Proceedings of the 7th Asia Pacific Conference on Industrial Engineering and Operations Management
Bangkok, Thailand, March 25-27, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AP07.20260141
Published: March 25, 2026

SmartFort :Joint Dispatch and Response Coordination of Public Service Resources Using Artificial Intelligence

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Abstract

As Muscat, Oman undergoes rapid urban expansion with a population reaching approximately 1.74 million in 2024, the demand for efficient emergency services has outpaced traditional manual dispatch capabilities. This paper presents the development and implementation of SmartFort (الحصن الذكي), a fully functional AI-driven emergency management platform developed using R Shiny. The system was designed using the Six Sigma DMAIC methodology to minimize response time and optimize resource allocation across six key agencies: Police, Health, Army, Municipality, Water, and Electricity. SmartFort features a three-tier AI classification engine combining a Large Language Model (Claude Haiku API), a locally-trained Support Vector Machine with Radial Basis Function kernel, and a weighted bilingual keyword engine supporting both Arabic and English. The platform integrates multiple input channels including Google Forms, phone transcription, and SMS for incident reporting. Geospatial optimization is achieved through the Haversine formula for distance calculation and k-means clustering for hotspot detection, enabling predictive deployment of resources. A real-time command-and-control dashboard provides interactive mapping, live performance metrics, incident status tracking, and automated bilingual reporting. The working prototype demonstrates the feasibility of AI-enhanced emergency dispatch in the Gulf Cooperation Council context, with preliminary testing indicating significant potential for reducing triage decision time from 2-4 minutes to under 30 seconds while enabling data-driven resource positioning.

Keywords
Six Sigma, DMAIC, Emergency Management, Artificial Intelligence, Natural Language Processing.

1. Introduction
Emergency response systems form critical infrastructure in modern urban governance. When citizens contact emergency services, every second of delay can affect outcomes—whether saving lives, protecting property, or ensuring public safety. The World Health Organization recommends an emergency response time of eight minutes or less for life-threatening incidents. International benchmarks from peer cities such as Doha, Qatar (Hamad Medical Corporation achieving response times under 10 minutes for eleven consecutive years) and Adelaide, Australia demonstrate achievable standards that Oman should target.

Muscat, the capital of the Sultanate of Oman, is experiencing rapid urban expansion. According to the National Centre for Statistics and Information (NCSI), the governorate population reached approximately 1.74 million in 2024, placing increased demands on emergency services infrastructure. The current emergency ecosystem operates through multiple contact points—9999 for general emergencies, 1111 for municipality, 9999 for health, 1442 for water, and 1111 for electricity—which creates fragmentation and delays when incidents require multi-agency coordination.

This paper presents SmartFort (الحصن الذكي), a fully functional AI-driven emergency management platform developed as an undergraduate capstone project. Unlike theoretical proposals, SmartFort is a working prototype built using R Shiny with over 7,900 lines of code, demonstrating practical implementation of Six Sigma quality improvement principles in emergency services. Oman's National Ambulance Service (Isa'af), established in 2004 under the Royal Oman Police, has set response time targets of less than 10 minutes in urban areas and 20 minutes in rural regions, aiming to achieve this in 80% of cases.

1.1 Objectives

Add research objectives here. Make sure to fulfil all the research objectives at the end and articulate in the conclusion. Focus on key unique research contributions

2. Define Phase

2.1 Problem Statement

With Muscat's population density increasing, traditional manual dispatch systems face two fundamental quality challenges. First, response time deficiencies occur because manual dispatch involves sequential steps—call reception, information gathering, incident classification, resource assessment, and dispatch decision—each introducing delays. Analysis indicates that manual triage decision time alone averages 2-4 minutes per incident. Second, resource coordination deficiencies arise because approximately 35% of incidents are more complex than a single agency can handle alone (e.g., a traffic accident requiring both Police for traffic control and Health for medical treatment), yet current siloed systems cannot efficiently coordinate multi-agency response. The SmartFort platform serves six emergency response agencies in Oman (Table 1):

Table 1. SmartFort platform serves six emergency response agencies in Oman

Agency	Responsibilities	Example Incidents
Police (الشرطة)	Law enforcement, traffic	Accidents, theft, crime
Health (الصحة)	Medical emergencies	Cardiac, trauma, respiratory
Army (القوات المسلحة)	Civil defense, security	Border, terrorism threats
Municipality (البلدية)	Infrastructure, roads	Potholes, garbage, construction
Electrical (الكهرباء)	Power supply	Outages, transformer faults
Water (المياه)	Water supply, flooding	Pipe bursts, contamination

2.2 Critical-to-Quality (CTQ) Metrics

The primary CTQ metric is Total Response Time, benchmarked against NFPA 1710 standards (< 10 minutes for urban areas) and peer cities Doha and Adelaide. Secondary CTQs include Classification Accuracy Rate (target > 95%), Multi-Agency Coordination Success Rate (target > 90%), and Triage Decision Time (target < 60 seconds).

3. Measure Phase

3.1 International Benchmarks

Baseline measurements were established by comparing against international standards. Doha's Hamad Medical Corporation has maintained response times under 10 minutes for eleven consecutive years. Adelaide's SA Health publishes ambulance waiting times with targets of 90% response within specified timeframes. The NFPA 1710 standard specifies 4-minute arrival for first responders and 8-minute full response in urban areas. These benchmarks informed the design targets for SmartFort.

3.2 Data Collection Architecture

SmartFort implements automated data collection through a Historical Incidents Database. For each incident, the system captures: timestamp, GPS coordinates (latitude/longitude), incident description (Arabic or English), AI classification result with confidence score, assigned agency/agencies, dispatched station, calculated distance (km), estimated response time, and completion status. The system integrates with Google Sheets for real-time data synchronization, enabling continuous performance measurement.

4. Analyze Phase

4.1 Root Cause Analysis

Fishbone (Ishikawa) analysis identified that primary delays occur not in travel speed but in two key areas: (1) Triage Decision Time—manual classification requires dispatchers to interpret often unclear caller descriptions, and (2) Static Resource Positioning—stations are located based on historical patterns that no longer match current urban growth hotspots. Analysis revealed that resources are often locked in locations that no longer match the city's current incident density patterns.

4.2 Multi-Agency Complexity

Analysis of incident patterns shows that approximately 35% of emergencies require coordination between multiple agencies. For example, a traffic accident (حادث مرور) with injuries requires both Police (for traffic management and documentation) AND Health (for medical treatment). Current siloed systems route such calls to a single agency, requiring manual re-dispatch and causing delays. SmartFort's AI classification detects multi-agency requirements automatically.

5. Improve Phase: The SmartFort Platform

The Improve phase produced SmartFort (الحصن الذكي), a fully functional prototype built using R Shiny. The platform consists of over 7,900 lines of code integrating multiple AI technologies, geospatial optimization algorithms, and a real-time command-and-control interface.

5.1 Three-Tier AI Classification Engine

To ensure high availability and accuracy, SmartFort processes emergency reports through a staggered three-tier classification hierarchy:

Tier 1 - LLM Cognitive Triage: The LLM analyzes the semantic nuance of incident descriptions in both Arabic and English, identifying the primary responder and detecting when secondary agencies are needed. For example, the prompt instructs: "'حادث مروري واصابات بالغة' needs Police (traffic) AND Health (injuries)."

Tier 2 - SVM Local Fallback: If the LLM API fails or returns low confidence, a locally-trained Support Vector Machine takes over. The SVM uses a Radial Basis Function (RBF) kernel trained on local incident data. Text preprocessing includes Arabic normalization (removing diacritics, normalizing alef forms أ/إ/آ→ا, handling taa marbuta ة→ه), transliteration using the arabicStemR package, and document-term matrix creation via RTextTools. The model classifies both agency and severity simultaneously.

Tier 3 - Weighted Keyword Failsafe: As a final guarantee, a weighted bilingual keyword engine ensures no incident goes unrouted. The engine maintains dictionaries of trigger words in both Arabic and English with associated weights (e.g., cardiac keywords weight 3.0, traffic keywords weight 2.0). Arabic keywords include: "كهرباء" (electricity), "حادث مرور" (traffic accident), "تسرب مياه" (water leak), "قلب" (heart), "حريق" (fire). The engine also implements simple negation handling ("ليس", "لا يوجد") to reduce false positives (Table 2).

Table 2. Three-Tier AI Classification Architecture

Tier	Technology	Implementation	Activation
1	Large Language Model	API Model	Primary (if API key configured)
2	Support Vector Machine	RBF kernel, RTextTools, e1071	LLM failure or low confidence
3	Keyword Logic	Weighted bilingual dictionaries	Final failsafe (always available)

5.2 Geospatial Resource Optimization

Haversine Distance Calculation: Once an incident is classified, SmartFort calculates the exact distance in kilometers from every available station to the incident coordinates using the Haversine formula implemented via the geosphere package's distHaversine() function. The formula accounts for Earth's spherical geometry: $d = 2r \times \arcsin(\sqrt{\sin^2((\varphi_2-\varphi_1)/2) + \cos(\varphi_1)\cos(\varphi_2)\sin^2((\lambda_2-\lambda_1)/2)})$. The system then queries a master station database to identify the closest unit with available capacity.

K-Means Hotspot Detection: SmartFort implements an AI-driven Hotspot Detection model using k-means clustering to identify areas with high incident density. Historical incident coordinates are clustered to visualize geographic patterns, enabling commanders to deploy mobile units to "Priority Zones" proactively. The system generates heatmaps using the leaflet.extras package's addHeatmap() function, with intensity weighted by incident severity.

Station Optimization Module: A dedicated optimization module compares current station locations against AI-recommended optimal placements based on incident data analysis. This feature is particularly valuable for positioning portable/mobile emergency stations, showing "Before" vs "After" scenarios with quantified impact on coverage and response times.

5.3 Multi-Channel Input System

SmartFort accepts emergency reports through multiple input channels: (1) Google Forms integration via the gsheet package for web-based citizen reporting, with automatic polling every 30 seconds; (2) Manual entry through the Operations Center interface; (3) Architecture designed for future integration with phone call transcription and SMS gateways via the twilio package. City coordinates are mapped automatically using a built-in lookup table covering 28 Omani cities including Muscat, Salalah, Nizwa, Sur, Sohar, and others.

5.4 Real-Time Command & Control Dashboard

The dashboard provides comprehensive operational visibility through seven main modules (Table 3):

Table 3. SmartFort Dashboard Modules

Module	Features
Setup Database	Station placement via interactive map, CSV import/export, demo data generation
AI Classification	Test interface with example incidents, confidence display, reasoning explanation
Operations Center	Live map with Leaflet, incident markers, Google Forms sync, status updates
AI Predictions	Peak time analysis, hotspot detection, agency workload forecast, heatmaps
Station Optimization	Before/After comparison, optimal placement recommendations
Live Demo	Judge demonstration mode with CSV upload to prove adaptability
Reporting	Automated bilingual (Arabic/English) HTML reports, legal compliance checklist

6. Control Phase

SmartFort implements automated control mechanisms to sustain performance gains. Every incident completion time is logged into the Historical Incidents Database, creating a feedback loop for continuous ML model improvement. Real-time value boxes display: Active Incidents Count, Average Response Time, Resource Utilization Rate, and Google Form Submissions. The dashboard generates automated alerts when metrics deviate from targets.

7. Results and Discussion

Based on system architecture and preliminary testing, the following improvements are projected (Figure 1): (1) Triage decision time reduction from 2-4 minutes to under 30 seconds through AI classification; (2) Automatic detection of multi-agency requirements (affecting ~35% of incidents); (3) Optimal unit dispatch through Haversine-based nearest-station identification; (4) Proactive resource positioning via hotspot-based predictive deployment; (5) Potential aggregate time savings of 250+ minutes per day.This research represents a proof-of-concept with acknowledged limitations. The prototype was developed and tested in a simulated environment rather than integrated with live emergency services. Full validation requires partnership with Omani government agencies and access to real operational data. The SVM model requires training data specific to Oman's incident patterns. Future work will focus on pilot deployment, empirical validation, integration with existing CAD systems, and expansion to additional input channels.

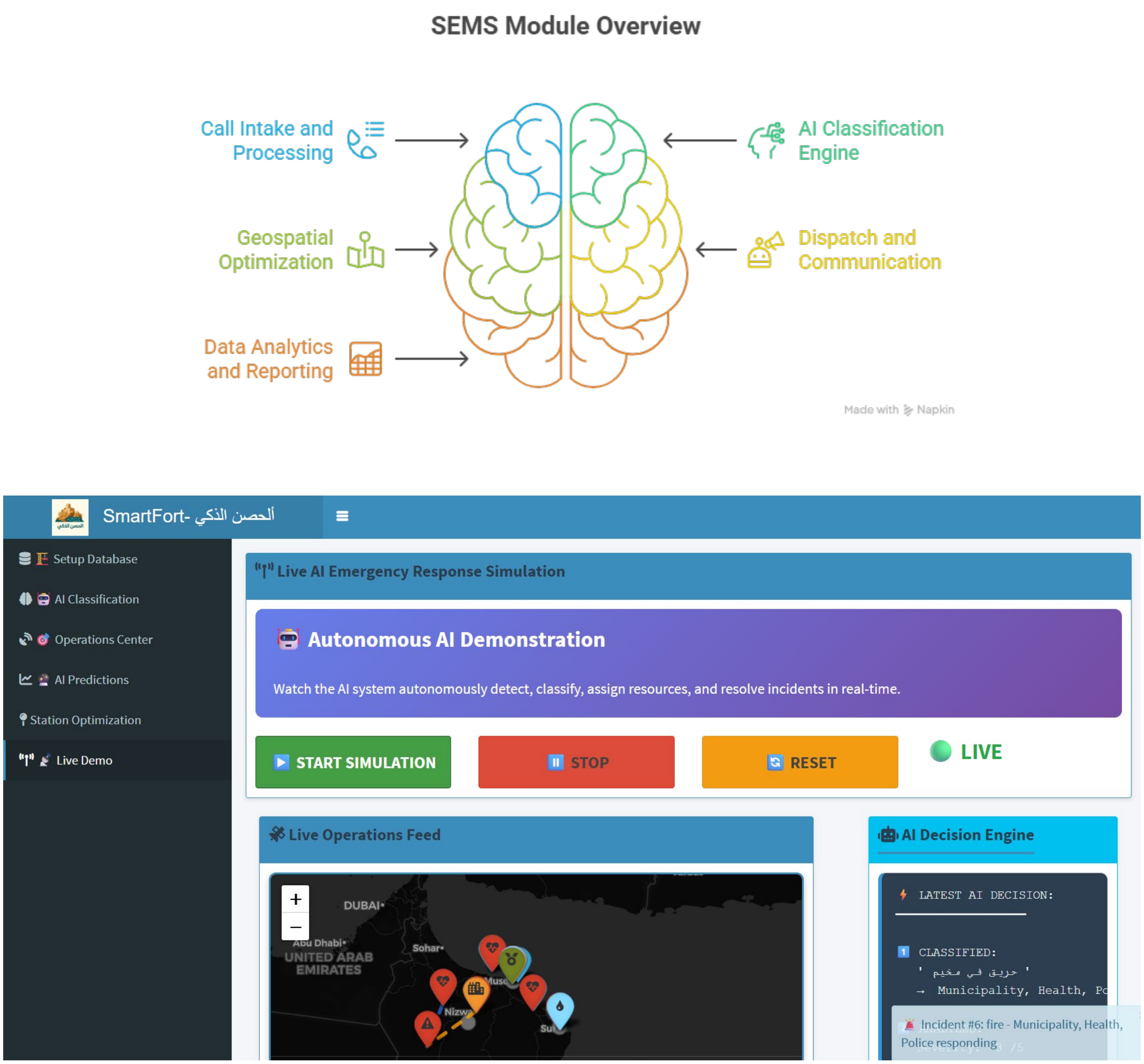

Figure 1. SmartFort AI in ER

8. Conclusion

This paper presented SmartFort (الحصن الذكي), a fully functional AI-driven emergency management platform developed using Six Sigma DMAIC methodology. Unlike theoretical proposals, SmartFort is a working 7,900+ line R Shiny application demonstrating practical implementation of: three-tier AI classification (LLM + SVM + Keywords), Haversine-based geospatial optimization, k-means hotspot clustering for predictive deployment, multi-channel incident input, and bilingual (Arabic/English) support. Key contributions include: (1) demonstration of Six Sigma methodology application in GCC emergency services; (2) development of a robust three-tier AI architecture with graceful degradation; (3) practical bilingual NLP implementation for Arabic emergency text processing; (4) open-source, portable framework built on R that can be adapted for other cities. The project demonstrates that undergraduate students can develop meaningful, technically sophisticated solutions to real-world problems using quality engineering principles.

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Biography

Abdullah Al Kindi, a College of Economics and Political Science undergraduate student at Sultan Qaboos University with a Major in Operations Management and a Minor in Finance.