3.1. Fire Propagation Probabilistic Risk Analysis

The primary objective of this dynamic modeling simulation is to establish the probability and rate of fire spread (in a relative time context) of the battery module. Assigning a probability range between 0 and 1 for fire propagation enables the analysis to calculate both the burning timesteps and the proportion of the battery module affected. However, this probabilistic analysis approximates the likelihood of directional spread originating from a randomly chosen fire source within a densely packed 2-D battery module. While each cell maintains a constant burning duration, the rate of propagation depends on the pathway of spread and the batteries that remain unburnt. It is noteworthy that this study involved 100,000 randomly generated simulations. This extensive number of simulations not only refines prior research but also significantly improves the accuracy in assessing the probability of fire spread.

The main simulation function is invoked to implement the updated parameters. The desired outcomes include a fire damage map alongside the maximum percentage burnt, minimum percentage burnt, average percentage burnt, maximum timesteps, minimum timesteps, and average timesteps for each step. Figure 11 shows an example of the fire map where the fire's origin is marked with an "*". The batteries that are already burnt are represented by a ".", while the batteries that remain unburnt are indicated by an "X".

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XXXXXXX...XXXXXX.XX.XXXX..XXXX..XXXX......X.......X..X
XXXXXX....XXXXXXX..X..XX..........X..........X.....X..
XXXXXX...*XXXXXXX.........X.X...................X.....
XXXXX.....XXXXXXX.X....X...................X..........
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XXXX.........XXXXX.XX...X...........XXXXXXX.X........X
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Figure 11. Example of map of fire damage in simulation: Fire started at "*"; burnt batteries are indicated by "."; and unburnt batteries are indicated by "X".

Figure 12 illustrates the average percentage of burnt batteries for different probabilities. At a probability of approximately 0.6 of a single cell igniting, nearly the entire battery module is burnt (~100 percent). Conversely, if the propagation probability remains at or below 0.4, a fire starting in a single cell will not extend throughout the entire module.

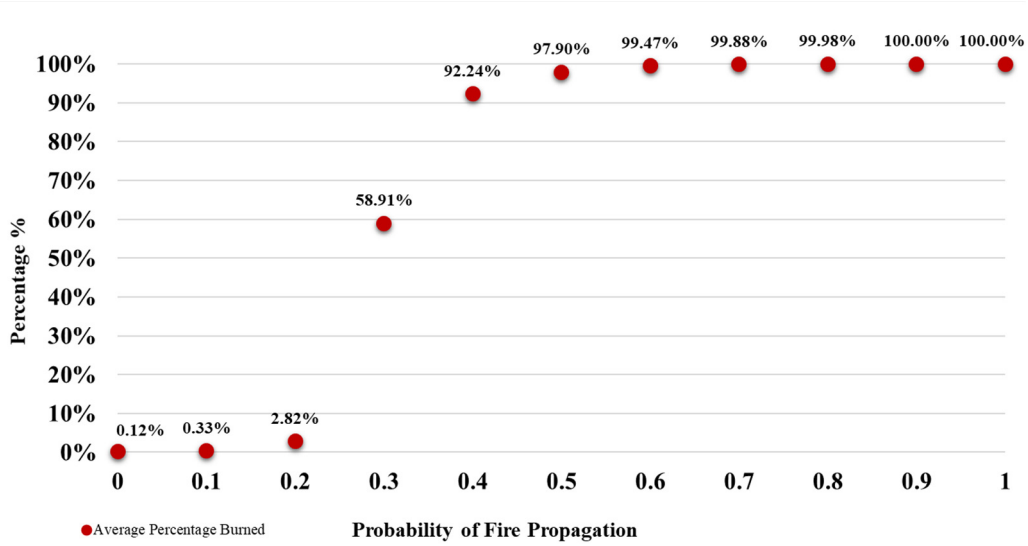


Figure 12. Impact of cell ignition probability on battery burns.

Furthermore, the timesteps required for the battery pack to be fully burnt exhibit substantial variability, as demonstrated in Figure 13. This variance appears to be directly linked to the potential fire scenarios and aligns with the percentage of the batteries consumed by fire. On average, approximately 42 timesteps are necessary for the battery pack to be fully burnt.

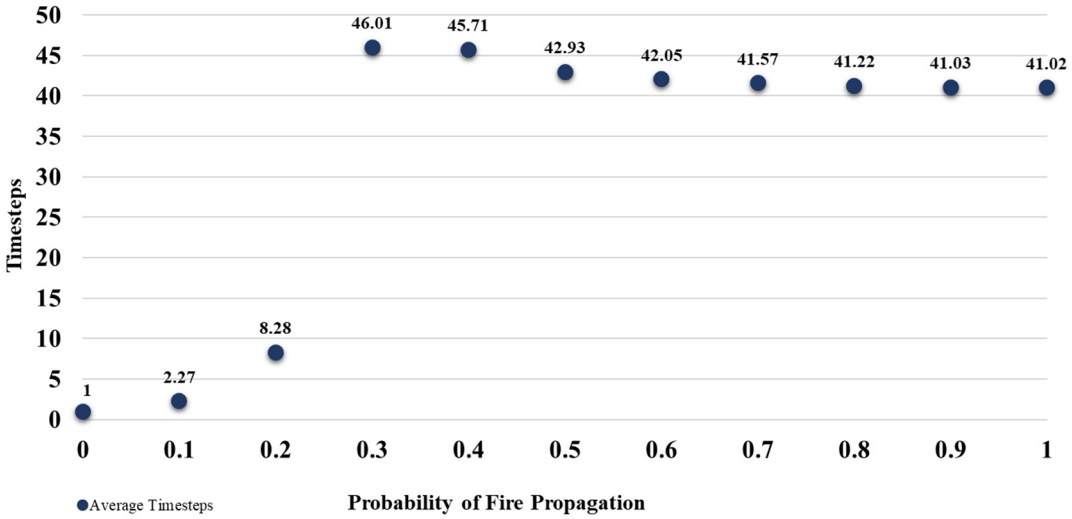


Figure 13. Variability in battery burn timesteps.

3.2. Experimental Fire Propagation Results

Figure 14 shows the temperature variation observed during the experiment in the bottom battery cell. The maximum temperature recorded throughout the test was 345.5 °C. The bottom cell exhibited multiple temperature peaks due to the multi-stage thermal runaway processes, along with the continued thermal input from the cells positioned above it.

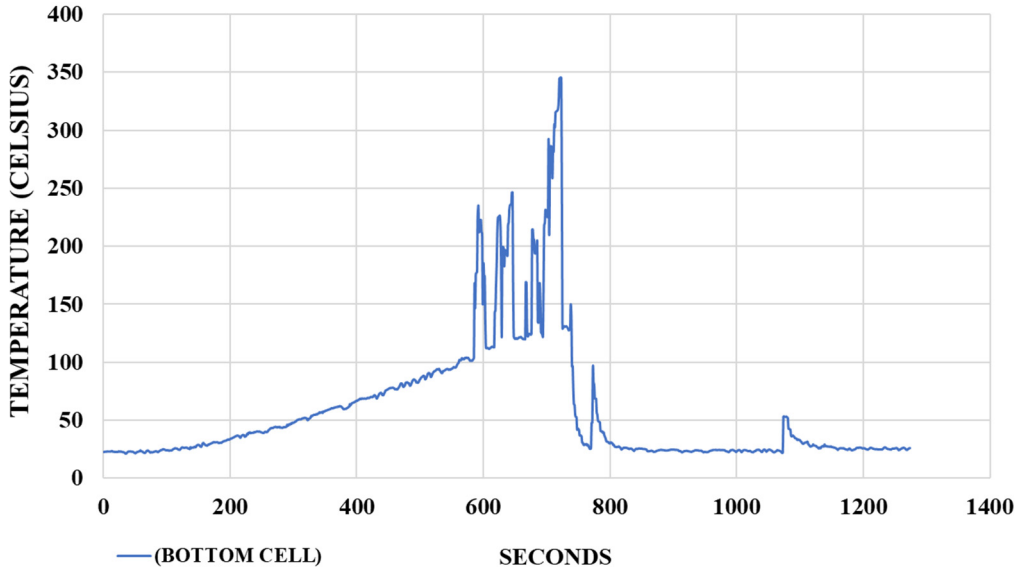


Figure 14. Thermocouple data for temperature variation vs. time (bottom cell). (data collection with SensorConnect).

Figure 15 shows the temperature variation over time for the middle and top battery cells, where the maximum temperature recorded was 847.46 °C, and 234.35 °C, respectively. It should be mentioned that after the fire event progression, the thermocouple attached to the middle cell detached due to the ignition process. However, the cooling process was captured, where a temperature of 678.18 °C, approximately 11 s after the second ignition, was recorded. The drastic increases in the temperatures of the middle and top cells are attributed to the occurrence of fire events.

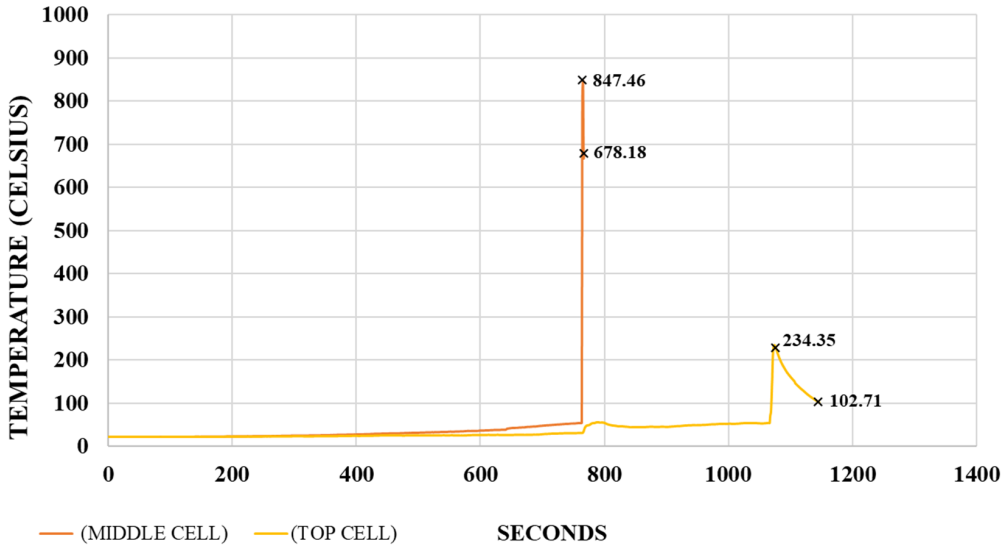


Figure 15. Thermal data for temperature variation vs. time (middle and top cell) (data collected with DAQ).

Figure 16 illustrates an explosive fire incident during the first and second battery ignitions, respectively. Both smoke and flames emanated from the battery during the fires.



Figure 16. The first and second fire event snapshots: (**a**) Moment of 1st ignition bottom cell, initial sparks [13:22 (vid.), 757 s (data)]; (**b**) Moment of 2nd ignition, 2nd cell, sparks [1:24 (2nd vid.), 1061 s (data)].

4. Discussion

4.1. CA Simulation Calibration

The simulation results provide an initial understanding of the probability of fire spreading within the battery module. At each discrete timestep, the simulation assesses the state of each cell in the forthcoming step based on its present condition. By advancing the timesteps, the simulation constructs a new grid for the subsequent timestep. A critical parameter in this context is the actual time when the burning occurred. Experimental test data can offer the necessary insight to apply the actual fire event timing to the large-scale battery facility and, consequently, convert the obtained timesteps from simulation to the actual time of fire spread. The resulting conversion of simulation timesteps to actual fire event time is shown in Table 1.

Table 1. Fire event data collection.

Fire Event 1 (s)	Fire Event 2 (s)	Rate of Fire Spread (s)
757	1061	304

According to the data collected from the experimental tests, the initial fire event occurs at 757 s, while the second fire event takes place at 1061 s. Using Equation 2, the rate of fire spread was calculated as 304 s (5.06 min), and using Equation 3, the different burning times for different fire propagation probabilities were calculated and are presented in Table 2.

Table 2. Actual time of burn in different probabilities.

Probability	Timesteps	Burning Time (h)
0	1	0.08433
0.1	2.27	0.19144
0.2	8.28	0.69828
0.3	46.01	3.88018
0.4	45.71	3.85488
0.5	42.93	3.62044
0.6	42.05	3.54622
0.7	41.57	3.50574
0.8	41.22	3.47623
0.9	41.03	3.46020
1	41.02	3.45936

Variations in battery topologies can lead to distinct fire propagation scenarios. At the cell level, the two primary designs are cylindrical and flat pouch shapes. These structural differences significantly influence failure and fire propagation mechanisms. For example, cylindrical batteries often exhibit more explosive behavior compared to pouch cells, highlighting how packaging design affects failure modes and underscoring the critical connection between fundamental research and advancements in battery technology.

Battery fire at the stack or rack level is a complex physio-chemical phenomenon that involves not only battery chemistry but also includes the packaging design, rack support design, battery management system (BMS) and sensors, cooling system, electronic wiring, and central controls [38–40]. The numerical simulation of the entire stack performance during a fire is multi-physical and too complicated for a single numerical modeling scheme. CA-MC modeling simplifies these interactions and can provide an estimate of the time for battery fire propagation. Battery fire research requires the involvement of two key elements: advancements in battery technology development and oversight by a multidisciplinary team of regulatory agencies. However, the transfer of knowledge between agencies can be time-consuming, and instruments (translational research) that can help accelerate interagency collaborations are needed.

4.2. CA Modeling for Battery Fire Translational Forensics

The advancement of battery technology encompasses various aspects of modern life, driven by the widespread use of microelectronics and mechatronics, which form the foundation of most contemporary electronic devices. Notably, a global awareness of LIB fires first emerged from incidents involving cell phone and laptop batteries [41]. Therefore, translational research must engage a wide range of regulatory bodies, including fire protection agencies, building code committees, the electronic packaging and design industry, federal risk response organizations (such as FEMA and DHS), energy and transportation

authorities, and medical emergency groups. Representation from the medical field is crucial, as battery-powered medical equipment and facilities housing such devices also face fire risk. The implications extend to additional federal and state agencies; for example, the US Naval Research Laboratory has published testing and mitigation guidelines for batteries intended for military use [42].

With further development in modeling techniques, the current CA-MC modeling can be extended to several other aspects of battery fire science and management studies. Drawing parallels from the forest fire literature, where CA has been applied to simulate fire propagation and fire prevention, this modeling technique applies to different aspects of LIB technologies. Figure 17 illustrates the different simulation parameters required for extending CA modeling to different aspects of battery fire research including cell chemistry, heat propagation, and factors affecting internal short-circuiting at the cell level, environmental factors and fire jump probabilities at the rack level, heat transfer rate and thermal properties when considering surrounding structures, fire detection and extinguishing, insulation material characteristics and site ventilation design for preventive measures, and residual material characteristics and storage site conditions for battery disposal.

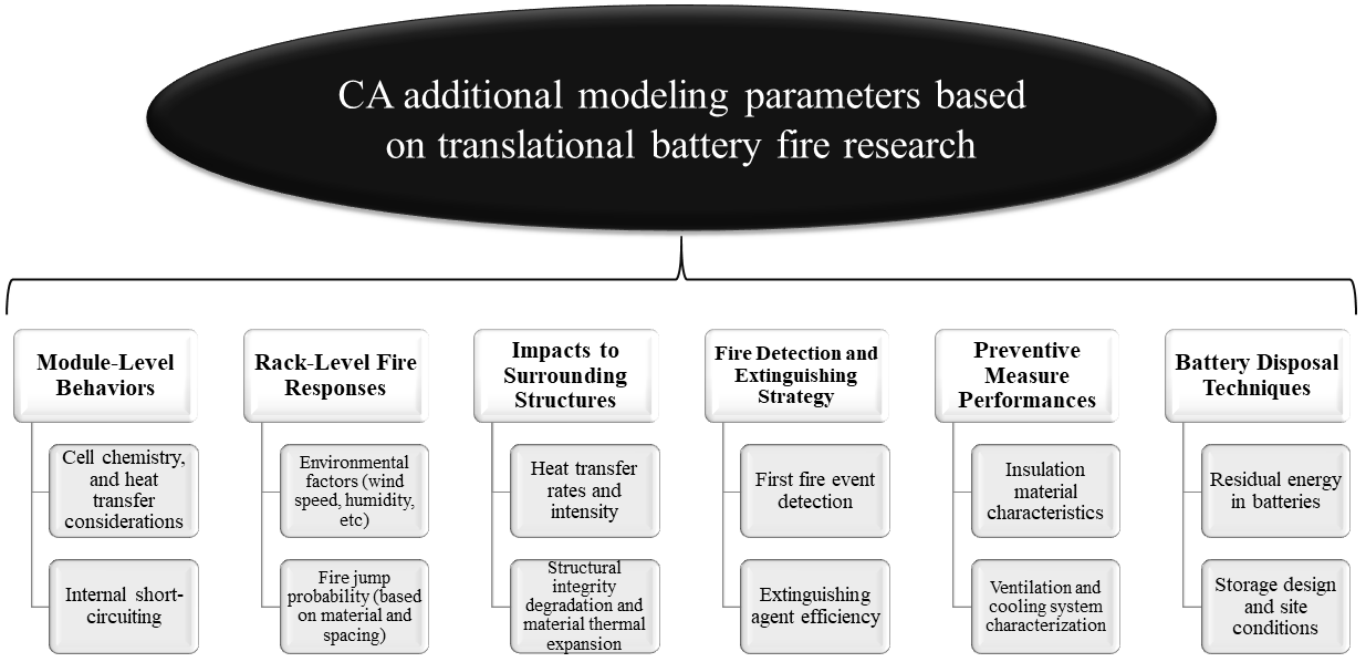


Figure 17. Cellular automata modeling parameters extended from translational battery fire forensics.

The incorporation of advanced analytical techniques such as machine learning can further enhance the capabilities of CA modeling, transforming it into a valuable tool for translational forensic applications. This potential has already been demonstrated by Grieshop and Wikle [28], who integrated a Markov chain Monte Carlo (MCMC) Gibbs sampler with an ordinal categorical CA modeler. Gilpin further suggested the use of cellular automata within the framework of convolutional neural networks (CNNs), resulting in the concept of a learning cellular automaton [43].

As we progress along the translational forensic pathway, a clear interdependence emerges between battery packaging, firefighting technologies, and regulatory code development. Currently, suppressing LIB fires typically necessitates the prolonged application of water or other extinguishing agents directly to the affected cells. Therefore, battery modules must be designed with accessibility for firefighters in mind. Effective firefighting strategies must prioritize access to batteries, while battery packaging designs should incorporate safety access as a critical consideration. Additionally, battery housing can be designed in such a way that compartmentalization and insulation provide fire protection to the batteries, and battery application can focus on providing appropriate fire separation distance—two

strategies that can be employed to aid in fire safety code development and code compliance. This can be the next goal for future CA modeling development. Figure 18 summarizes both the CA-MC modeling scheme outlined in the current paper and its application to translational research envisioned. As shown, CA-MC can be applied to cell-to-module, module-to-rack, and rack-to-facility translations. Thus, CA-MC can be developed into an all-encompassing instrument to translate the advancements in each level of battery fire research to other levels.

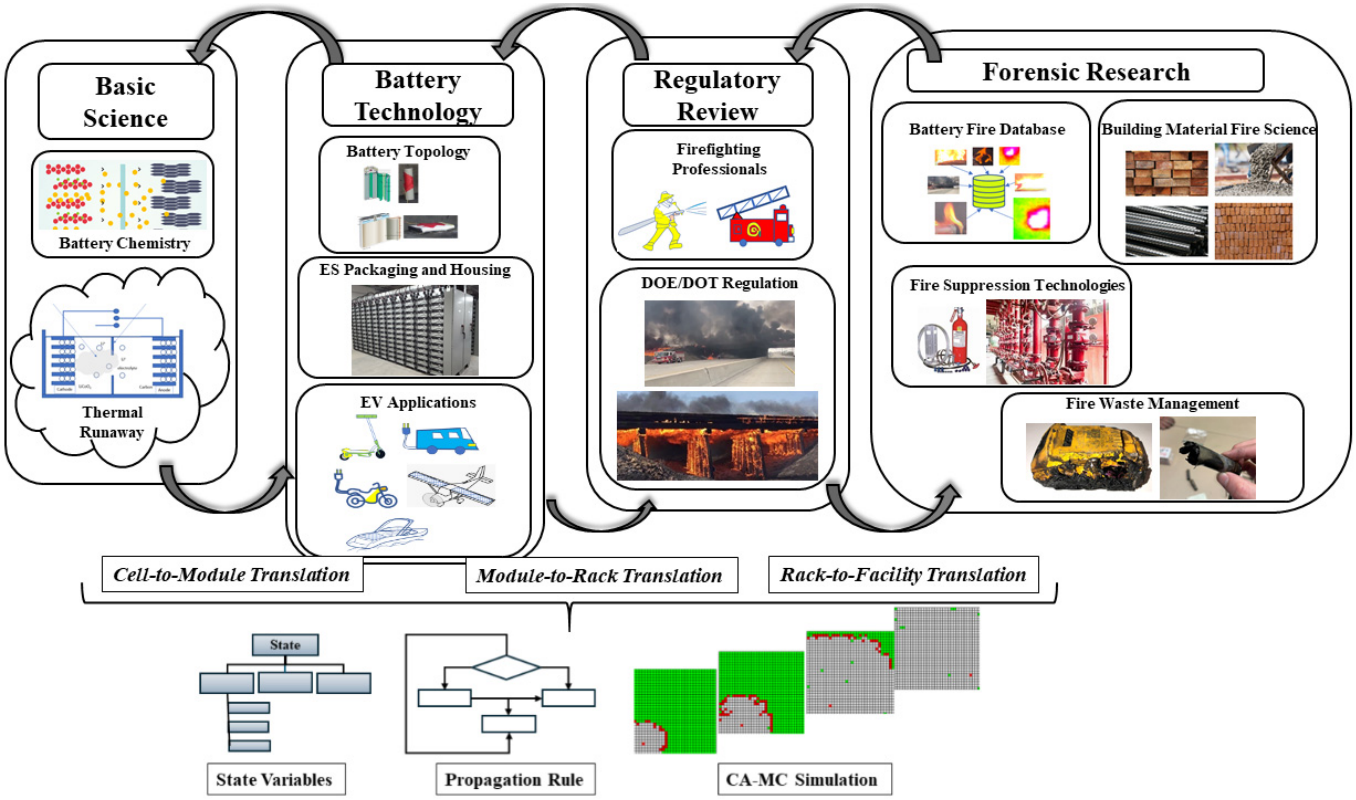


Figure 18. CA-MC modeling applications for translational research between different agencies and levels of research.

Ultimately, the proposed battery fire translational forensics aims to unify practical strategies for fire safety in buildings, battery fire prevention and suppression, and effective waste management. Success hinges on seamless collaboration among the research, development, and implementation sectors. Implementing CA modeling can convert the LIB fire safety challenge into a simulation-driven translational tool for the industry and beyond.

5. Conclusions

The cellular automata approach is a tool for modeling highly complex and dynamic systems and has been applied to wildfire propagation analyses. The modeling technique utilizes simple interaction and fire propagation rules to explain otherwise complex natural phenomena. While successful in modeling general physical, biological, and medical systems, CA has been used extensively in the simulation of forest fires. This paper extends the modeling technique to the study of multiple LIB fire propagation with calibrated fire propagation times from actual experiments. The successful modeling demonstrated the effectiveness of expanding CA for large-scale battery fire safety studies.

In the present investigation, a new model for LIB fire propagation risk assessment based on CA and Monte Carlo simulation has been proposed. In this regard, some of the remarkable outcomes are summarized below:

With respect to the rise in the probability of fire propagation, at 0.3 probability, more than half of the battery module will be lost. Also, at 0.6 probability, the fire will spread to almost the entire module by about 99.47%. The average timesteps of fire propagation from the simulation at 0.6 probability, which leads to approximately total burn, are calculated to be about 42 steps.

This paper outlines the need for translational research and the potential role of CA in modeling system-level responses at all aspects of LIB fire research from model-level performance to battery disposal strategies. This includes the necessity to develop different system parameters for each aspect of the study, be it fundamental battery fire studies (cell level), battery packaging design (module and rack levels), fire prevention (suppression and detection), or battery disposal. For each aspect of the study, a separate set of simulation parameters should be developed and quantified.

The CA-MC modeling of LIB fires is presented with the purpose of establishing a strategy for translational forensics for the entire battery industry. Citing forest fire studies as an example, CA-MC modeling can be creatively expanded to embrace any large and complex systems. Hence, it is an ideal tool to instrument translational research for the battery fire industry.

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