

Toward an Operational Integration of Drones into Immersive Simulation Applied to Civil and Industrial Safety: Design, Applications, and Perspectives of the EVE©-Drone Model



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Keywords

Immersive simulation, virtual reality, multi-agent systems, multi-UAV coordination, adaptive cognition, situational awareness, human–machine cooperation, multi-sensor fusion, embedded artificial intelligence.

Abstract

This article analyzes the operational integration of drones within immersive simulation systems applied to civil and industrial safety. It examines the transformation of aerial sensor data into actionable information for decision-making, as well as the mechanisms of human–machine cooperation in complex virtual environments. The study highlights the contributions of multi-agent systems, multi-sensor fusion, and embedded artificial intelligence to enhancing situational awareness. Finally, it discusses the current limitations and future perspectives of these approaches for operational training and the validation of intervention doctrines.

Introduction

The multiplication of unmanned aerial systems (UAS) in activities related to civil — and also military — safety requires an adaptation of learning and training methods. Recent work by Somerville (2024) highlights the necessity of integrating more immersive and adaptive simulation environments in order to better prepare operators for the dynamic and complex conditions of real

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missions.² Volkov and Komar, 2019³ ; Kuchеров, 2023⁴ tend to demonstrate that simulation — and virtual reality (VR) — can significantly enhance operator preparedness while reducing both cost and risk.

We present here several research and development components resulting from the integration of an operational simulator — initially designed for training — with a drone component tested in complex virtual environments. This approach aims to assess the prospects for human–machine (AI) cooperation, the transformation of drone-generated data into actionable information, and the replicability of multi-environment operational scenarios within immersive contexts.

Our project aims to integrate the use of drones across all EVE© scenarios, within diverse operational environments. The objective is not technical piloting but human training — the operators’ ability to analyze, decide, and coordinate. In this framework, drones are employed as sensors and data carriers (rather than mere sources of raw information) for reconnaissance, measurement, and decision support. Typical applications include thermal detection, victim search, post-crisis reconnaissance, and damage assessment.

Simulation enables the integration of diverse data streams (video, thermal, or 3D mapping) within the EVE© ecosystem, paving the way for interservice training and procedure validation.

The ultimate objective is the development of integrated human–drone–AI training, capable of reproducing multiple environments and enhancing both situational awareness and operational coordination.

Our approach follows this same trajectory but differs by maintaining a strictly operational objective: it is not about learning how to pilot a drone, but about learning how to act during a mission by integrating drone-generated data streams into decision-making. Whereas traditional simulators emphasize aerial maneuvering, the method reproduces a complete tactical environment in which the operator must analyze, coordinate, and interact with both human and algorithmic systems. Unlike platforms centered on individual piloting, the EVE© system primarily trains field operators for the conduct of integrated missions. As a collaborative and immersive tool, EVE©

² A. Somerville, (2024). Use of Simulation for Pre-Training of Drone Pilots. *Drones*, 8(11), 640. DOI: <https://doi.org/10.3390/drones8110640>

³ Volkov, Oleksandr., Mykola Komar., Kateryna Synytsya., et Dmytro Volosheniuk, (2019). “The UAV Simulation Complex for Operator Training.” *Proceedings of the International Conference on e-Learning 2019*. (https://www.researchgate.net/publication/335375137_THE_UAV_SIMULATION_COMPLEX_FOR_OPERATOR_TRAINING).

⁴ Kuchеров, D. et alii (2023). “Assessing the Readiness of UAS Operators Based on the Simulation Complex.” *CEUR Workshop Proceedings* 3624 (Paper 9) (https://ceur-ws.org/Vol-3624/Paper_9.pdf).

reconstructs 3D operational environments from real data, thus providing a ready-to-use simulation framework for collective training and for validating intervention doctrines.

Moreover, beyond its relevance for the training of first responders —as confirmed by the research of Chen et al. (2023)⁵ and Chan (2024)⁶ —our findings further indicate that highly realistic virtual environments constitute a critical lever for the joint training of human operators and artificial intelligence systems, particularly in multi-agent coordination scenarios where behavioral synchronization and information flow directly determine collective performance.

Keywords — *Reinforcement learning; distributed self-organization; adaptive cognition; situational awareness; human–machine (AI) cooperation; verifiable distributed control doctrine; firefighting drones; drone swarms (swarm control); tactical AI experimentation; embedded AI and adaptive planning; human–drone interfaces and embedded systems; integrated mission planner; immersive operational simulation; VR-CRISE / EVE©-Drone; virtual reality applied to crisis management.*

I. Technological Context and Market Maturity

Our approach fits within a rapidly expanding market segment: drones dedicated to firefighting. The simulation products represent an enabling technology supporting this growth and market maturity. The combination of a firefighting drone module with virtual reality is particularly relevant, as these systems are evolving rapidly both technologically and commercially.

According to *Future Market Insights* (2025),⁷ the global firefighting drone market is estimated at USD 2.2 billion in 2025 and is expected to reach USD 6.3 billion by 2035, representing an average annual growth rate of approximately 11%. Among the key contributing factors are the increasing number of urban and forest fires, the growing demand for prevention technologies, and the miniaturization of onboard sensors.

The emergence of new technological standards in this sector will have medium-term structuring effects: the combination of thermal cameras, high-resolution optical sensors, and autonomous navigation systems now makes it possible to map and analyze an incident rapidly and safely. This technological and commercial momentum generates—and will continue to generate—a parallel need for specialized operator training, fully justifying the use of interactive and immersive simulations.

⁵ Chen, Z. et al. (2023). A Survey on Open-Source Simulation Platforms for Multi-Copter UAV Swarms. *Robotics*, 12(2), 53. DOI: <https://doi.org/10.3390/robotics12020053>

⁶ Chan, J.H. (2024). Reinforcement Learning-Based Drone Simulators: Survey, Taxonomy, and Trends. *Artificial Intelligence Review*. DOI: <https://doi.org/10.1007/s10462-024-10933-w>

⁷ <https://www.futuremarketinsights.com/reports/firefighting-drone-market>

The rapid growth of the firefighting drone market thus enables the training sector to reach a critical mass. In this context, the combination of drones and virtual reality becomes a concrete lever for modernizing civil-safety response capabilities.

II. Drone modeling and simulation

Strictly speaking, conventional drone flight simulators have a limited role: to teach piloting. This entails priorities such as the realism of flight dynamics — physical models, inertia, and the behavior of multirotor or VTOL drones. A drone simulator is, in fact, a program that reproduces flight behavior and real environmental conditions. It simulates aerodynamics, sometimes in a far more sophisticated way than certain widely used software tools such as *AirSim*⁸. Likewise, for this type of tool, engine response and sensor feedback—allowing pilots to train for takeoff, navigation, and emergency procedures—remain a major challenge. From this perspective, an effective simulator is one that integrates the physical and dynamic variables influencing algorithm performance. In this sense, recent simulators incorporate FPV views, transmitter configuration, and compatibility with professional controllers, providing enhanced realism. Similarly, the diversity of flight environments—urban, forest, or post-crisis—has now become a common standard.

The VR-based operational simulator was originally designed for human tactical training in complex environments. Unlike simulators focused on piloting skills, this platform—integrated into the immersive EVE framework—trains human operators in missions such as hot-spot detection (in the firefighting sense), post-bombardment reconnaissance, and support for debris-clearing operations. The physico-dynamic flight model remains deliberately simplified while maintaining compatibility with physical control devices used on commercial and firefighting drones.

The integration of the VR simulator with a drone component primarily serves to train operators and first responders within a reproduced operational environment and to test doctrines of coordination and interservice integration (rescue services, fire brigades, civil–military debris-removal teams, reconnaissance units). In the short term, the key issue of this VR + drone association also lies in testing hardware–software interfacing with real or realistic controllers available on the commercial market. In the longer term, the objective is the algorithmic learning of artificial-intelligence modules integrated into a realistic operational context, particularly for automatic detection and adaptive planning.

Recent literature (Peña et al., 2022; Nagasawa et al., 2021) highlights the growing importance of hybrid simulators that combine virtual environments, multi-UAV coordination, and sensor data processing (optical and thermal). Nagasawa et al. present a multi-drone coverage approach for the

⁸ Kim, Woosung, Tuan Luong, Yoonwoo Ha, Myeongyun Doh, Juan Fernando Medrano Yax, and Hyungpil Moon. 2023. “High-Fidelity Drone Simulation with Depth Camera Noise and Improved Air Drag Force Models.” *Applied Sciences* 13, no. 19: 10631. <https://doi.org/10.3390/app131910631>

simulated 3D reconstruction of post-disaster damaged buildings. The methodology was implemented in NetLogo3D, a multi-agent modeling environment, and later tested in a virtual built environment using Unity3D.⁹ Peña et al. describe a cooperative multi-drone system collaborating during remote sensing missions. The researchers developed a multi-agent model, first tested again in NetLogo3D and then reproduced in a three-dimensional Unity3D environment to evaluate collective behavior. The experiments show that this approach improves terrain coverage and execution speed while minimizing interference among drones through adaptive coordination.¹⁰

From this perspective, the drone component's role is less to deliver raw information ("seeing events from above") than to provide actionable data. Raw information or data consists of unprocessed measurements or captures (images, telemetry, GPS coordinates, audio streams, etc.) collected by the drone or its sensors. Actionable data emerges when this information is filtered, correlated, and contextualized—for example, the geolocation of a confirmed hot spot. This transition from raw to analyzed data requires processing that includes multi-sensor fusion, artifact cleaning (removal of visual or digital noise from sensors), precise time-stamping for temporal synchronization, and alignment with an operational model.¹¹

In a VR simulator, it is both relevant and necessary to reproduce what can be described as the "texture" of raw data (latency, noise, viewing angle) while simultaneously providing the layers of actionable information required for decision-making.¹² Situational awareness is characterized by three levels: perception, comprehension, and projection. Ultimately, operational value depends less on the volume of data than on the quality of its processing and presentation (visualization, alerts, and filtering options).

III. The EVE©-Drone System: Architecture, Interface, and Adaptive Learning

The EVE-Drone© system is based on a multilayer architecture that integrates an advanced virtualization layer faithfully reproducing an operational environment—either a building and its

⁹ Nagasawa, R., et al. 2021. "Model-Based Analysis of Multi-UAV Path Planning for 3D Reconstruction of Post-Disaster Buildings." *Scientific Reports* 11: 22221. <https://doi.org/10.1038/s41598-021-97804-4>.

¹⁰ Flores Peña, Pablo, Marco Andrés Luna, Mohammad Sadeq Ale Isaac, Ahmed Refaat Ragab, Khaled Elmenshawy, David Martín Gómez, Pascual Campoy, and Martin Molina. 2022. "A Proposed System for Multi-UAVs in Remote Sensing Operations" *Sensors* 22, no. 23: 9180. <https://doi.org/10.3390/s22239180>

¹¹ Harris DJ, Arthur T, Kearse J, Olonilua M, Hassan EK, De Burgh TC, Wilson MR and Vine SJ (2023), Exploring the role of virtual reality in military decision training. *Virtual Real.* 4:1165030. doi: 10.3389/frvir.2023.1165030 <https://www.frontiersin.org/journals/virtual-reality/articles/10.3389/frvir.2023.1165030/full?utm>

¹² Piaseczna, Natalia, Rafał Doniec, Szymon Sieciński, Klaudia Barańska, Marek Jędrychowski, and Marcin Grzegorzek. 2024. "Driving Reality vs. Simulator: Data Distinctions" *Electronics* 13, no. 14: 2708. <https://doi.org/10.3390/electronics13142708>

immediate surroundings or a natural area whose dimensions vary according to the specific mission requirements. This layer uses 3D mapping derived from real geospatial data and relies on a library of photorealistic objects and avatars (intervention vehicles, firefighting equipment, and visual effects such as flames, smoke, explosions, foam flows, or debris). When applicable, it can be supplemented by the EVE© database, which catalogs physicochemical effects and their potential interactions—including domino effects likely to occur during technological or industrial incidents.

The entire system thus combines a simplified drone flight engine, simulated optical and thermal sensors based on physical models, and a hardware interface compatible with real peripherals. This modular structure connects aerial simulation to a coherent and realistic operational environment. Two experiments illustrate this approach: the first, conducted with a civil–military drone manufacturer, focused on post-disaster reconnaissance and 3D analysis of damaged structures; the second, carried out with a fire and rescue department in southern France (aka. SDIS), dealt with the detection and thermal characterization of residual hot spots. The evaluations assess operator precision, cognitive load, and the performance of decision-support algorithms, with the objective of progressively integrating adaptive intelligence and achieving field validation.

Interaction with operators is achieved through interfaces compatible with real piloting peripherals and external planners. For integrated drones, the flight model is based on simplified kinematics ensuring fast and smooth response while maintaining altitude and speed constraints. The optical simulation module accounts for focal length, resolution, and sensor noise, while the thermal module, based on a simplified heat diffusion model, enables operators to train effectively in hot-spot detection.

The EVE©-Drone system prioritizes a modular architecture that promotes interoperability among the flight engine, virtual environment, and control interfaces. This approach allows seamless integration of new sensors, mission planners, or peripherals without altering the software core.

Whereas Volkov and Komar (2019) primarily emphasized strict functional separation for stability reasons, we introduce a logic of dynamic exchange and standardization of data flows, more consistent with the flexibility and continuous evolution required by immersive environments and next-generation simulators. We therefore adopt a simplified kinematic flight model, more consistent with the practices of training-centric simulators (Kille et al., 2021)¹³, ensuring responsiveness and low latency while preserving the operational constraints selected as relevant. The essential focus lies in the interpretation of the data transmitted by the drone or drones, not in mastering the fine combinatorial subtleties of hyper-realistic flight dynamics. Visualization and virtualization modes are designed to reinforce professional situational awareness.

¹³ Kille, T., Bates, P. R., Lee, S. Y., & Kille, D. M. (2021). “Situational Awareness Training for Operators of Unmanned Aerial Vehicles”. *21st International Symposium on Aviation Psychology*, 391-396. https://corescholar.libraries.wright.edu/isap_2021/65

IV. Use cases

The two R&D applications mentioned above illustrate the system: cooperation with a European drone company for post-disaster reconnaissance integrating 3D reconstruction and cross-platform coordination, and experimentation with a southern France fire and rescue department for thermal anomaly detection supported by automatic recognition algorithms. These applications, developed through cooperation, are consistent with the training and collective operation recommendations for drones presented by Salamí et al. (2020)¹⁴ and Checker (2025)¹⁵, which emphasize the importance of networked UAV collaboration in multi-objective scenarios.

With the drone manufacturer, we are developing a module tailored for future quadcopters—initially for rescue and post-disaster assessment missions, and later for operations related to civil safety. In this phase, the simulator focuses on 3D reconnaissance of damaged structures and coordination between fixed-wing and rotary-wing drones.

With the fire and rescue department, the approach prioritizes contextual fidelity and is coupled with an algorithm developed by a university laboratory to analyze thermal data and automatically detect hot spots.

Research conducted in recent years—particularly that of Alqudsi et al. (2025)¹⁶ and of Li et al. (2024)¹⁷—confirm this trend of placing adaptive cognition at the core of simulation systems. The challenge is no longer flight control or the management of an isolated system, but the coordination of multiple entities acting under principles of self-organization. In this framework, joint human-machine training becomes a privileged experimental domain: when calibrated with realistic parameters of complexity, simulators offer an unparalleled field of observation for the analysis of assisted collective behavior. They make it possible to test algorithms serving diverse functions while evaluating the human capacity to maintain operational situational awareness.

The transition to drone-swarm operations—transmitting meaningful yet non-overloading interpretive data to human operators—is not only possible and already emerging, but must now be

¹⁴ Skorobogatov, G., Barrado, C., & Salamí, E. (2020). “Multiple UAV Systems: A Survey”. *Unmanned Systems*, 8(2), 149-169. <https://doi.org/10.1142/S2301385020500090>.

¹⁵ Checker, L., H. Xie, S. Khaksar, and I. Murray. 2025. “Systematic Review of Multi-Objective UAV Swarm Mission Planning Systems from Regulatory Perspective.” *Drones* 9 (7): 509. <https://doi.org/10.3390/drones9070509>

¹⁶ Alqudsi, Y., et al. 2025. “UAV Swarms: Research, Challenges, and Future Directions.” *Journal of Engineering and Applied Science*. <https://doi.org/10.1186/s44147-025-00582-3>.

¹⁷ Li, Y., C. Li, J. Chen, and C. Roinou. 2024. “Energy-Aware Multi-Agent Reinforcement Learning for Collaborative Execution in Mission-Oriented Drone Networks.” *arXiv preprint arXiv:2410.22578*. <https://arxiv.org/abs/2410.22578>.

addressed within simulation tools. Ultimately, research converges toward a single objective: increasing operational performance without compromising the operator's cognitive clarity.

One of the major limitations here is the absence—or incomplete development—of an integrated mission planner: software capable of directly transforming simulation scenarios into real flight plans, or vice versa, in order to ensure continuity between real-flight preparation and simulation (GPS waypoints, speeds, altitudes, automatic sequences). In its absence, the chain between virtual training and operational mission is disrupted, and more empirical solutions must be adopted.

The transition toward autonomously behaving swarms introduces additional requirements and challenges, as highlighted for example by Checker (2025)¹⁸ — the integration of AI modules for dynamic trajectory management, the use of deep reinforcement learning¹⁹ to optimize collective responses, or *hardware-in-the-loop* experimentation,²⁰ and to bring simulation closer to real physical conditions. These emerging developments—which, when relevant, should increasingly be reflected in simulation tools—represent a decisive step toward a controlled and verifiable distributed-control doctrine.

Conclusion

The EVE© simulator, combined with its drone component, begins to illustrate a renewed approach to training and operational preparedness that potentially merges immersive virtual reality, multi-drone coordination, and AI-assisted decision-making.

By emphasizing mission execution rather than piloting skill alone, it enables operators to interpret real-time data, refine situational awareness, and practice coordinated collective responses across diverse environments.

Experiments conducted within the R&D program confirm the platform's potential to strengthen civil-safety capabilities and promote the development of adaptive systems based on artificial intelligence. Ultimately, EVE-Drone© demonstrates how immersive simulation can serve as a concrete enabler for more integrated, efficient, and synchronized crisis management among multiple actors.

¹⁸ Checker, Luke et alii, op. cit.

¹⁹ Chen, J., H. Xie, S. Khaksar, and I. Murray. “Application of Self-Play Deep Reinforcement Learning in Task Planning for UAV Swarms under Capacity Constraints.” *Proceedings of the ACM/IEEE Conference on Intelligent Systems and Applications*, October 2025. <https://doi.org/10.1145/3757110.3757143>

²⁰ Xin, Ziwei, Jie Li, Ziquan Wang, and Juan Li. “A Hardware-in-the-Loop Simulation Platform for UAV Swarm Decision-Making.” In *Proceedings of the 2021 5th Chinese Conference on Swarm Intelligence and Cooperative Control (CCSICC 2021)*, Lecture Notes in Electrical Engineering, vol. 934, 189-199. Springer, 2023. https://doi.org/10.1007/978-981-19-3998-3_19