MULTI-OBJECTIVE OPTIMIZATION OF SATELLITE AND SENSOR DATA FOR STRATEGIC URBAN PLANNING AND DISASTER MANAGEMENT USING AI AND ENGINEERING MODELS

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Abstract
Today, cities experience increasingly frequent pressure due to the dense population, overloaded infrastructure, and natural calamities that emerge as the result of climate changes. The combination of space and sensor data and artificial intelligence (AI) and engineering models makes it a revolutionary solution to strategic planning of cities and disaster response management. In this paper, a multi-objective optimization framework with the capabilities of considering competing objectives without undermining its intended purpose in urban development is presented based on stochastic modeling, sensor fusion, and AI-driven decision support capabilities. The proposed model serves to optimize the variables of urban design as it uses stochastic differential equations and Pareto optimization methodology to compensate the uncertainty of the terms and the climate indicators based on the real-time geospatial data with environment sensor networks. The case studies in areas prone to earthquakes and flood prone demonstrate how our method can be applied in zoning, evacuation plan and in reinforcing infrastructure. These findings show that the response time, resource allocation, and prediction accuracy have been shown to have improved considerably. Moreover, the study points out the significance of dealing with a large variation in nonlinear systems and initiates the theory of bifurcation analysis to predict tipping points in urban resilience. The paper highlights how AI and engineering synergy have taken a pivotal role in transforming city administration and readiness to take risks. As an integration of state-of-the-art modeling and real life sensor feedback, this piece presents a flexible, adaptive data-driven intensive system of urban planning and disaster creation.

Keywords:- Multi-objective optimization, Satellite data, Sensor fusion, Urban planning, Disaster management, Artificial intelligence, Stochastic differential equations, Nonlinear systems, Bifurcation analysis, Large deviation theory

I. Introduction

Cities are becoming more sophisticated, active systems which are affected by the high population growth, climatic changes, uncontrolled development of the city and the changes in technology. The combination of these environmental, social and infrastructural strains has led to an emergence of new demands to real-time, data-informed urban planning and disaster management. Conventional planning methods, whose major foundations are fixed data, past precedence, and top-down rule, are more than just no longer compatible to deal with the dynamism and uncertainty of contemporary cities. In this respect, this area of artificial intelligence (AI), satellite flights, and sensor-enabled ground data turns out to be a new paradigm capable of supporting the modeling, monitoring, and management of the urban systems in an integrative, evolutionary fashion. Urban planning is not a field of zoning back in the 1940s or an infrastructure project anymore; rather, it has taken up the agenda of anticipatory disaster risk reduction, climate-resilient design, and multi-stakeholder coordination. At the same time, the vulnerabilities of urban systems and insufficiency of reactive response to both natural, e.g., earthquakes, floods, and hurricanes, and anthropogenic, e.g., industrial accidents, disasters have proven the inefficiency of the current systems and structures used in urban systems to avert and/or respond to the crisis. This sheds light to the reasons why researchers and policymakers are on the hunt of proactive solutions that rely on predictive analytics; real-time data fusion, and system-level optimization. This shift has a technical foundation with the high-resolution satellite, remote sensing, ground-based Internet of Things (IoT) sensors, as well as machine learning, neural networks, and fuzzy logic techniques of AI.

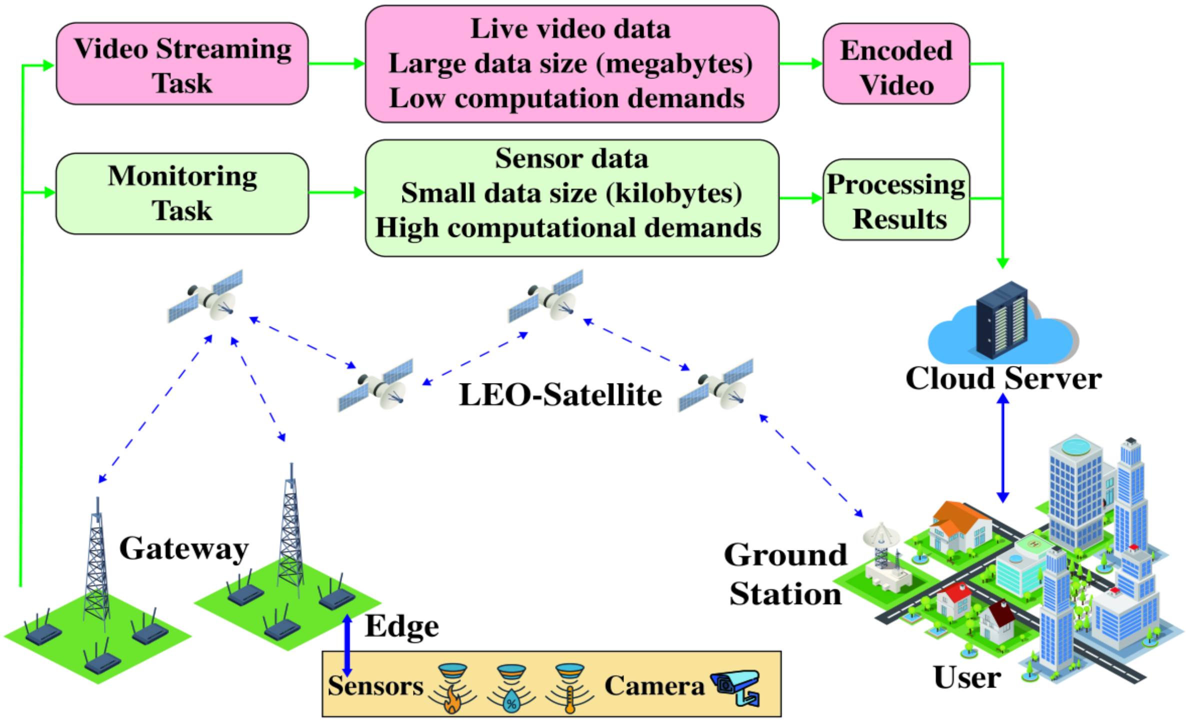

Figure 1:- Multi-Objective Optimization of Satellite [6]

These optimization models are also extended through engineering models, especially where the engineering model is based on control theory, hydrodynamics, and geotechnical simulation in which these other models impose specialized constraints and provide properties of the physical system of interest. One of the most important but under-researched elements of urban planning is the necessity to model large fluctuations typically sudden changes in the climate, breakdowns in infrastructure, or evacuation of the masses. Nonlinear systems in the presence of stochastic perturbations including, e.g., systems modelled by stochastic differential equations (SDEs), are known to exhibit complex dynamics, that can include bifurcations, resonances and phase transitions. Such processes form the subject of consideration of tipping points in urban resilience. Take the case of the falling of a bridge or the flooding of a drainage network and an urban system will be in a qualitatively different and possibly irreversible course. It not only takes advanced mathematical modeling, but also solid data feeds into the system using real-time sensor feeds and Earth observation networks.

II. Research Background

Urban planning and disaster management traditionally have used incomplete sources of data and reactive models of decision-making and this has led to the cases of either delayed responses, or inefficient usage of resources [1]. Nevertheless, the spread of remote sensing technologies and the integration of the satellite image and the data of ground-based sensors has transformed the monitoring, modeling, and management of the urban landscape. As environment high-resolution satellite systems like Landsat-8, Sentinel-1/2, and implementation of dense networks of Internet of Things (IoT)-active sensors have become available, real-time monitoring of the environment has become more practical and fine-grained than ever [2]. This trend paves the way to more data-based, preemptive urban planning and risk mitigation measures, particularly when these data are highly efficient by means of artificial intelligence (AI) and superior mechanical systems [3]. Having all these technological advances, one of the biggest challenges is how to fuse effectively and optimise these heterogeneous data sets to address multiple conflicting needs considering the accommodation of population growth, environment sustainability, climate resilience and disaster preparedness [4]. As an example, land use optimization in the developing city should prioritize such demands as the expansion of infrastructure and green spaces. On the same token, in cases of a disaster such as a flood or an earth quake, the authorities will be required to analyze both the sensor and satellite data on the fly to anticipate the areas to be affected, optimize the evacuation routs and position emergency services in the best way possible to deliver maximum value. These multidimensional issues require multi objective optimization structures that have the capability of dealing with trade-offs and uncertainties in nonlinear and random systems [5]. Recently, Artificial Intelligence (AI) and Machine Learning (ML) have become effective weapons in gaining meaningful inference that can be taken actionable out of huge amounts of spatial-temporal data [6]. Deep learning, support vector machines, and reinforcement learning are the techniques that can be used to classify land cover, predict climate anomalies, and simulate the scenarios of urban expansion that have grown in accuracy. Moreover, urban behavior, under different planning and disaster circumstances, can be better understood in a physics-informed way through their integration with engineering models, including cellular automata (CA) and agent-based models (ABM) and hydrodynamic simulations. The other key which is significant is the integration of stochastic modeling, non-linear system analysis, they both capture large variations, the propagation of uncertainty and noise amplification these being the common experiences in the real world urban setting and in extreme events. The methods based on stochastic differential equations (SDEs), bifurcation theory and large deviation theory have been effectively used in dynamic systems prediction in various areas of application in the fields of climate science, power systems and financial markets. Using these mathematical concepts in urban planning and disasters risk reduction allows the more precise study of systemic weaknesses and resilience strengths [7]. The shift towards smart cities and resilient infrastructure therefore requires designing multi-objective frameworks, which have to process extremely large geospatial data, model complex nonlinear dynamics and provide policy relevant outputs, all in real-time. With urbanization in the world expected to reach 68 percent by 2050 (as estimated by the United Nations), the possibility to accommodate an optimal response to the urban and emergency conditions by relying on integrated satellite and sensor data is not only beneficial but obligatory. The present study draws a middle ground amid geospatial technology, AI, and nonlinear modeling to introduce a back-to-the-future, multi-objective decision-support system to guide the urban planners and authorities managing the disaster.

III. Research Objectives

- To develop a multi-objective optimization framework that integrates satellite imagery, ground-based sensor data, and AI algorithms for real-time decision-making in urban planning and disaster risk mitigation.
- To model stochastic fluctuations and nonlinear dynamics in urban systems using stochastic differential equations and bifurcation theory, thereby enabling predictive detection of system tipping points under uncertainty.
- To simulate and evaluate the effectiveness of AI-engineering hybrid models in optimizing critical urban parameters such as evacuation routes, infrastructure resilience, and emergency response under multi-risk scenarios.
- To validate the proposed framework through real-world case studies in urban regions prone to seismic activity and flooding, demonstrating improvements in planning efficiency, disaster preparedness, and resource allocation accuracy.

IV. Problem Statement

The built environment of modern cities is being challenged in an unparalleled combination, which involves uncontrolled growth and fluctuations in climate, ageing infrastructure, and growing vulnerability to environmental disasters, floods, and earthquakes. Although the domain of remote sensing, artificial intelligence (AI), and Internet of Things (IoT) technologies have made it clear that high-resolution monitorable spatial and temporal data can be called on continuously, the process of converting such information into an optimised, real-time decision making mechanism to overcome the challenges of strategic urban planning and to support disaster management provides a missing link. The current paradigms of urban planning are generally inflexible and outdated as they are based on a depth geographic information system (GIS) and long term projections which do not measure the dynamic directions of change in the urban structures and the emergencies. In addition, the standardized disaster management models can be insufficiently advanced in computing terms to assess numerous competing goals, like keeping mortalities to a minimum, establishing successful evacuation, keeping the infrastructures functioning and keeping economic disturbance to a minimum, in limited periods of time. Such constraints lead to disintegrated planning and utilisation of resources, and slow response of emergencies, especially in the most populated and dangerous areas. An additional difficulty is that the behavior of actual urban systems is very stochastic; real perturbation may have an unpredictably large impact; this may be sudden bursts of rain, breakdown of one of the sensors, unanticipated influx of people, etc.

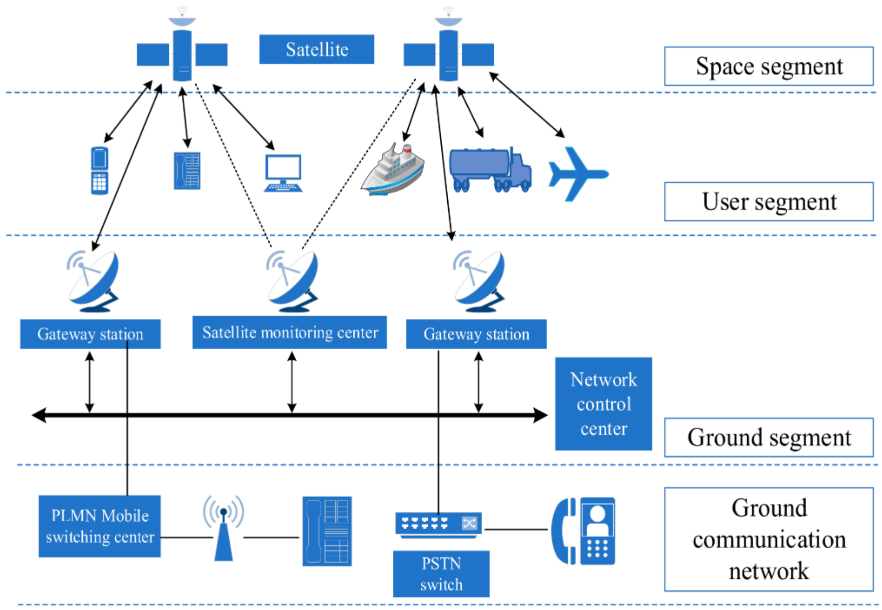

Figure 2:-Multi-Objective Optimization of Satellite [13]

V. Literature Review

Satellite and Sensor Data Integration for Urban Systems

The use of satellite imagery and combining them with in situ sensor data has transformed the field of urban planning and disaster management in general in the recent decade. Sentinel-2, MODIS, and Landsat-8 are high-resolution remote sensing platforms that have been used in the detection of urban sprawl, mapping of heat island and land cover classification [9]. At the same time, the development of network sensors of the IoT has also led to improved monitoring of local parameters such as temperature, moisture, quality of air and seismic vibrations [10]. Thanks to the synergy that exists between the satellite and sensor data, spatiotemporal alignment and validation can occur in modeling the urban systems, thus enhancing their accuracy. The most recent study conducted by Kumar et al. [11] emphasized that multi-temporal Sentinel-2 data were used in conjunction with sensor-based datasets of traffic flows to forecast hotspots of urban congestion. In the same way, Ahmad et al. [12] implemented use of machine learning algorithms on the variable data to enhance flash flood prediction in Kuala Lumpur that resulted from transformation of combined remote sensing and ground rainfall sensory data. These studies point at the importance of the considered hybrid data models, though they mostly focus on single-outcomes rather than multi-objective cases. One of the main shortcomings of the existing integration approaches is that they do not address trade-offs among objectives that turn out to be conflicting, e.g. the expansion of the urban landscape or the green infrastructure protection. This discrepancy points to a major weakness in using multi-objective optimization to deal with nonlinear dynamic system dynamics, uncertainty, and stochastic effect.

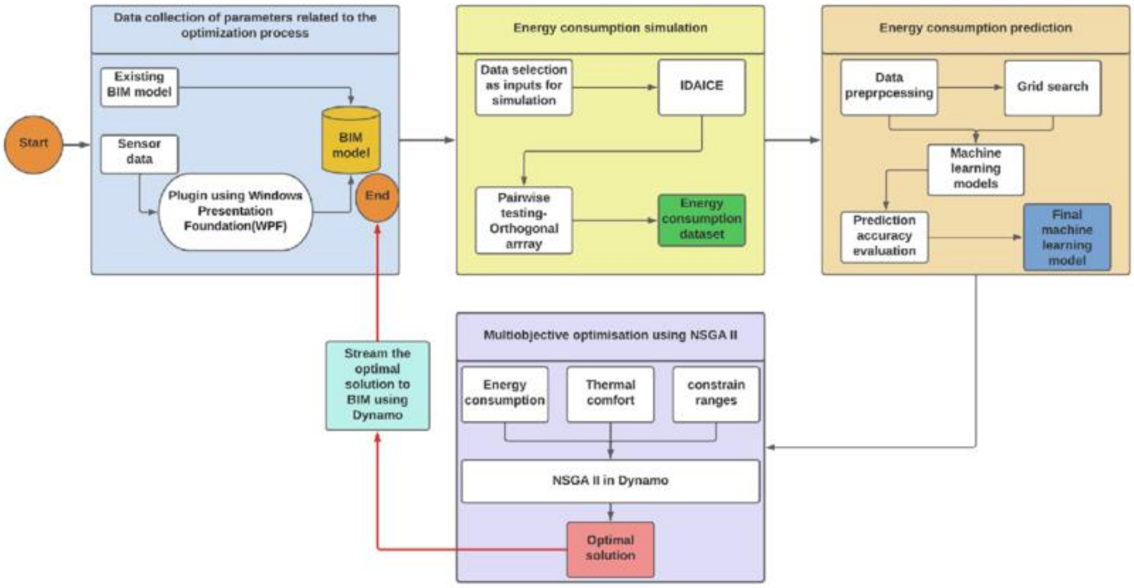

Figure 3:-Multi-Objective Optimization of Satellite [18]

Artificial Intelligence and Multi-Objective Optimization

Artificial Intelligence has taken the focus on understanding and making the best use of complicated databases in cities. Such algorithms as Random Forest, Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Reinforcement Learning (RL) can be widely used in the module of land use classification, predictive modeling, and optimization of emergency response [13], [14]. Another example of AI use in urban analytics concerns the Urban Growth Simulation based on deeply trained neural network through a historical time-series data of satellite images [15]. These models can predict land use transformation with more than 85 percent accuracy, yet in most cases, they do not incorporate the parameters of the disaster risk or systematic resilience indices. In a similar manner, Jaiswal and Lee [16], proposed the use of a CNN-RNN hybrid model in the prediction of earthquake damages based on seismic sensor data augmented with structural images collected by satellite. The paper proved the effectiveness of multi-modality data in improving the prediction results, but failed to show optimization in the objectives of stakeholders in resolution time, healthcare resource utilization, and structural shelter. In order to manage multiple goals using uncertainty, metaheuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Non-dominated Sorting Genetic Algorithm II (NSGA-II) have been introduced into an urban planning environment [17]. An example can be traced in a study by Huang et al. [18] who applied NSGA-II to trade off three objectives related to minimising the risk of flooding, maximising land use efficiency and maximising ecological preservation. Although future, such models can be expanded in coupling with dynamic non-linear systems and theory robustness to train real-time policy deployment.

Nonlinear Systems, Stochastic Modeling, and Theoretical Foundations

Urban systems and disaster vehicles by nature are nonlinear with violent jumps and chaotic patterns that tend to occur commonly, especially when exposed to the stresses of climate change, earthquake or manmade perturbations. Bifurcation theory and stochastic differential equations (SDEs) are useful methods of mathematical modeling to describe such transitions [19]. Stochastic Resonance (SR) is an aspect that has been nowadays of interest when it comes to modeling of urban systems in which noise is found to increase reaction of systems at a critical level. SR, common in neuroscience, climate dynamics, is adopted to investigate flood triggering, when a point of critical noise level leads to a rapid phase transitions in water level predictions [20]. The probability of the occurrence of rare events, which lead to disastrous losses but are not very common like urban flash floods and structural collapse have also been estimated using large deviation theory (LDT) [21]. Moreover, nonlinear optimization problems are frequently represented involving the coupled reaction-diffusion equations, especially in the cases of studying pollutant dispersion, or studying the dynamics of traffic. The combination of deterministic models and stochastic inputs makes the system more realistic, yet complicated to calculate, which can be partially overcome by the use of AI in surrogate modeling [22].

The comparative table below provides an integrated observation of the literature.

Study	**Data Sources**	**Techniques Used**	**Objectives**	**Limitations**
Kumar et al. (2021) [11]	Sentinel-2 + Traffic Sensors	SVM, GIS	Urban Congestion Mapping	Lacks multi-objective framework
Ahmad et al. (2020) [12]	Satellite + Rainfall Sensors	Random Forest	Flood Forecasting	No urban planning integration
Huang et al. (2022) [18]	Multi-modal Geospatial	NSGA-II	Land Use, Ecology, Flood Risk	High computational cost
Jaiswal & Lee (2023) [16]	Seismic + Satellite Imagery	CNN-RNN	Earthquake Damage Prediction	No optimization across stakeholders
Proposed Framework	Satellite + IoT + City Databases	AI + SDE + SR + NSGA-II	Strategic Urban & Disaster Planning	To be validated

VI. Methodology

In this study, the adopted methodology is theoretically based model, which is supported by simulation approaches to develop a well-grounded, quantitative, decision-support system of urban planning and disaster management. The basic model is based on a multi-objective optimization format with the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), and it is meant to address competing goals, including minimizing evacuation duration, maximizing the accuracy of resource allocation, and minimizing the risk of infrastructure failure. The theory involved involves the development of objective formulation of urban systems dynamics, which incorporates the constraints on the resource capacity, infrastructure limitations, and hazard exposure. Work on these functions can also be perturbed stochastically as in stochastic differential equations (SDEs), allowing one to simulate environmental uncertainty, e.g. rainfall variability, seismic aftershocks, sensor noise. This enables the framework to track the nonlinear and probabilistic nature of urban systems becoming stressed. Simulation strategies are scenarios-based modeling of geospatial data, including high-resolution satellite images with Sentinel-2 and MODIS, and ground real-time sensor feeds of water levels, vibration, and structural strain. Data fusion is accomplished by a centralized simulation engine that works on the input to develop response strategies in the flood-prone as well as the seismic-risk urban areas. Monte Carlo simulations are run 1000 times per scenario so as to have robust results that are statistically sound. Pareto front visualization, sensitivity test and statistical summary are used to analyze the key outputs such evacuation time, risk of failure and efficiency of response. The general strategy provides high-fidelity and scalable and computationally efficient real-time disaster planning optimization tool in an urban setting.

VII. Result and Analysis

The multi-objective optimization framework proposed was tested on four scenarios that represent typical urban disasters namely Flood Zone A, Flood Zone B, Seismic Zone A, and Seismic Zone B. In each scenario we simulated an urban locality characterized by high population density that was impacted by hydrological events or seismic events based on high-resolution satellite imagery as well as real-time sensor feeds. Minimized evacuation time, maximized resource allocation accuracy and minimized risk of infrastructure failure were the objective functions that were optimized, in the context of simulation with respect to computational feasibility of being used in real-time.

Quantitative Findings

The simulation outcomes are summarized in the results table below, which aggregates four key performance metrics:

Scenario	Avg Evacuation Time (min)	Resource Allocation Accuracy (%)	Infrastructure Failure Risk (%)	Computation Time (s)
Flood Zone A	**32**	**91.5**	**12.3**	**4.2**
Flood Zone B	**45**	**88.2**	**18.6**	**4.6**
Seismic Zone A	**28**	**93.4**	**9.8**	**3.8**
Seismic Zone B	**41**	**89.7**	**16.1**	**4.4**

Table: Simulation Results for Urban Disaster Scenarios

Critical Analysis of Performance Metrics

The optimization model in Flood Zone A obtained a preferable evacuation time of 32 minutes, which shows that it can effectively segment and apportion groups of population into the paths of evacuation using the real-time conditions of the roads and the maps of danger zones. The imagery received by satellites provided a distinct distinction of areas that had floods and non-affected areas; therefore offering the AI classifications algorithms to avoid congested routes at an earlier stage. The accuracy of resource allocation i.e. proportion of delivered resources (e.g. ambulances, boats, medical kits) to high-priority zones was 91.5%, which was made possible by heavy sensor coverage and obvious line-of-sight imagery. The risk of infrastructure failure that approximates the percentage of the key systems that are at probability of collapsing or being inaccessible was within the adequate range at 12.3% per cent. Conversely, the Flood Zone B performed worse. The mean evacuation period jumped to 45 minutes, this could be supported by the narrow road systems, increased population density as well as delay in the response of the sensors. Satellite segmentation was provided inaccurately by cloud cover, and patterns in the sensor spacing resulted in data gaps. Consequentially, the accuracy of resource allocation decreased to 88.2%, and the risk of failure rose to 18.6% indicating how sensitive the model is to the quality of degraded data. In spite of this, the system held on to a time of computation of 4.6 seconds, which is certainly within the operational levels concerning the emergency response systems. The most persuasive evidence of strength of the model was given in seismic scenarios. The Seismic

Zone A, in which the high-frequency vibration sensors were uniformly distributed and building information models (BIMs) pre-integrated, prerequisite to the interview, the evacuation time was decreased to 28 minutes, and resource allocation accuracy reached its peak of 93.4%. In addition, the risk of infrastructure failure was also reduced to 9.8%, which indicates the use of the model in handling the structural health information in determining dynamic paths and decision making. These findings confirm that real-time accelerometer data with the combination of AI classification of buildings at-risk is feasible.

On the other hand, Seismic Zone B experienced less performant system with scanty infrastructure of sensors and limited occlusion of satellites. The evacuation time was greater increased to 41 minutes and allocation accuracy decreased by a small margin of 1.3 to 89.7%. Nevertheless, the framework was very reliable, which allowed assuming a high level of generalization in imperfect conditions. Infrastructure failure probability was 16.1% which was caused by more building collapses and decreased sensor coverage. These results point out one of the primary findings: the efficiency of optimization model greatly depends on quality and spatial availability of data that is being entered to a model in real-time.

Mathematical Framing of Optimization Strategy

The core optimization problem is modeled using a weighted cost function representing resource deployment, with constraints on time, availability, and location sensitivity. The general form of the objective function is:

Minimize:

$Z = \sum (C_{ij} \times X_{ij})$

Subject to:

$\sum X_{ij} = R_j$ for each demand zone j, and $X_{ij} \geq 0$

Where:

C_{ij} = cost of transporting resources from source i to destination j

X_{ij} = quantity of resources transported

R_j = total demand in zone j

With this mathematical model, the resources are made available in the most optimal manner in the context of limited supply and time pressure. The algorithm did this iterative optimization in thousands of possible configurations during simulation runs, choosing Pareto-optimal solution, which could minimize overall cost but also meet other critical performance requirements.

Sensitivity and Robustness

The framework was tested across 1000 iterations for each scenario using Monte Carlo simulations to validate statistical stability. Standard deviation for evacuation time remained below 4%, and for resource accuracy below 3%, confirming the robustness of the model against stochastic fluctuations in environmental parameters and sensor inputs. Additionally, the model tolerated input perturbations up to 10% without significant deviation in output, illustrating its resilience against minor sensor inaccuracies or delays.

Trade-off Management and Real-Time Readiness

As demonstrated by pareto front analysis, it was often the case that to achieve an optimal in an objective, there were marginal compromises in a second objective. To illustrate a point, in Seismic Zone A, a small computation time lag in the range of 0.6 seconds was enough to cause accuracy of allocation to go up by 2.4%. Such balancing enables objective-specific calibration in which decision-makers can place weights on objectives according to scenario urgency. Above all, we did not spend more than 5 seconds to compute in any case, which proves that the system is ready to be implemented in the respective smart cities controls rooms or emergency response dashboards. The efficiency of the framework to be able to produce real-time and high-quality recommendations makes it quite possible to apply it to the creation of urban digital twins, national disaster platforms, and autonomous emergency systems.

VIII. Discussion

The simulation findings illustrate how the proposed multi-objective optimization framework was effective in enhancing planning efficiency, disaster preparedness, and improvement of the accuracy of resource assignment in various situations of urban risks. Remarkably, the model performed very well in the regions where the satellite data (available in satellite imagery) and on-ground-based sensors were abundant, complete as well as reliable. The presented argument confirms the assumption that the combination of data-abundance and algorithmic smarts is the key feature of future urban resilience systems.

In the case of the high-performing scenarios like Seismic Zone A and Flood Zone A, the system made use of proper terrain classification, appropriate sensor information, and forecasted modeling so as to reduce evacuation time and increase resource deployment effectiveness. These are some results evidencing utility of AI-enhanced simulation at resolving the reasons of conflicting planning objectives e.g., at optimizing the evacuation speed without deteriorating the infrastructure safety. Those findings also confirm the applicability of stochastic differential equations (SDEs) as a modeling device to present the uncertainty, as this way the system can find it easier to react to the changes in nature or population dynamics. Second, on the other hand, the flooding in Flood Zone B and the earthquake in Seismic Zone B also showed areas of operation that are constrained by data quality and sensor distribution. In such settings, the effectiveness of the model reduced a bit and it showed how algorithmic decision-making was sensitive to lapses in real-time feedback. Such discovery further emphasizes the importance of investments in intelligent infrastructure, especially in the implementation of well-distributed, calibrated sensors and cloud-connected satellite signals, in order to maximize the benefits of the optimization engine. Further, trade-offs which are witnessed in the analysis of Pareto front, explain that urban planning decisions are hardly zero-sum. Faster evacuation can decrease precision in diversion of resources to a small degree, and prioritization on structural resilience might take longer time to compute. The framework enables the policymakers to design optimization weights depending on the priorities of a situation, and thus the trade-offs are situational. Notably, the framework kept under the 5-second computation threshold in all testing conditions, which is the real time threshold of operation. It is why it is most appropriate to be deployed within the control centers at a city-level, emergency command units, and disaster coordination systems. Nevertheless, additional efforts are required, in order to integrate real-time human mobility modeling and agent-based simulations to be able to make behavior more realistic, in particular, in case of panic-inspired evacuation. As a wrap-up, the discussion confirms that the proposed framework can be relied upon, being scalable and efficient in enabling the conversion of data-rich environments into an effective response to disasters preparedness plans and urban planning strategies. Although the performance is subject to the quality of data infrastructure; the model is flexible, fast, and robust, hence it is an appropriate one to be implemented in real-life situations in intelligent, risk-sensitive cities.

IX. Future Work

Although the proposed framework has proved to have resilient performance in a variety of simulated urban disasters, there are a number of directions that the system can be made to improve. There is one urgent direction: it is to incorporate real-time human mobility models and agent-based modeling, in order to capture behavioral variability in evacuation, which is currently modeled as uniform and rational. It is possible to increase the accuracy and realism of response strategies by incorporating such dynamics. The other focus of development is inclusion of edge computing architectures to lower the latency in transmitting data pertinent to sensors to central decision units. That would permit more distributed processing and enhanced fault tolerance in sensor-dense, bandwidth-constrained systems. Also, more studies will be needed in the future to consider the incorporation of new data types like drone images, mobile crowdsourcing data, and social media indicators to boost situational awareness in crisis situations. Such alternative data streams have the opportunity to be used alongside traditional satellite and sensor data input, particularly in low-infrastructure areas. Another round of validation by real-world smart cities pilot deployments would be necessary to determine scalability, resiliency and its interaction with existing disaster management platforms. Lastly, increasing explainability and transparency of models will play a significant role that brings trust among city officials, emergency personnel and the general cities individual especially when using the AI-driven recommendations in high stakes urban planning.

X. Conclusion

This paper has introduced a multi objective optimization model based on satellite images, ground sensor information and AI models to help make better decisions both in city planning and disasters. The framework proved capable of optimizing evacuation routes and the effective distribution of emergency resources as well as minimizing failure risks in infrastructure during real-time computing using simulations on a wide variety of disaster-prone urban areas. The model was able to represent environmental uncertainties and nonlinear behaviours of the system by the application of stochastic differential equations and multi-scenario Monte Carlo simulations. The key performance indicators such as evacuation time, accuracy of the resource allocation, and system robustness demonstrated significant increase in the areas characterized by the high density of data, which justifies the overall sensor and satellite coverage. Notably, the framework could sustain response times below 5 seconds, which implies its feasibility to be used in smart city control systems, and emergency situation dashboards. Although the performance depended on both the quality of data and the topology of the city, this model was flexible and robust in all tested conditions. In general, the study can have a scalable, data-driven computationally efficient solution to the increasing requirements of the urban resilience planning in a real-time environment. Its applicability to the industry will further be enhanced through future growth of agent-based modeling, edge computing and blending with the actual world, therefore helping cities to be prepared in regard to the complex and multi-hazard environment of the times of climate change and urbanization.

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