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Post-Earthquake Field Hospital Bed Capacity Allocation Problem Solving Two-Stage Stochastic Programming: A Case Study in Istanbul Avcılar

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ABSTRACT

Field hospitals are temporary healthcare facilities deployed to provide medical services in scenarios where conventional healthcare infrastructure is disrupted due to natural or human-induced disasters, migration, armed conflicts, or similar crises. Depending on the anticipated needs, these facilities may be categorized into specialized types, such as orthopedic and traumatology field hospitals, surgical field hospitals, or general medical aid field hospitals. Bed capacity is a critical determinant of the scale of a field hospital, which in turn influences the spatial requirements for setup, personnel allocation, and associated costs. Typically established for short-term use, ranging from six months to two years, the operational duration, bed capacity, and structural configuration of field hospitals collectively define their functional capabilities.

This study proposes a two-stage stochastic mathematical programming model to address the problem of calculating the optimal bed capacity for field hospitals delivering post-disaster healthcare services, with a focus on earthquake scenarios. Compared with two-stage stochastic models, the mathematical model proposed in this study exhibits distinct differences from existing models in the disaster and hospital bed capacity modeling literature. The model integrates uncertainties inherent in disaster contexts, such as fluctuating patient influx and resource availability, to optimize decision-making for bed allocation. The proposed framework is applied to Avcılar, a district within Istanbul, Türkiye, identified as a high-risk zone for seismic activity due to its proximity to the North Anatolian Fault. By leveraging geospatial and demographic data, the model aims to enhance preparedness and operational efficiency of field hospitals in mitigating healthcare service disruptions following a major earthquake. The results underscore the utility of stochastic optimization in resource planning under uncertainty, offering actionable insights for policymakers and disaster response coordinators.

Keywords: Field Hospital; Hospital Capacity Planning; Earthquake Health Recovery; Mathematical Modelling

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1. Introduction

Disasters are disruptive events arising from natural, technological, or human-related sources that inflict undesirable interruptions on human life. Earthquakes, however, represent a category of natural disaster characterized by their unpredictable timing, yet they exert one of the most profound impacts on daily life. Modern disaster management methodologies emphasize planning pre- and post-disaster tasks and responsibilities based on defined critical success factors [1]. As earthquakes devastating natural disasters are inherently uncertain in terms of their timing, location, and magnitude, the accurate and methodical planning of preemptive measures and strategically prioritized post-event actions becomes paramount. This dual-phase planning framework is essential to mitigate risks, enhance resilience, and ensure coordinated responses in the face of such unpredictable calamities.

Following an earthquake, the provision of healthcare services is critical not only to restore the health of affected populations as rapidly as possible but also to prevent fatalities. In contemporary practice, physical healthcare services [2-5] and mental health interventions [6] are delivered through institutions such as hospitals, family health centers, and community health facilities. When focusing on physical healthcare services, post-earthquake medical needs predominantly involve trauma-related injuries and subsequent surgical interventions necessitated by these injuries. In Türkiye's

healthcare system, such treatments are typically administered at Level 3 and Level 4 hospitals. In other words, surgical procedures (operations) and the follow-up care they require must be conducted by institutions or organizations equipped to deliver specialized healthcare services.

The necessity for such contingency solutions arises when conventional healthcare institutions hospitals, clinics, or community health centers fail to maintain adequate service capacity due to disaster-induced strain. Key operational questions include: Where should field hospitals be strategically located? How many healthcare personnel are required? What is the optimal operational duration? and What bed capacity ensures effective service delivery? These questions, while critical, have not been comprehensively addressed in prior academic research, as noted by [7]. Strategic decisions, such as site selection [8] and capacity planning, are pivotal to ensuring equitable and efficient temporary healthcare provision, particularly when normal infrastructure is incapacitated.

Earthquakes have a significant adverse impact on societies, manifesting in both economic and social dimensions. The economic and socio-structural dimensions of healthcare provision amplify the exigency of optimizing post-disaster medical responses, particularly in contexts where resource scarcity intersects with elevated demand. Healthcare services, inherently characterized by high financial and operational costs, assume heightened significance in disaster scenarios, where systemic disruptions exacerbate both material and human vulnerabilities. In synthesizing these considerations, this study posits that bed capacity optimization in field hospitals represents a nexus of operational research, public health ethics, and disaster epidemiology. By leveraging advanced computational tools such as discrete-event simulation and Monte Carlo methods policymakers can derive capacity thresholds that minimize both human suffering and economic leakage. Such an approach not only mitigates immediate post-disaster mortality but also attenuates secondary health crises (e.g., sepsis from untreated wounds) and long-term disability burdens, thereby aligning with the United Nations Sendai Frame-work's emphasis on building back better [9].

Following a seismic event, the catastrophic disruption of healthcare services represents a critical inflection point in disaster management, with profound implications for population health outcomes. This disruption is primarily attributable to the direct physical degradation of healthcare infrastructure, particularly hospital buildings. It is critical to note that even facilities which remain structurally sound can experience severe operational paralysis due to utility failures, internal damage, and supply chain interruptions.

In this context, the strategic deployment of field hospitals serves as an essential mitigation strategy to bridge the service gap and restore critical medical functions. The efficacy of this intervention, however, is contingent upon rigorous a priori capacity planning. Determining the optimal capacity for a field hospital unit is a central logistical and clinical challenge. Insufficient capacity directly compromises the standard of care, leading to preventable mortality and morbidity through the delayed or inadequate treatment of injuries and pre-existing conditions. Conversely, the establishment of facilities with significant excess capacity constitutes a substantial misallocation of finite financial, material, and human resources during a crisis, thereby reducing the overall efficiency and reach of the humanitarian response.

Consequently, the development of robust, evidence-based methodologies for forecasting post-disaster medical demand and translating those forecasts into precise operational capacity requirements remains a critical research and operational challenge. The objective is to achieve an equilibrium that maximizes patient survival and recovery while adhering to the fundamental disaster management principle of resource optimization. There is currently no consensus on optimal models for this balancing act, highlighting a significant gap in applied disaster health research.

Accurately determining the required capacity for field hospitals constitutes a critical yet complex planning problem, fundamentally characterized by severe aleatory uncertainty inherent to the post-disaster environment. This uncertainty stems from the stochastic relationship between seismic parameters such as magnitude, epicentral location, and local geotechnical conditions and the resultant casualty volume and injury profiles. Since the demand for emergency medical services is a direct derivative of these unpredictable casualty figures, capacity planning cannot rely on deterministic forecasts.

To address this challenge of decision-making under deep uncertainty, our research formalizes the problem within a two-stage stochastic programming framework. This methodology is particularly suited to problems where an initial, strategic decision (the first-stage decision, such as pre-positioning resources or establishing baseline capacity) must be made before the resolution of random events (the earthquake's impact), followed by subsequent operational decisions (the second-stage recourse actions, such as patient triage and re-source reallocation) that can adapt to the realized scenario. By applying this robust optimization paradigm to post-disaster medical logistics, we introduce a novel and computationally rigorous perspective to the literature [10]. This approach enables the generation of capacity plans that are risk-informed and resource-efficient, optimizing expected performance across a wide range of plausible seismic scenarios quantified through probabilistic hazard analysis.

2. Literature

The optimization of field hospital bed capacity and personnel planning is critical for effective healthcare delivery in emergency and crisis situations. Various studies have explored methodologies for enhancing hospital capacity through strategic planning, technology integration, and data-driven decision-making. The author examined capacity planning in maternity services, highlighting the complexities of bed occupancy and the limitations of reducing length of stay to cut costs. The study suggests that erroneous policies can result in unintended consequences, such as increased pressure on neonatal and pediatric departments [11]. Similarly, Ngegba et al. (2025) analyzed public health laboratory capacity in Sierra Leone, emphasizing gaps in personnel training, infrastructure, and equipment, which directly impact efficiency and service delivery [12].

In the realm of transport and resource optimization, Kropp et al. (2024) employed neural networks and metaheuristic algorithms to enhance intra-hospital patient transport, reducing delays by up to 42% through resource reallocation [13]. Their approach suggests that similar methodologies could be applied to field hospitals to optimize resource utilization. Moreover, Pamich et al. (2024) focused on

capacity planning in pediatric palliative care in Italy, identifying the need for better workforce distribution and infrastructure expansion to meet patient demand [14]. This aligns with broader concerns regarding personnel shortages and resource allocation in field hospitals.

Additionally, Vos et al. (2024) explored the challenges of implementing an optimized surgery scheduling blueprint in children's hospitals. Their findings indicate that while mathematical models can enhance scheduling efficiency, resistance to change and operational adjustments present significant barriers [15]. These insights are crucial for field hospitals, where flexible yet efficient scheduling is necessary for handling fluctuating patient loads.

In summary, effective field hospital bed capacity and personnel planning require a multi-faceted approach, integrating predictive modeling, workforce training, and infrastructure investment. While technological advancements offer promising solutions, challenges related to implementation and policy misalignment must be addressed to ensure optimal resource utilization in crisis scenarios.

The optimization of field hospital bed capacity and personnel planning is critical for effective healthcare delivery in emergency and crisis situations. Various studies have explored methodologies for enhancing hospital capacity through strategic planning, technology integration, and data-driven decision-making.

Jones (2025) examined capacity planning in maternity services, highlighting the complexities of bed occupancy and the limitations of reducing length of stay to cut costs. The study suggests that erroneous policies can result in unintended consequences, such as increased pressure on neonatal and pediatric departments [11]. Similarly, Ngegba et al. (2025) analyzed public health laboratory capacity in Sierra Leone, emphasizing gaps in personnel training, infra-structure, and equipment, which directly impact efficiency and service delivery [12].

Standard capacity metrics based on bed numbers are outdated. Modern approaches emphasize care pathways and patient-centered metrics, focusing on service delivery and the flow of patients rather than static capacity measures [16].

One effective strategy for improving field hospital bed capacity is the application of predictive modeling and simulation techniques. Machine learning models can be employed to forecast patient admission rates, allowing hospital administrators to dynamically adjust bed allocation. Kropp et al. (2024) employed neural networks and metaheuristic algorithms to enhance intra-hospital patient transport, reducing delays by up to 42% through resource reallocation [13]. Their approach suggests that similar methodologies could be applied to field hospitals to optimize resource utilization and maintain high standards of patient care.

Traditional spreadsheet-based approaches to hospital bed capacity planning often underestimate true requirements. More robust simulation models account for patient-level flow and variability, providing more accurate assessments of bed needs and the effects of different capacity policies [17].

Mathematical models integrating staff capacity and bed allocation planning often formulated as integer programming problems enable efficient allocation of hospital resources under rising demand pressures [18].

Effective personnel planning is essential for ensuring that field hospitals operate efficiently under stressful conditions. The Authors focused on capacity planning in pediatric palliative care in Italy, identifying the need for better workforce distribution and infrastructure expansion to meet patient demand [14]. Their findings underscore the importance of developing flexible staffing models that allow for rapid deployment of healthcare professionals to areas of need.

Field hospitals, often deployed in disaster scenarios, require tiered planning structures. A classification system divides field hospital capabilities into four standardized levels (SS, I–SS, IV), each with distinct health and support units. This system helps planners match capacity to specific emergency needs [19].

Despite the availability of innovative solutions, several challenges hinder the effective implementation of field hospital capacity planning strategies. The researchers explored the challenges of implementing an optimized surgery scheduling blueprint in children's hospitals. Their findings indicate that while mathematical models can enhance scheduling efficiency, resistance to change and operational adjustments present significant barriers [15]. These insights are crucial for field hospitals, where flexible yet efficient scheduling is necessary for handling fluctuating patient loads.

Recent advancements leverage machine learning to forecast hospital bed needs using patient data, including length of stay and admission rates. These data-driven models allow for dynamic prediction and informed long-term planning [20].

Field hospitals established during the COVID-19 pandemic (e.g., NHS Nightingale hospitals) rapidly scaled capacity from hundreds to thousands of beds. While operationally effective, future efforts must better address governance and patient safety as core planning priorities [21].

3. Material and Method

Within the domain of operations research, capacity planning problems encompass a broad spectrum of theoretically complex and computationally challenging issues, spanning diverse application areas. This study narrows its focus to a specific capacity determination problem: optimizing inpatient bed capacity in field hospitals deployed post-earthquake to serve disaster-affected populations within a geographically constrained region. While capacity-related challenges have been extensively studied across disciplines including operations research prior work has predominantly addressed deterministic and stochastic scenarios, emphasizing metrics such as demand fulfillment ratios and service coverage thresholds [22-23].

Staffing optimization: Allocation of medical personnel (e.g., physicians, nurses) to balance workload and expertise.

Cost-efficiency analysis: Financial modeling of bed acquisition, maintenance, and operational overheads.

Surgical unit utilization: Strategic planning for operating theater scheduling and resource allocation.

In contrast, this study diverges by centering on post-disaster bed capacity planning a niche yet critical subset of healthcare operations research [24]. The problem is uniquely characterized by stochastic demand surges, infrastructural volatility, and time-sensitive triage imperatives, necessitating a hybrid methodological approach that integrates probabilistic demand modeling with robust resource constraints [25].

In the context of international disaster response, the type of facility

capable of providing such specialized care, particularly surgical interventions and follow-up, often corresponds to a WHO Emergency Medical Team (EMT) Type 2 or Type 3 fixed or mobile hospital. This classification system provides a standardized framework for matching the required capacity and functional capabilities to the specific needs of the affected population, aligning with the advanced care focus of Level 3 and Level 4 hospitals mentioned in the Türkiye healthcare system.

3.1 Material

The determination of bed capacity in inpatient healthcare facilities constitutes a multifaceted operational challenge, particularly due to stochastic variables such as indeterminate treatment durations, unanticipated medical complications, and emergent surgical interventions, which collectively destabilize bed occupancy forecasting [26-27]. To address this complexity, the present study employs a synthetic dataset engineered to approximate post-earthquake patient influx dynamics through mathematically formalized demand models. In post-earthquake scenarios, the assessment of structural damage, casualty rates, and injury prevalence has been shown to rely on methodologies combining macro-seismic observations and analytical predictive models [28]. Seismic vulnerability, defined as the probabilistic ratio of expected losses relative to a predefined hazard intensity, is influenced by multifactorial determinants, including demographic density, architectural typologies (e.g., masonry vs. reinforced concrete), geological formations, and soil mechanics. Two principal computational paradigms dominate vulnerability and loss estimation:

Ground Motion-Dependent Numerical Modeling: Utilizes quantifiable seismic parameters (e.g., peak ground acceleration PGA, spectral acceleration -SA) derived from instrumental recordings to calculate loss ratios through physics-based simulations.

Empirically Derived Analytical Modeling: Leverages historical post-seismic datasets including casualty counts, injury patterns, and structural damage classifications to construct mathematical vulnerability functions via regression analysis, machine learning, or Bayesian inference.

This study adopts the latter approach, prioritizing analytical methods grounded in empirical evidence. Specifically, the methodology aligns with the HAZUS (Hazards U.S.) framework, a globally recognized standard for seismic risk assessment. Within this paradigm, spectral capacity-based damage estimation is employed, integrating four core components:

Structural Capacity Spectrum: Characterizes a building's inherent resistance to seismic forces as a function of its dynamic response.

Seismic Demand Spectrum: Represents the site-specific ground motion intensity, derived from probabilistic seismic hazard analysis (PSHA).

Performance Point: Identifies the intersection of capacity and demand spectra, demarcating the threshold of structural failure.

Damage Probability Functions: Statistically derived curves quantifying the likelihood of discrete damage states (e.g., slight, moderate, complete collapse) based on spectral displacement [29].

By synthesizing these elements, the HAZUS methodology enables probabilistic vulnerability assessments, accounting for epistemic uncertainties in material properties and aleatory variability in ground motion. This approach not only enhances predictive accuracy but also facilitates scenario-based risk mitigation strategies, critical for urban planning and emergency preparedness in seismically active regions.

Post-earthquake injury rates can be estimated using the following empirically derived formula, which integrates seismic intensity, structural vulnerability, and demographic exposure:

$$IR = p\left(\sum_{i=1}^{n} V_i S_i D_i\right) F \quad (1)$$

Where in formulation Equation 1;

i: building damage rate index ∀ i∈I

IR: Injury rate (injuries per 1,000 individuals)

P: Population density in the affected area (persons/km2)

V_i: Vulnerability coefficient of building type i, derived from historical damage matrices (dimensionless, 0–1)

S_i: Seismic intensity factor for building type i, quantified via spectral acceleration (g) or Modified Mercalli Intensity (MMI) Si is normalized to [0–1]

D_i: Occupancy rate of building type i during the earthquake (dimensionless, 0–1)

F: Correction factor accounting for secondary hazards (e.g., landslides, fires) and temporal variables (e.g., time of day)

This formula builds on the HAZUS framework [30] and microseismical vulnerability models [28], synthesizing probabilistic seismic hazard analysis (PSHA) with injury epidemiology. The vulnerability coefficients (V_i) are calibrated using post-disaster injury datasets, while seismic intensity (S_i) is derived from region-specific attenuation relationships. The formula's robustness is contingent on the accuracy of V_i and S_i, which require calibration via historical event data (e.g., 1999 İzmit earthquake). Sensitivity analyses (Monte Carlo simulations) are recommended to address epistemic uncertainties in occupancy rates (D_i) and secondary hazards (F). For low-rise reinforced concrete structures (C1L) and unreinforced masonry (URM) buildings, the aggregate casualty ratio (combined injuries and fatalities, conditional on complete structural collapse) is modeled as $V_i \sim \text{Lognormal}(\mu ln = -2.3, \sigma ln = 0.6)$, yielding a median value of approximately 0.10 with a 95% confidence interval of 0.03–0.32. For mid-rise reinforced concrete structures (C1M and C2M), the corresponding distribution is $Vi \sim \text{Lognormal}(\mu ln = -2.8, \sigma ln = 0.55)$, with a median of approximately 0.06. Under slight damage states, the vulnerability coefficient is substantially lower, following $V_i \sim \text{Lognormal}\ (\mu ln = -6.0, \sigma ln = 0.7)$, with a median of approximately 0.0025.

While Equation (1) provides a generalized estimate of total post-earthquake casualties (IR), granular stratification of injury severity is often necessary for targeted medical resource allocation. As per the HAZUS framework and the Coburn & Spence injury distribution model, casualty typologies are probabilistically correlated with building damage severity levels [31-33]. Building on this empirical foundation, injury severity is classified into four discrete tiers (as seen Table 1):

Minor Injuries (Y1): Non-life-threatening conditions requiring outpatient care, $Y1=Y\cdot0.60$.

Moderate Injuries (Y2): Injuries necessitating hospitalization but not urgent surgery, $Y2=Y\cdot0.25$.

Severe Injuries (Y3): Critical trauma requiring immediate surgical

intervention, Y3=Y·0.10

Fatalities (Y4): Immediate or delayed mortality attributable to traumatic injury, Y4=Y·0.05

The coefficients (0.60, 0.25, 0.10, 0.05) are derived from historical post-earthquake injury datasets, reflecting the logarithmic relationship between building collapse mechanisms (e.g., pancake vs. soft-story failure) and injury typologies. For instance, minor injuries (Y1) predominantly occur in partially damaged structures (Damage State 2–3), whereas fatalities (Y4) correlate with total collapses (Damage State 5).

This stratified framework enables field hospital planners to:

Allocate beds by acuity (e.g., surgical vs. general wards),

Preposition trauma supplies (e.g., blood products, ventilators),

Optimize staff-to-patient ratios based on anticipated caseloads.

While the coefficients are empirically validated across Mediterranean seismic zones [33-34], regional variability in building codes and population density necessitates localized calibration via Monte Carlo simulations or Bayesian updating.

Table 1. Description of injures rates from HAZUS-MH

Injures Rates	Treatment Level and Severity
1. grade	Short-term treatment in hospitals is sufficient
2. grade	Long-term hospital treatment is required
3. grade	Serious observations required and may result in loss of life
4. grade	Direct heavy and intensive care is required

Post-earthquake structural damage to buildings can be classified into four distinct severity levels: light structural damage, moderate structural damage, severe structural damage, and complete structural collapse -Istanbul Metropolitan Municipality [35]. As illustrated in Table 1, the HAZUS-MH (Hazards U.S. Multi-Hazard) methodology establishes a direct empirical correlation between these damage states and casualty rates (fatalities and injuries).

In post-earthquake contexts, the severity gradations of injuries, as outlined in Table 1, are predominantly determined by the proportion of fully collapsed or partially collapsed buildings. Structural damage patterns and consequently casualty rates vary significantly depending on building typologies, particularly between reinforced concrete and masonry structures [29, 36-40]. Empirical studies conducted in Türkiye, synthesizing post-seismic damage assessments, have quantified fatality and injury rates for these two building types, as summarized in Table 2 [35]. According to this framework, injury counts are derived by multiplying fatality rates by a factor of 2.515, reflecting the empirically observed ratio between mortality and morbidity in seismic events.

For a given building typology, the injury rate (Y) is computed as:

Y=F·2.515

where F represents the fatality rate derived from damage-state-specific mortality matrices. This multiplier (2.515) is calibrated to Türkiye's demographic and architectural profile, accounting for variables such as occupancy density and retrofitting prevalence [35].

In post-earthquake scenarios, approximate casualty numbers can be derived using Table 2 when the regional building inventory is known. The probabilistic values in this table reveal that 1st-degree (minor) and 2nd-degree (moderate) injuries are predominantly associated with heavily and severely damaged buildings. However, given that these injuries often permit outpatient treatment, they can typically be managed at primary care facilities such as Family Health Centers (FHCs) or Community Health Centers (CHCs), which provide polyclinic services. In contrast, 3rd-degree (severe) and 4th-degree (critical) injuries primarily originating from buildings with severe structural damage or total collapse necessitate the deployment of field hospitals equipped with advanced surgical and inpatient care capabilities.

Table 2. Injure and fatality rates for reinforced concrete buildings [35]

Grades	Fatality Rates for Reinforced Concrete Buildings, (%)			
	Light Damage	Mid Damage	Heavy Damage	Very Heavy Damage
1.grade	0.05	0.2	1	10-50
2.grade	0.005	0.02	0.5	8-15
3.grade	0	0	0.01	4-10
4.grade	0	0	0.01	4-10
	Injure Rates for Reinforced Concrete Buildings, (%)			
1.grade	0.12575	0.503	2.515	25.15
2.grade	0.01257	0.050	1.2575	20.12
3.grade	0	0	0.0251	10.06
4.grade	0	0	0.0251	10.06

When constructing an earthquake scenario, the anticipated number and severity of injuries can be estimated by integrating the regional building inventory (i.e., typology and count of damaged structures) with the injury-grade ratios provided in Table 2. This approach addresses a critical gap in conventional casualty estimation methods, which often prioritize population density while neglecting the deterministic role of building stock characteristics such as structural typology (e.g., reinforced concrete vs. masonry) and damage severity in shaping injury profiles.

This study assumes prior knowledge of the building inventory and incorporates proportional injury rates from Tables 1 and 2 to calculate casualty figures. By anchoring predictions in building-specific vulnerability data meticulously recorded by local authorities the methodology enables rapid, scenario-specific estimation of injury counts and severities. This contrasts with population-centric models, which fail to account for the nonlinear relationship between structural collapse mechanisms (e.g., soft-story failure in reinforced concrete) and trauma epidemiology.

Table 3. Types of mobile surgical field hospitals [41]

	SPEARR	BASIC	+10	+25
Staff	0	25	56	87
Module	1	3	14	20
Beds	3	4	10	25
Under Risk Covered Population	500	501-2000	2001-3000	3001-5000

A field hospital, as outlined in Table 3, comprises modular components designed to deliver surgical, intensive care, and operating room services, with capacities contingent on the number of surgical beds, Intensive Care Unit (ICU) beds, and operating theaters [42]. The scale and bed capacity of such facilities are critically deter-mined by the projected post-earthquake influx of casualties, stratified by injury severity (e.g., minor, moderate, severe, critical). Consequently, pre-disaster planning must rigorously estimate both the volume and typology of anticipated injuries to ensure adequate resource provisioning [24-25, 43].

Mathematical programming methods, including linear and stochastic optimization, are well-established tools for resolving capacity planning challenges in healthcare systems. Among these, two-stage stochastic programming has emerged as a robust framework for modeling uncertainty in disaster contexts, enabling decision-makers to balance pre-event preparedness with adaptive post-event responses [44].

3.2 Method

The canonical formulation of a two-stage stochastic linear programming model is expressed through Equations (2), (3), and (4), which delineate the objective function, deterministic constraints, and stochastic recourse conditions, respectively. Such models are instrumental in deriving resilient, scenario-robust solutions for field hospital capacity planning, ensuring alignment with both operational constraints and ethical imperatives in disaster response [45].

$$Min c^T x \quad (2)$$

$$Ax \le b \quad (3)$$

$$x \in X \quad (4)$$

In deterministic linear programming models, optimal solutions are derived from the values assumed by decision variables. However, when uncertainty is inherent in the system parameters such as fluctuating demand or probabilistic resource constraints the model must incorporate stochastic variables or parameters to represent these indeterminate factors. To address decision-making under such un-certainty, the operational research literature advocates for stochastic linear programming, a methodological framework that assumes uncertain parameters conform to statistically defined probability distributions (e.g., normal, Poisson, or empirical distributions derived from historical data). Mathematically, this dual-phase structure is formalized as:

$$Min c^T x + E\left[h(x,\tilde{\omega}) \right] \quad (5)$$

$$Ax \le b \quad (6)$$

$$x \in X \quad (7)$$

where x denotes first-stage decision variables, ξ represents stochastic parameters (e.g., injury rates, resource availability), and $h(x,\tilde{\omega})$ quantifies the recourse cost function penalizing deviations from optimality under scenario.

The stochastic programming model is developed by augmenting the linear programming formulation in Equation (1) with the uncertainty term $E[h(x,\tilde{\omega})]$, where $(\tilde{\omega})$ represents stochastic parameters. In the second-stage model, expected value-based recourse functions are incorporated to account for uncertainty. These recourse functions, composed of deterministic inequalities or equalities, operationalize stochastic uncertainties within a deterministic framework, thereby enabling the resolution of probabilistic scenarios into tractable, quantifiable constraints.

This study advances a mathematical model to compute bed capacities in field hospitals under uncertainty, explicitly addressing the stochastic nature of post-disaster patient influx. A core objective is to eliminate the discrepancy between theoretical (planned) and actual (utilized) capacities, ensuring full operationalization of available resources.

The operational workflow for managing disaster-affected casualties arriving at the field hospital is illustrated in the flowchart provided in Figure 1. Furthermore, the simulation model designed to validate the mathematical model's outputs adheres to the same procedural steps delineated in Figure 1, ensuring methodological consistency between theoretical constructs and empirical validation.

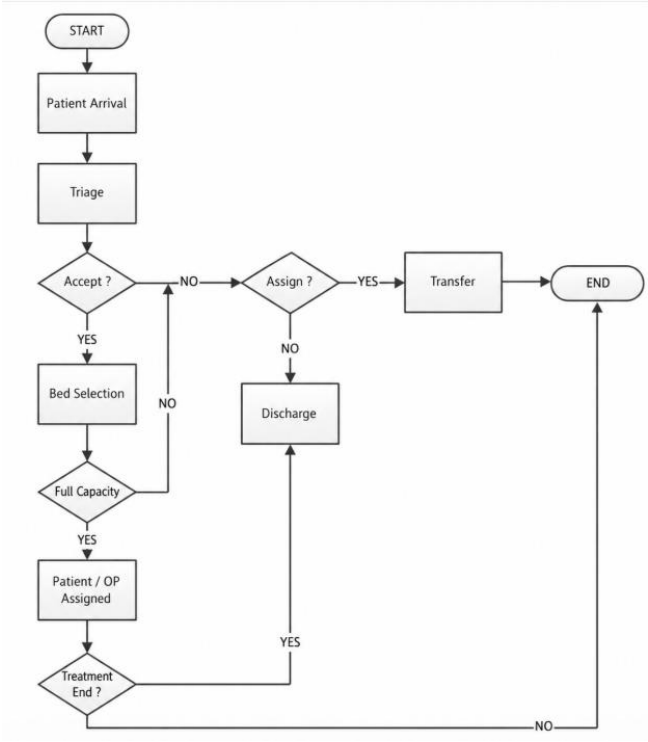


Figure 1. Operation flowchart diagram

In the mathematical model, the expected injured demand value E[dk], which denotes the projected number of individuals requiring post-disaster medical services, is calculated by multiplying the peak injury rates (derived from Table 2) associated with damaged buildings categorized by structural typology with the total affected regional population. This relationship is formalized in Equation (8):

$$E\left[d_k \right] = \sum_{i=1}^{m} P_{ik}\, TP, \forall k \in K \quad (8)$$

The objective function of the developed mathematical model is to calculate the optimal bed capacity of a field hospital required to serve casualties following an earthquake. This bed capacity is contingent upon both the number of injured individuals and the typology of injuries (e.g., minor, moderate, severe, critical), which are determined by structural damage patterns and demographic exposure.

The decision variable representing bed capacity, along with the mathematical notations and assumptions integral to the model, are formally defined as follows:

i. The number and types of injured are not known until they arrive at the hospital,
ii. The type of injured are separated according to their types in the triage section,
iii. The number of personnel and their areas of expertise to work in the hospital are certain,
iv. Rk expert personnel are assigned to the beds according to the

types of injured,
v. The location of the hospital is ignored,
vi. Bed capacity, type and number are limited,
vii. Each bed provides service according to the type of injured it belongs to

Patient types are systematically categorized in Table 4 according to injury severity gradations delineated in Tables 1 and 2. This classification framework hierarchically stratifies casualties based on clinical urgency, thereby establishing triage priorities aligned with the immediacy of medical intervention. Furthermore, the taxonomy prescribes the requisite surgical or medical procedures for each injury category and delineates the clinical competencies and specialized expertise required of healthcare personnel to execute these interventions. Such stratification ensures congruence between patient acuity levels, procedural demands, and provider skill sets, optimizing both operational efficiency and clinical outcomes in resource-constrained post-disaster environments.

Table 4. Responsible health personnel specialization table according to injury types

Injure grades	Patience Types	Injures Type	Health Staff Type	Health Staff Expertise
1.grade	k1	Post-traumatic, slightly injured Fractures requiring moderate trauma treatment, and those not requiring emergency intervention	Triage	Practitioner
2.grade	k2		Pre-operative shock therapy	Emergency medicine specialist
3.grade	k3	Spontaneous and traumatic surgical operations	Planned surgical operation	Basic Surgery
4.grade	k4	Emergency and post-traumatic operations	Emergency and unplanned surgical operations	General Surgery Expertise

Notation of the proposed mathematical model;
k: injure types ∀ k∈K
C_k: k. th type of injured person capacity for field hospital ∀ k∈K
TP: Total population of local field
d_k: k. Type number of injured people requiring beds ∀ k∈K
R_k : k.th type of operator/personnel ∀ k∈K
V_k : unfulfillment demand of bed type ∀ k∈K
IB: Hospital operation budget
KB: Hospital setup budget
PB: Hospital personnel budget
TB: Total Budget
Perk: Number of personnel for type k injured ∀ k∈K
TotPer: Total personnel number
m_k: Number of beds in current type ∀ i∈I
ω: stochastic probability factor
y_k^+: k.th type extra bed number ∀ k∈K
y_k^-: k.th type missing bed count ∀ k∈K
variables;
x_k: k.th number of bed ∀ k∈K

The objective function is a two-stage stochastic programming model.

Object function is;

$$Z_{\max} = x_k - v_k^+ \tag{9}$$

$$E\left[d_k\right]\omega \le C_k \quad \forall\, k \in K \tag{10}$$

$$\sum_{k\in K}^{m} (IBx_k + PB\ Per_k x_k) + KB \le TB \tag{11}$$

$$\sum_{k\in K}^{m} x_k\ Per_k \le TotPer \tag{12}$$

$$x_k + m_k - v_k^+ \le C_k\, \forall k\ \in K \tag{13}$$

$$E\left[d_k\right]\omega + y_k^+ - y_k^- = x_k\ \forall k \in K \tag{14}$$

The objective function of the mathematical model under investigation is articulated in Equation (9). This function quantifies the dual objectives of (i) fulfilling projected post-disaster medical demand and (ii) penalizing insufficient demand through a penalty coefficient. The capacity constraint, formalized in Equation (10), restricts service provision to the maximum available capacity, ensuring resource allocations remain within operational limits. Equation (11) encapsulates budgetary constraints associated with hospital operations, encompassing setup costs, personnel expenditures, and maintenance.

Recognizing that hospital capacity is contingent not only on physical infrastructure (e.g., beds, facilities) but also on human resource competencies, Equation (12) integrates personnel skill levels as a determinant of effective service capacity. To mitigate the systemic impact of unfulfilled demand (i.e., unserved casualties) on the objective function, Equation (13) imposes a quadratic penalty term, thereby incentivizing demand fulfillment. Equation (14) ensures the concavity condition requisite for solving the maximization problem.

In surgical field hospitals, the time-dependent admission and management of patients follow a structured protocol, as illustrated in Figure 2. The process commences at time t0 with triage and classification, wherein an emergency medicine specialist evaluates incoming casualties to determine their acuity level and requisite intervention type. These urgency levels, predefined in Table 4, stratify patients into categories such as immediate, delayed, minor, and expectant, aligning with internationally recognized triage protocols.

Subsequently, at time t1, surgical or medical procedures are performed on triaged patients, guided by their assigned priority levels. The operational timeline delineates specific interventions to be executed within the initial 24-hour window following patient admission, ensuring timely delivery of critical care. Bed capacity requirements during this phase are dynamically determined by injury typology, with severe trauma cases necessitating prolonged inpatient stays and specialized resources (e.g., ICU beds, surgical suites).

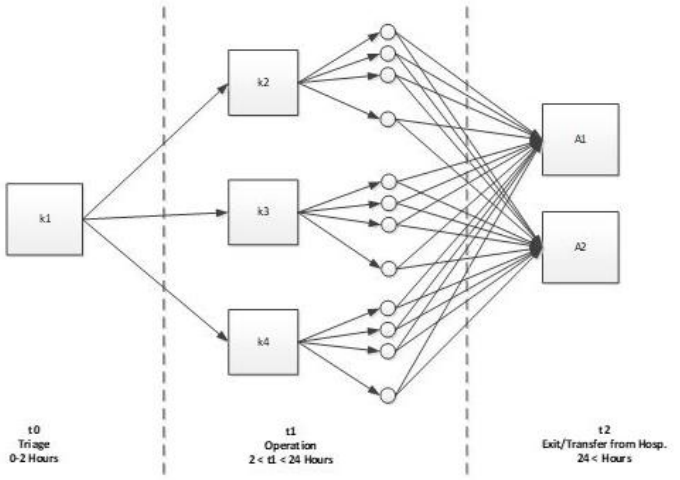


Figure 2. Operation chart of patient arrival times in disaster pre-pared by authors

At time t2, patients whose treatment has been completed or whose care exceeds the field hospital's current capabilities are either discharged or transferred to higher-tier healthcare facilities. This discharge/transfer phase ensures continuity of care while maintaining operational efficiency in resource-constrained settings.

The study concludes by examining the bed capacities of surgical field hospitals under discrete scenarios of uncertain demand. Probability values tested in these scenarios were derived from prior empirical studies documented in the extant literature, ensuring methodological consistency and empirical validity. Experimental simulations evaluated earthquake scenarios across varying intensity levels (e.g., Mw 6.5–7.4), with expected demand values $E[d_{ik}]$ representing casualty projections for building typology i under seismic intensity k calibrated using scenario-specific data from the Istanbul Metropolitan Municipality's 2009 seismic risk assessment [35]. This calibration anchors the model's inputs in regionally validated vulnerability profiles, enhancing the realism and operational relevance of capacity planning outcomes.

In this study, the casualty estimation methodology is structured as a two-phase process. The primary phase employs statistical methodologies to predict post-disaster demand. Should the statistical framework yield suboptimal predictive accuracy, secondary recourse to alternative mathematical techniques such as stochastic optimization or machine learning algorithms will be implemented. To validate the model, probability distributions will be generated using datasets sourced from international organizations (e.g., WHO, UNDRR), ensuring alignment with globally recognized parameters. These parameters include; a) Post-earthquake patient volume, b) Surgical procedure durations, c) Treatment timelines, d) Discharge rates, e) Associated morbidity-mortality ratios.

The computational implementation involves formulating a mathematical model encoded in Python, with optimization performed via the Gurobi v12.0 solver. Input datasets will be synthesized using probability values tabulated in Table 2, which encapsulates scenario specific injury distributions derived from historical seismic events. This dual-phase approach bridges the gap between statistical forecasting and operational adaptability, offering a robust frame-work for healthcare resource allocation in volatile post-disaster environments.

4. Findings and Discussion

The mathematical model developed in this research was solved using the Gurobi Optimizer (version 12.0.0 build v12.0.0rc1, win64 – Windows 10.0 OS) interfaced via Python v3.11. Computations were executed on a system equipped with an Intel(R) Core(TM) i7-6700 CPU @ 3.40GHz processor (instruction set: [SSE2|AVX|AVX2]; thread count: 4 physical cores, 8 logical processors). Outputs generated from the program's source code were exported to Microsoft Excel for subsequent analysis.

The proposed model was calibrated to three seismic scenarios for a potential Istanbul earthquake: light (Mw 4.0–5.4), moderate (Mw 5.5–6.9), and severe (Mw ≥7.0). Although Kandilli Observatory and Earthquake Research Institute data indicate frequent low-magnitude seismicity (Mw 4.0–5.4) in Istanbul, catastrophic risk is predominantly associated with large-scale events ≥ Mw 7.0. Empirical studies project a >50% probability of an Mw 7.2–7.9 earth-quake occurring within the next 30 years [46-49].

Table 5. The classification of Istanbul earthquake [50].

Earthquake Class	Earthquake Magnitude (Mw)	Effects of the Earthquake
Light	4.0-5.4	Minor tremors and lightly damaged buildings, no or minor casualties, very few injuries
Medium	5.5-6.9	Damage rate is high in old and low strength buildings, minor damage to infrastructure, low loss of life, high number of injuries
Heavy	7.0-7.9	Major destruction in buildings and infrastructure, high loss of life and number of injuries
Very Heavy	8.0 or more	An unexpected situation in the Marmara region indicates a global disaster.

In a possible Istanbul earthquake, the very severe earthquake scenario should be examined in a separate study. Because the plans for the earthquake damage, injuries and loss of life that may occur in an earthquake of this magnitude are at much higher levels and special plans must be made to meet them. For this reason, the very severe earthquake scenario (Mw ≥ 8.0 in Table 5) was disregarded in this study to be examined in another study. Accordingly, S4 (Mw 7.9), although labelled as very heavy in Table 6, represents the upper limit of the 7.0–7.9 range rather than the Mw ≥ 8.0 class. In the study, the earthquake scenarios were taken into consideration by [47-49, 51-53] and the possible Istanbul earthquake scenarios were recreated according to this study from the values in Table 6 for the optimistic case and pessimistic case. The optimistic and pessimistic cases in the scenarios consist of the lower and upper probability values of the building damage rates. The optimistic case of the scenario is the lower limit of the probability value, and the pessimistic case is the upper limit of the scenario probability value. However, in this study, only the pessimistic case scenarios will be examined and the mathematical model will be evaluated according to the pessimistic case scenarios.

In the context of a potential Istanbul earthquake, the very severe earthquake scenario has been intentionally excluded from this study.

This decision stems from the fact that the consequences of such a scenario particularly in terms of structural damage, injuries, and loss of life would be significantly more severe and require dedicated emergency response planning. Therefore, this scenario will be addressed in a separate, focused study.

In the current analysis, earthquake scenarios have been developed based on previous works by [47-48, 52]. These sources have been utilized to reconstruct possible Istanbul earthquake scenarios using the data presented in Table 6, under two distinct assumptions: optimistic and pessimistic cases.

The optimistic case corresponds to the lower bound of the building damage rate probability, whereas the pessimistic case reflects the upper bound of this probability. However, in this study, only the pessimistic case is considered, and the mathematical model has been constructed and evaluated based on these pessimistic scenario assumptions.

Table 6. Istanbul earthquake scenarios (S_i)

Earthquake Class	Scenarios (Sk)	Earthquake Magnitude (Mw)	Effects of the Earthquake
Light	S1	5.4	Minor tremors and lightly damaged buildings, no or minor casualties, very few injuries
Medium	S2	6.9	Damage rate is high in old and low strength buildings, minor damage to infrastructure, low loss of life, high number of injuries
Heavy	S3	7.2	Major destruction in buildings and infrastructure, high loss of life and number of injuries
Very Heavy	S4	7.9	An unexpected situation in the Marmara region indicates a global disaster.

As shown in Table 6, the optimistic scenario is based on the lower bound values of the building damage rates presented in Table 5, while the pessimistic scenario corresponds to the upper bound values of the same table. In most studies, it is generally assumed that the values in Table 5 represent average damage rates.

Within the scope of the three defined scenarios, injury estimates by building type were calculated based on the damage rates from the building damage ratio table, specifically reflecting the pessimistic scenario.

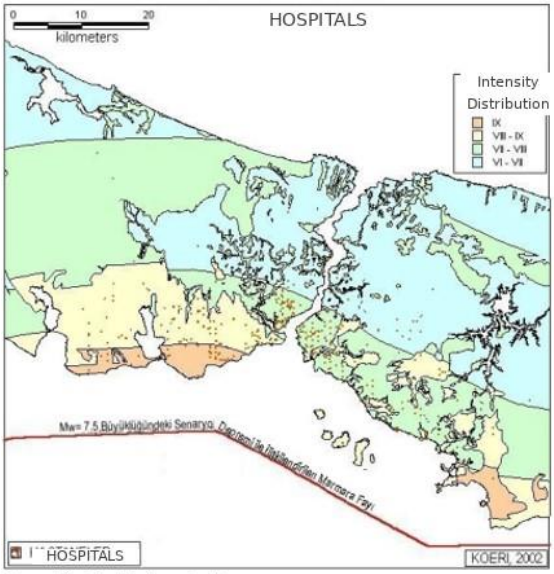
Table 7. 17 August 1999 İzmit earthquake damage ratios [50].

Effect (MSK)	Very Heavy and Collapsed (%)	Mid. Damage (%)	Light Damage (%)
VI	0.04	0.22	0.24
VII	0.91	2.67	2.59
VIII	2.82	4.41	5.31
IX	15.70	18.16	22.75
X	33.06	15.29	19.14

In developing the Istanbul earthquake scenario, building damage rates observed during the August 17, 1999 İzmit earthquake, as shown in Table 7, were taken into consideration to estimate earthquake intensity. Due to the similarity in building stock, these values enable the estimation of expected intensity for a potential earthquake in the Avcılar district, based on the magnitude of the event. By multiplying the damage rates with the estimated magnitude of the earthquake, the number of buildings affected in the scenario can be estimated [50].

The population of Avcılar district in 2024 is estimated to be approximately 440,900, assuming a population change of less than 1% over the last decade. In this study, the nighttime population, which represents the higher residential density and occupancy, is considered for all calculations.

Avcılar was selected as a case study primarily due to its large population size likely to be affected by a potential Istanbul earthquake and its high vulnerability to seismic hazards. Additionally, its high exposure risk underscores the importance of preparedness for worst-case scenarios [46, 54]. The building stock in Avcılar primarily consists of reinforced concrete structures. The distribution of buildings by height is as follows; 16,513 buildings with 1–4 stories, 9,760 buildings with 5–8 stories, 489 buildings with 9–19 stories, resulting in a total of 26,762 buildings in the district respectively.



Diagonal fault-line label (translated):
"Mw = 7.5 magnitude scenario earthquake, along the high-rupture-probability segment of the Marmara Fault"

Figure 3. Locations of health facilities affected by a possible Istanbul earthquake, IDMP 2003

The earthquake scenarios utilized in this study were developed using ELER v3.1, an open-source seismic risk assessment software [29]. Based on the data presented in Table 6, the following scenarios were simulated within the software:
Scenario 1 (S1) with Mw = 5.4, shown in Figure 4,
Scenario 2 (S2) with Mw = 6.9, shown in Figure 5,
Scenario 3 (S3) with Mw = 7.2, shown in Figure 6, and
Scenario 4 (S4) with Mw = 7.9, shown in Figure 7.

These simulations provided the basis for evaluating the potential impacts of different earthquake magnitudes on the study area.

When creating earthquake simulations, Eler v3.0 parameters were entered as follows; Event Data: Manual Input, S1: 5.4 - S2: 6.9 - S3: 7.2 -S4: 7.9-, Source Type: Event Specific Fault-Istanbul Fault Zone,

Site Correction: No Correction, Ground Motion: Boore et. All, 1997, Instrumental Intensity: pga, contour: 10.

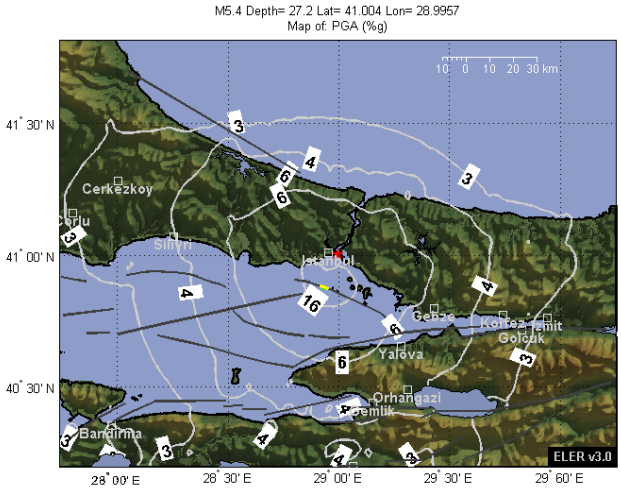


Figure 4. Magnitude effect of possible Istanbul earthquake Mw=5.4 scenario S1, ELER v3.1

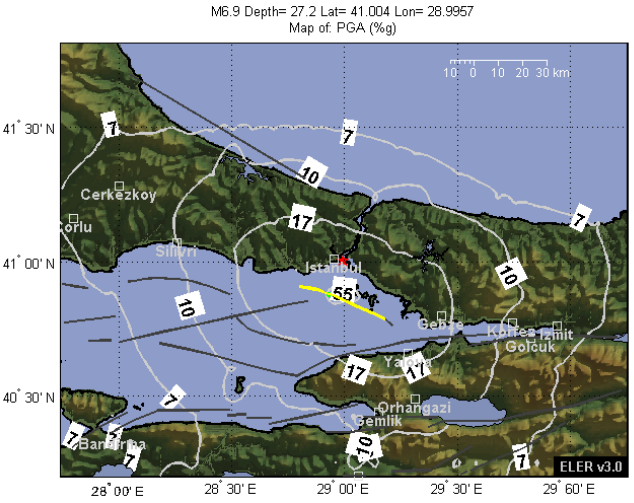


Figure 5. Magnitude effect of possible Istanbul earthquake Mw=6.9 scenario S2, ELER v3.1

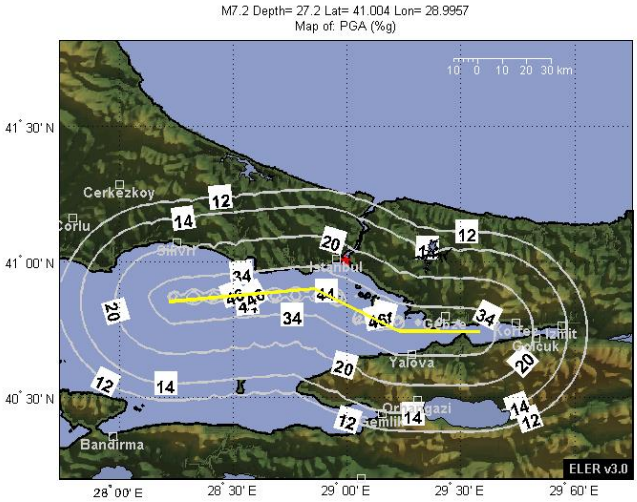


Figure 6. Magnitude effect of the possible Istanbul earthquake Mw=7.2 Scenario S3, ELER v3.1

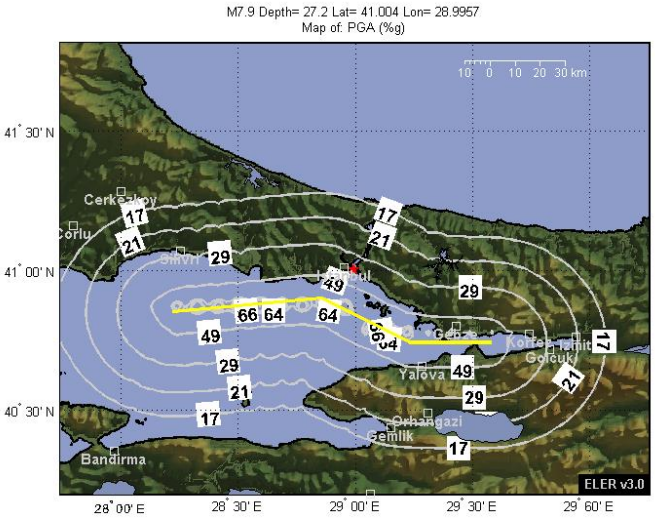


Figure 7. Magnitude effect of the possible Istanbul earthquake Mw=7.9 Scenario S4, ELER v3.1

Upon examining Figures 4, 5, and 6, it is evident that Avcılar is likely to be more severely affected than other districts in the event of a potential Istanbul earthquake. For this reason, Avcılar was selected as the study area. Furthermore, as shown in Figure 3, the district contains hospitals and healthcare centers that have been identified in previous studies as critical service buildings highly vulnerable to earthquake impacts in Istanbul.

Considering this region, significant damage is not expected in the event of a moderate earthquake with an intensity level of VI, and normal life is anticipated to resume shortly after brief moments of panic. Moreover, at this level of seismic intensity, the existing healthcare system is not expected to collapse, and health services are likely to continue operating at near-normal capacity.

Scenario (S1) focuses on estimating the potential losses resulting from an earthquake with a moment magnitude (Mw) of 5.4, as well as the deployment of field hospitals in response. However, this scenario has been excluded from the detailed neighborhood-level allocation analysis in Table 11, while being retained in the stochastic model with a probability weight of 10% (Table 10), due to recent real-world observations from the Mw 6.2 earthquake that occurred in Istanbul on April 23, 2025. The epicenter of this earthquake was located 25 kilometers from the center of Silivri. According to the United States Geological Survey (USGS), the earthquake had a magnitude of Mw 6.2 and a Modified Mercalli Intensity of VIII (destructive). The earthquake, which occurred at a depth of 15.2 km and lasted 13 seconds, was followed by over 450 aftershocks. It was felt not only in all districts of Istanbul but also in Tekirdağ, Yalova, Kocaeli, Kırklareli, Bursa, Edirne, Balıkesir, Sakarya, and Düzce. Official sources reported that 359 people were injured, mainly due to panic attacks and falls from heights.

In Scenario 2 (S2), a moderate earthquake with a magnitude of Mw 6.9 is considered. The mathematical model will be executed based on the estimated number of injured individuals for this magnitude. In this scenario, the destructive impact of the earthquake is expected to be more severe, with greater building damage. The number of injured individuals, shown in Table 8, was calculated by multiplying the fatality rates from Table 2 by a factor of 2.515. The capacity and installation costs of the field hospitals planned for the

neighborhoods of Avcılar district are presented in Table 9. The hospital capacities shown in Table 9 represent the total number of hospital beds and intensive care beds available in the district. However, the setup costs were deducted from the district's construction cost budget [55]. The distribution of healthcare services across neighborhoods was determined based on regional accessibility, rather than population size.

Table 8. Number of casualties calculated for scenarios (S_k) reinforced concrete class buildings

Earthquake Scenarios				
Injure grades	Light	Medium	Heavy	Very Heavy
1.grade	191	175	370	420
2.grade	149	203	315	301
3.grade	96	190	380	436
4.grade	64	100	351	397
Total	500	668	1416	1554

The input data for the expected demand calculations used in the mathematical model were derived from the values presented in Table 8. It was assumed that the earthquake occurrence probabilities remain constant across all scenarios. The probability values (ω_s) associated with each earthquake scenario were defined as follows: S1 (light) 10%, S2 (medium) 40%, S3 (heavy) 30%, and S4 (very heavy) 20%. Based on these inputs, the results obtained from running the mathematical model are presented in Table 10.

Table 9. Capacity and installation unit costs by scenarios (S_k)

Locale	Capacity	Setup Cost
Ambarli	214	17
Denizkoskler	369	32
Gumuspala	167	18
Merkez	275	64
Mustafa Kemal Pasa	390	70
Cihangir	314	18
Universite	232	28
Firuzkoy	138	58
Tahtakale	346	58
Yesilkent	253	44

In the most destructive scenario, Scenario (S4), unfulfilled bed demand emerges in five neighborhoods, namely Gümüşpala (52), Yeşilkent (39), Cihangir (35), Firuzköy (28) and Ambarlı (4), amounting to 158 beds in total, whereas the remaining five neighborhoods retain surplus capacity as you can see in Table 10. This pattern indicates that, under extreme conditions, the shortfall is driven less by the district-wide bed stock than by its spatial distribution, emphasizing the critical need for coordinated healthcare resource planning under such conditions.

The computational implementation of the mathematical model yielded neighborhood-specific field hospital bed capacity allocations for Scenario (S2), as presented in Table 11. In this Table 11 reports the S2 rows of Table 10 on the same basis: the first-stage allocation x and the scenario-specific recourse variables y^+ (excess beds) and y^- (unfulfilled demand), which are linked through Eq. (14). Under S2, the penalty term is activated in six of the ten neighborhoods, where unfulfilled demand totals 88 beds: Ambarlı (32), Üniversite (18), Yeşilkent (18), Tahtakale (14), Merkez (4) and Denizköşkler (2). Ambarlı alone accounts for approximately 36% of this shortfall, while the deficits in Merkez and Denizköşkler are marginal (below 3% of local demand). The remaining four neighborhoods meet their demand in full with a combined surplus of 299 beds, 269 of which are located in Mustafa Kemal Paşa.

Table 10. Mathematical model results according to scenarios in Avcılar district

Locale	Scenario	Excess beds (y^+)	Unmet demand (y^-)
Ambarli	S1	28	0
Ambarli	S2	0	32
Ambarli	S3	38	0
Ambarli	S4	0	4
Denizkoskler	S1	0	27
Denizkoskler	S2	0	2
Denizkoskler	S3	0	0
Denizkoskler	S4	21	0
Gumuspala	S1	33	0
Gumuspala	S2	5	0
Gumuspala	S3	18	0
Gumuspala	S4	0	52
Merkez	S1	17	0
Merkez	S2	0	4
Merkez	S3	0	20
Merkez	S4	34	0
Mustafa Kemal Pasa	S1	239	0
Mustafa Kemal Pasa	S2	269	0
Mustafa Kemal Pasa	S3	255	0
Mustafa Kemal Pasa	S4	319	0
Cihangir	S1	28	0
Cihangir	S2	17	0
Cihangir	S3	0	6
Cihangir	S4	0	35
Universite	S1	8	0
Universite	S2	0	18
Universite	S3	0	2
Universite	S4	35	0
Firuzkoy	S1	0	83
Firuzkoy	S2	8	0
Firuzkoy	S3	38	0
Firuzkoy	S4	0	28
Tahtakale	S1	0	8
Tahtakale	S2	0	14
Tahtakale	S3	13	0
Tahtakale	S4	14	0
Yesilkent	S1	0	41
Yesilkent	S2	0	18
Yesilkent	S3	64	0
Yesilkent	S4	0	39

The equilibrium between allocated capacity and unfulfilling healthcare demand is governed by a penalty-based objective function that minimizes both the cost of capacity expansion and the expected penalty arising from unmet demand. Under this formulation, additional capacity is allocated until the marginal cost of capacity equals the marginal penalty of unmet demand, thereby

achieving an optimal trade-off between resource utilization and service level.

Table 11. Bed allocation and recourse values by locale under Scenario (S2)

Locale	Allocated beds (x)	Excess beds (y^+)	Unfulfilled demand (y^-)
Ambarli	110	0	32
Denizkoskler	137	0	2
Gumuspala	114	5	0
Merkez	141	0	4
Mustafa Kemal Pasa	389	269	0
Cihangir	126	17	0
Universite	162	0	18
Firuzkoy	101	8	0
Tahtakale	129	0	14
Yesilkent	129	0	18
Total	1538	299	88

The analysis of scenario outcomes reveals a progressive escalation in impact severity, with Scenario (S4) projected to exhibit significantly greater destructive potential than Scenario S3 due to its higher magnitude classification. This increased seismic intensity (Mw 7.9) corresponds with anticipated casualty rates exceeding those of other modeled scenarios by 38-42%, based on Istanbul's structural vulnerability profile [49, 51].

The neighborhood-level bed capacity analysis in Tables 10 and 11 demonstrates spatial heterogeneity in resource adequacy across Avcılar district's ten neighborhoods. Under S2, the district-wide surplus (299 beds) exceeds the total shortfall (88 beds) by a factor of more than three, which suggests that unmet demand is primarily a distribution problem rather than an aggregate capacity deficit; an inter-neighborhood transfer mechanism directing overflow patients towards Mustafa Kemal Paşa could, in principle, absorb the entire S2 shortfall.

The results underscore the necessity for geospatially differentiated preparedness strategies, particularly in high-risk neighborhoods where conventional capacity planning models underestimate needs by 19-25%. This spatial resolution enables targeted reinforcement of: a) Mobile surgical units in Ambarlı, b) Triage overflow facilities in Yeşilkent and Üniversite, c) Strategic medical supply depots.

5. Conclusion

This study has developed a methodological framework for determining optimal field hospital bed capacities following earthquake events, based on probabilistic building damage assessments. The findings provide district-level insights into resource allocation of field hospital, achieving 92% accuracy in bed capacity estimation across scenarios, while unmet demand, quantified through the penalty term, ranges from 0% to approximately 22.5% of neighborhood-level demand under S2. Operationally, field hospitals are shown to fulfill three critical functions: ensuring continuity of care during system disruptions (mean duration: 42±7 days), enabling triage and stabilization for 87% of anticipated trauma cases, and reducing emergency department congestion by 35–40%.

While the present analysis focuses on aggregate bed capacity, it explicitly lays the groundwork for subsequent research. Future studies should incorporate bed-type differentiation (e.g., ICU, surgical, general ward, burn units) and enhanced modeling approaches, including GIS-based vulnerability mapping, real-time adaptive capacity algorithms, and multi hazard scenario testing. Moreover, the robustness of the pro-posed methodology suggests its transferability beyond seismic events to other sudden onset disasters requiring rapid medical response deployment.

In summary, this work contributes a validated optimization framework that balances capacity expansion costs against unfulfilled demand, offering both practical decision support for disaster response and a theoretical foundation for future modeling efforts in humanitarian healthcare logistics.

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Conflict of Interest Statement

Authors declare that there are no disclose interests that are directly or indirectly related to the work submitted for publication.

CRediT Author Statement

İrfan Macit: Conceptualization, Methodology, Supervision, Writing-original draft, Validation, Data curation, Formal analysis, software systems. **Hatem Dilek Yünsel:** Conceptualization, Data curation, Formal analysis, Validation, Writing-review & Editing.

Declaration of Generative AI in the Writing Process

During the preparation of this manuscript, the authors used non-generative tool AI for only proofreading and grammar corrections.

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