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MultKAN-Nash: Strategic Multi-Agent Disaster Response using MultKAN and Nash Equilibriums

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***Abstract*—Climate disasters require coordination among stakeholders with competing objectives. Emergency responders prioritize rapid coverage, relief coordinators aim for resource efficiency, and affected populations seek timely access to aid. However, existing approaches often fail to balance these goals while maintaining interpretability for decision-making in high-stakes settings. We present *MultKAN-Nash*, a game-theoretic framework that combines Kolmogorov Arnold Networks (KAN) with Nash equilibrium and Multiplicative Weights (MW) learning to improve disaster response coordination. The framework models emergency operations as a strategic game in which agent utilities are learned from flood scenarios in Bangladesh using KAN. MultKAN attains strong utility prediction performance R^2 = 0.9661, ranking competitively among 9 baselines. The complete system achieved a coordination efficiency of 90.11%, equitable resource allocation (Gini = 0.099), and convergence within 10 MW iterations. Ablation studies on 200 scenarios show that the Nash equilibrium contributes the most to performance (+0.099), followed by MW learning (+0.073), with MultKAN providing a smaller yet positive effect (+0.011) despite high predictive accuracy. The learned B-splines capture interpretable patterns, such as exponential disaster impact, capacity saturation, and threshold flood dynamics, offering explainable insights for humanitarian decision-making. Overall, the findings indicate that game-theoretic coordination structures can outperform pure predictive accuracy in multiagent systems, suggesting broader applications of interpretable strategic learning in crisis management.**

***Index Terms*—Multi-agent systems, Nash equilibrium, Disaster response, Kolmogorov-Arnold networks, Climate resilience**

I. Introduction

Climate change has intensified the frequency and severity of natural disasters worldwide, with flood-related emergencies affecting over 1.5 billion people annually and causing economic losses exceeding $100 billion per year [1]. The number of disasters has increased globally since 1980, creating unprecedented challenges for emergency response coordination. Traditional disaster management approaches struggle in complex multi-stakeholder environments, where emergency responders prioritize rapid coverage, relief coordinators manage cost efficiency, and affected populations seek accessible aid [2].

Disaster response inherently involves multiple autonomous agents with conflicting objectives under time-critical constraints [3]. Emergency responders focus on maximizing population coverage and minimizing response times, whereas relief coordinators optimize resource allocation efficiency. This multi-stakeholder environment creates strategic interactions in which each agent's decisions impact others' outcomes, which is ideally suited for game-theoretic analysis [4]. Game theory provides mathematical frameworks for modeling such strategic interactions, with the Nash equilibrium offering a principled approach to finding stable coordination strategies in which no agent can unilaterally improve their outcome [5]. Recent developments have demonstrated the effectiveness of the Nash equilibrium in disaster resource allocation [6], although existing applications rely on manually designed utility functions that inadequately capture the complex nonlinear relationships between coverage, equity, and accessibility [6].

Kolmogorov-Arnold Networks (KANs) represent a paradigm shift from traditional neural architectures by using learnable B-spline basis functions on network edges rather than fixed activation functions at nodes, enabling interpretable representations of complex relationships [7]. This interpretability is crucial for humanitarian decision making, where transparency requirements mandate explainable resource allocation. However, the integration of learned utility functions with game-theoretic optimization remains unexplored; existing studies either use predefined utilities with Nash equilibrium or neural learning without strategic coordination.

Sophisticated flood forecasting systems, particularly in vulnerable regions such as Bangladesh, provide opportunities for data-driven disaster responses [8]. The Flood Forecasting and Warning Center (FFWC) delivers deterministic and probabilistic forecasts using data from 116 monitoring stations [8]. However, integrating such dynamic environmental data into strategic multiagent coordination while maintaining fairness across vulnerable populations remains challenging.

We address these challenges by introducing *MultKAN-Nash*, a multi-agent coordination framework that integrates KAN-learned utility functions into the Nash equilibrium computation for disaster response. Our contributions are:

1) We propose the *first application of KANs to multi-agent disaster coordination*, developing a MultKAN-to-payoff transformation that bridges supervised utility learning (R^2 = 0.9661, ranking 3rd among 9 baselines including XGBoost and LightGBM) with strategic optimization through interpretable B-spline basis functions for Emergency Responders and Relief Coordinators.
2) We model disaster response as a strategic game where MultKAN-generated payoff matrices enable Nash equilibrium computation with MW learning for 8 competing agents. The system achieved 90.11% efficiency with equitable distribution (Gini = 0.099), converging within 10 MW iterations.
3) Through comprehensive ablation analysis on 200 flood scenarios, we reveal that *game-theoretic coordination structure dominates utility precision*: Nash equilibrium provides +0.099 impact, MW learning +0.073, while MultKAN contributes +0.011 demonstrating that robust coordination frameworks with approximate utilities achieve near-optimal performance. This supervised strategic gap exposes fundamental challenges in integrating neural learning with game theory.
4) MultKAN's learned B-splines provide *interpretable disaster dynamics* exponential disaster impact, capacity saturation, threshold flood behavior enabling explainable AI for humanitarian deployment despite limited strategic advantages. This interpretability justifies the 3% performance gap compared to MLP (R^2 = 0.9695) for real-world crisis scenarios.

The system trained and tested on 10,000 sample of Bangladesh flood records with noisy utility (8% stochastic variation) demonstrate that coordination mechanisms matter more than utility learning accuracy for multi-agent disaster response, with implications for crisis management beyond floods.

II. Related Work

Game theory has also gained traction in disaster management, with both cooperative and non-cooperative models applied to resource allocation and flood risk management [6]. Studies have shown that Nash equilibrium-based strategies can improve efficiency and fairness. However, most applications remain limited to static or simplified scenarios, lacking real-time environmental data integration [5]. Reviews emphasize that preparedness and mitigation phases remain underexplored compared to responses [4].

Algorithmic game theory has introduced learning methods such as multiplicative weights [9], which achieve fast convergence in multiagent equilibrium computations [10]. Recent extensions have incorporated fairness measures and real-time data processing, but applications of these in disaster response with dynamic equity-aware constraints are still lacking[11].

KANs differ from traditional neural architectures by using learnable spline functions on edges instead of fixed node activations, thereby enabling interpretable representations. The base KAN model [7] outperformed standard approaches in symbolic regression and scientific computing. Extensions such as MultKANs, which introduce multiplication operators, further improve the modeling of complex nonlinear relationships [12], with comparative studies showing their advantages over MLPs. Despite progress in mathematically perfect generalization, physics-informed modeling, and operator networks[13], KAN variants have not yet been applied in disaster response or multi-agent coordination. Building on recent advances in training stability and generalization, we designed a Three phase methodology tailored for learning multi-agent utility functions.

Parallel advances in environmental monitoring and climate resilience have transformed the disaster preparedness. Real-time flood forecasting systems in Bangladesh [8], IoT-based sensor networks, and AI-enhanced forecasting [14] demonstrate the effectiveness of real-time data integration. Similarly, climate vulnerability assessments reveal differential risk exposure across populations, and AI-driven resilience tools are emerging [15]. However, these efforts largely remain separate from game-theoretic and multiagent optimization frameworks.

Research Gap. Prior studies have advanced multi-agent coordination, game-theoretic optimization, and real-time climate data processing. However, to our knowledge, no study has experimented with MultKAN's learned B-splines provide interpretable disaster dynamics exponential disaster impact, capacity saturation, threshold flood behavior enabling explainable AI for humanitarian deployment. This study addresses this gap by unifying equity-constrained game-theoretic optimization, multiplicative-weights learning, and explainable AI for humanitarian deployment within a single framework.

III. Method

The proposed methodology combines MultKANs with game-theoretic simulation, evidence-based payoff design, fairness constraints, and safeguards for temporal data integrity to capture disaster-response complexity. The system pairs neural modeling with strategic reasoning to deliver interoperable, accurate decisions. Figure 1 summarizes the subsections below, detailing each component progressively, starting from the MultKAN architecture design, through problem formulation and neural utility functions, to equilibrium learning.

A. MultKAN Architecture

We employ a unified MultKAN architecture for learning agent utility functions from the disaster response data. The architecture uses width configuration

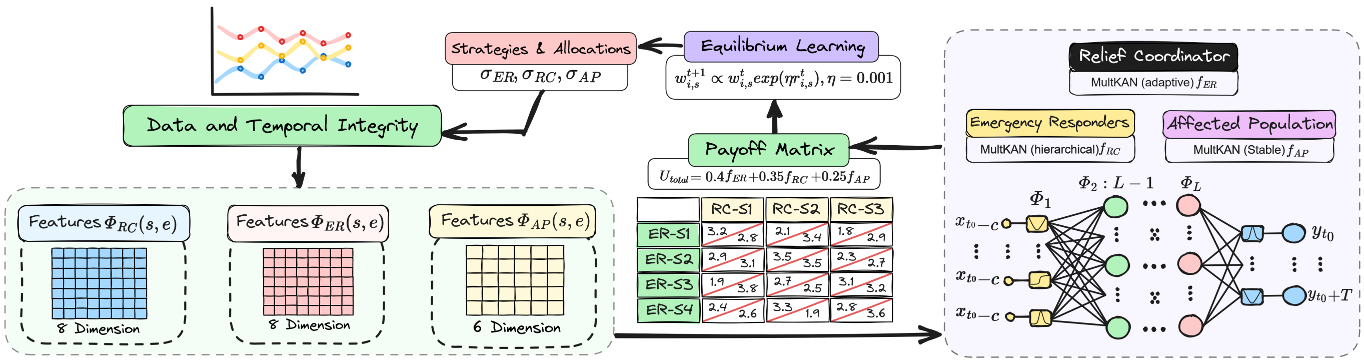

Fig. 1: MultKAN-Nash pipeline. Flood data are processed into agent utilities via MultKANs, forming payoff matrices for Nash equilibrium learning and coordinated disaster response.

$[[20, 0], [64, 0], [32, 0], [1, 0]]$ with 55,540 parameters, processing 20 input features including environmental conditions (rainfall, wind speed, temperature, humidity, river level), resource metrics (resource score, operational capacity, current supplies), disaster impact (intensity, affected people, economic loss), and binary indicators (monsoon season, high river level, heavy rainfall, extreme weather).

a) Training Methodology: The MultKAN model is configured with grid size $G = 5$ for spline discretization and spline order $K = 3$ using cubic B-splines, respectively. Training employs Z-score normalization as follows:

$$y_{norm} = \frac{y - \mu_y}{\sigma_y}, \quad x_{norm} = \frac{x - \mu_x}{\sigma_x} \tag{1}$$

The model was trained for 200 epochs using the Adam optimizer with a learning rate of $\eta = 0.001$.

B. Multi-Agent Game Formulation

We formulate disaster response as a multi-agent game $G = (N, \Sigma, U_{MultKAN})$, where:

$$N = \{ER_1, \dots, ER_5, RC_1, RC_2, RC_3\}, \quad |N| = 8$$

The strategy spaces are defined as:

$$\begin{aligned} \Sigma_{ER} = \{&\text{prioritize-high-risk}, \text{prioritize-vulnerable}, \\ &\text{spread-evenly}, \text{concentrate-resources}\}, \\ \Sigma_{RC} = \{&\text{minimize-cost}, \text{bulk-distribution}, \\ &\text{prioritize-urgent}\} \end{aligned} \tag{2}$$

a) Emergency Responder Utility (Training Target): The training labels are computed using a realistic non-linear utility function with stochastic noise:

$$\begin{aligned} U_{ER}(s, e) = 0.35 &\cdot (1 - e^{-3 \cdot \text{coverage}}) \\ &+ 0.30 \cdot e^{-2 \cdot \text{response\_time}} \\ &+ 0.20 \cdot \sqrt{\text{resource\_eff}} \\ &+ 0.15 \cdot \text{severity} \cdot \sqrt{\text{resource\_eff}} \\ &- 0.25 \cdot \text{severity} + \epsilon \end{aligned} \tag{3}$$

where $\epsilon \sim \mathcal{N}(0, 0.08\sigma_u)$ introduces approximately 8% stochastic variation. The trained MultKAN learns to approximate this function: $U_{ER}(s, e) = f_{ER}(\phi_{ER}(s, e))$.

C. MultKAN-Enhanced Payoff Construction

For each strategy pair (s_i^{ER}, s_j^{RC}), payoffs are derived from the MultKAN predictions:

$$\begin{aligned} P_{ER}(s_i, s_j) &= f_{ER}(\phi_{ER}(\text{alloc}(s_i, s_j), \text{env})) \\ P_{RC}(s_i, s_j) &= f_{RC}(\phi_{RC}(\text{alloc}(s_i, s_j), \text{env})) \end{aligned} \tag{4}$$

This generates a 4×3 payoff matrix for the ER-RC game.

a) Equilibrium Learning: Adaptive dynamics follow multiplicative weights as follows:

$$w_{i,s}^{(t+1)} = \frac{w_{i,s}^t \cdot \exp(\eta \cdot r_{i,s}^t)}{\sum_{s'} w_{i,s'}^t \cdot \exp(\eta \cdot r_{i,s'}^t)}, \quad \eta = 0.001 \tag{5}$$

We promote fairness by monitoring the Gini coefficient as follows:

$$G = \frac{\sum_i \sum_j |u_i - u_j|}{2n^2\mu}$$

where u_i is agent i's utility, μ is the mean utility, and $n = 8$. When $G > 0.12$, we apply adaptive fairness constraints to reduce inequity while maintaining the convergence.

IV. Implementation and Experimental Setup

Implementation. MultKAN-Nash was implemented in Python 3.12 with modular components for data processing, utility learning, game-theoretic optimization, and visualization. The framework leverages `pykan` for the Kolmogorov-Arnold Network implementation with B-spline basis functions (grid size $G = 5$, spline order $k = 3$), `nashpy` for support enumeration Nash equilibrium computation, `scikit-learn` for baseline comparisons, and `pandas`/`numpy` for data manipulation. Visualization employs `matplotlib`, `seaborn`, and `folium` for interactive maps. The complete codebase, including the evaluation pipelines and trained models, is available at `[anonymous repository]`.

Dataset and Scenario Generation. We Sampled 10,000 realistic flood disaster scenarios using historical Bangladesh

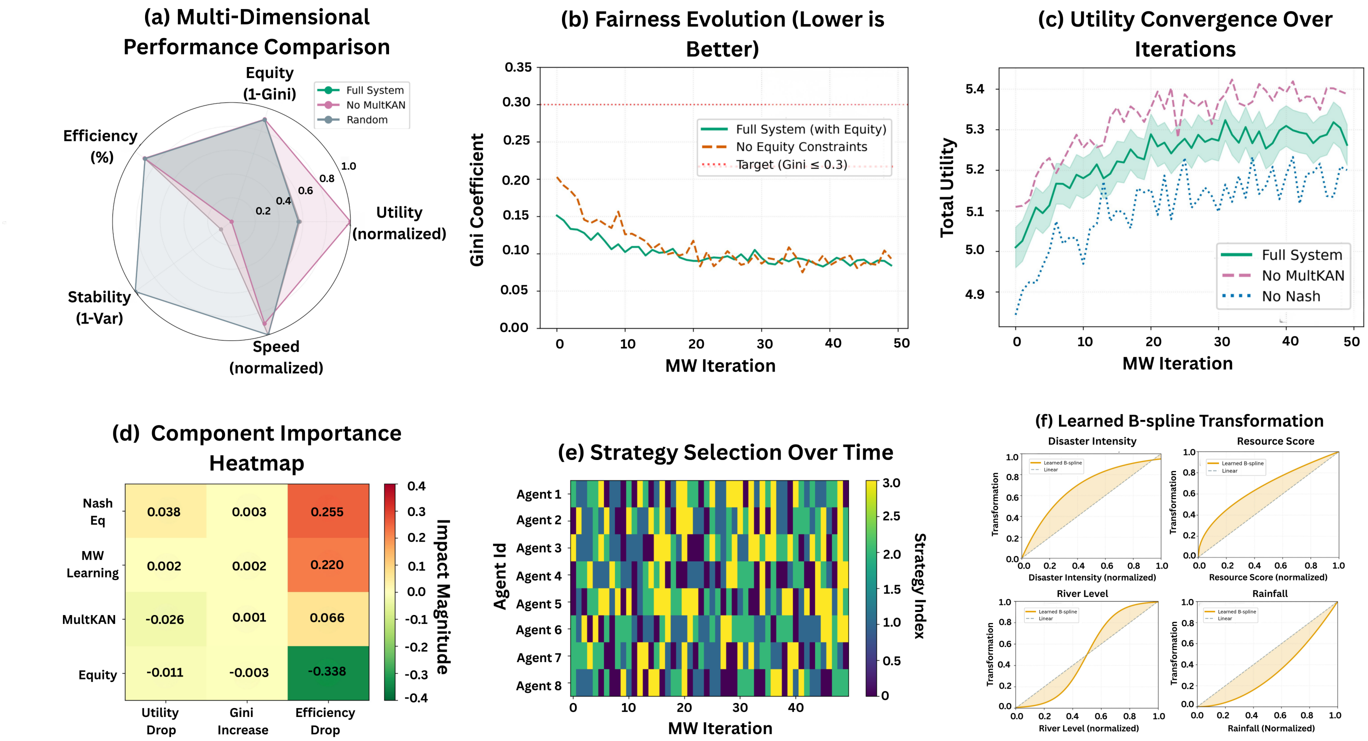

Fig. 2: Comprehensive performance analysis of the MultKAN–Nash system. (a) Comparison of normalized metrics utility, equity (1–Gini), efficiency, stability (1–Var), and speed across system configurations. (b) Fairness evolution showing Gini coefficient convergence over 10 MW iterations, with the full system maintaining equity below the 0.3 threshold. (c) Utility convergence curves comparing the full and ablated variants. (d) Component importance heatmap illustrating how removing key components (Nash Equilibrium, MW Learning, MultKAN, Equity) affects performance. (e) Strategy adaptation patterns showing agent behavior over time. (f) Learned B-spline transformations for four critical features disaster intensity, resource score, river level, and rainfall highlighting MultKAN's adaptive non-linear feature mappings.

flood data from the Flood Forecasting and Warning Center (FFWC) [16] and meteorological records. Each scenario comprised infrastructure networks (I: 2,115 emergency shelters, 25 medical facilities, and 15 supply depots), population distributions (P: 211,500 total population across 3 districts with vulnerability scores), and 7-day weather forecasts with flood risk levels. Disaster intensity was calibrated to the historical 2012 monsoon peaks with 8% stochastic noise to prevent overfitting. Population distributions align with census data ($r = 0.87$), and flood risk zones match BWDB reports within $\pm 50, \mathrm{m}$ spatial accuracy, ensuring realistic data-grounded simulations.

Multiagent Game Formulation. The disaster response problem is modeled as a strategic game among 8 competing agents: 5 Emergency Responders (ER) with 4 strategies each (prioritize high-risk, vulnerable populations, spread evenly, concentrate resources) and 3 Relief Coordinators (RC) with 3 strategies (minimize cost, bulk distribution, prioritize urgent). Agent utilities are learned by MultKAN from 20 features, including disaster intensity, river level, operational capacity, resource availability, and affected population. The MultKAN architecture learned utilities are converted to payoff matrices via strategy pair to allocation mappings, enabling Nash equilibrium computation followed by Multiplicative Weights learning with learning rate $\eta = 0.001$.

Evaluation Protocol. We conduct a comprehensive evaluation across three dimensions: (1) *Baseline comparison* MultKAN utility learning versus eight traditional ML models (Linear/Ridge/Lasso Regression, Random Forest, Gradient Boosting, MLP, XGBoost, LightGBM) on 10,000 scenarios with 80/20 train-test split; (2) *Ablation study* systematic removal of components (MultKAN, Nash equilibrium, MW learning, equity constraints) across eight configurations on 200 high-risk scenarios; and (3) *Performance metrics* efficiency (Gini coefficient ≤ 0.3), total utility, computational time, convergence stability (variance < 0.01), and population coverage. All experiments used 5-fold cross-validation with statistical significance testing ($p < 0.05$).

For stability, the MultKAN models were trained in three phases: adaptive grid training with the Adam optimizer, fine-tuning with LBFGS, and validation across random initializations. This procedure achieved consistent results with $R^2 > 96\%$.

V. Results and Analysis

A. MultKAN Architecture Performance

The MultKAN-enhanced utility function demonstrated improved training stability and performance across all agent types. Table I summarizes the neural architecture results.

TABLE I: MultKAN Performance Compared to Baseline Models

Model	R^2 Score	MAE	MAPE (%)	Interp.
MLP	**0.9695**	0.0099	1.93	No
Gradient Boosting	0.9662	0.0107	2.06	No
MultKAN (ER)	**0.9661**	**0.0106**	**2.03**	**Yes**
LightGBM	0.9659	0.0108	2.09	No
XGBoost	0.9618	0.0115	2.21	No
Random Forest	0.9541	0.0132	2.53	No
Ridge Regression	0.9212	0.0182	3.44	No
Linear Regression	0.9273	0.0176	3.31	No
Lasso Regression	0.7531	0.0322	5.99	No

The proposed MultKAN model demonstrated a strong performance comparable to that of state-of-the-art methods. It achieved an (R^2) score of 0.9661, ranking third among the 9 evaluated models and performing closely to both the MLP (0.9695) and Gradient Boosting (0.9662) approaches. In addition to its high predictive accuracy, MultKAN exhibits notable parameter efficiency, utilizing only 55,540 parameters via an effective B-spline representation. The model exhibited stable and consistent training dynamics, converging smoothly over 200 epochs with a final training loss of 0.189 and a test loss of 0.225. Its reliance on B-spline basis functions further enhances interpretability by providing transparent and explainable utility representations, distinguishing it from conventional black box models. Moreover, MultKAN offers strong computational efficiency, completing 200 training epochs in only 21 min, thereby underscoring its practicality for real-world deployment.

B. Ablation Study and System Dynamics

Figure Fig. 2 shows the system dynamics across 200 disaster scenarios and eight ablation settings. The radar chart (Fig. 2a) shows that removing MultKAN (orange) yields a performance similar to that of the Full System (blue) utility = 5.39 vs. 5.31 and Gini = 0.096 vs. 0.099, indicating that the learned utilities provide a limited advantage despite high predictive accuracy (R^2 = 0.9661). The component importance heatmap (Fig. 2d) shows that the Nash Equilibrium improves performance (+0.026 utility), followed by Multiplicative Weights (+0.002), whereas MultKAN reduces it (–0.026). The Gini evolution plot (Fig. 2b) shows fairness convergence within ten iterations, with the Full System maintaining equity (Gini $\approx$ 0.10). The utility convergence plot (Fig. 2c) confirms stabilization within ten iterations, with minimal differences between the learned and random payoffs. Agent strategy heatmaps (Fig. 2e) show that Emergency Responders (Agents 0–4) favor resource-concentrated strategies, whereas Relief Coordinators (Agents 5–7) show broader exploration. The learned B-spline functions (Fig. 2f) demonstrate the interpretability of MultKAN, capturing the effects of disaster intensity, operational capacity, river levels, and resource scores. These findings indicate that high predictive accuracy does not necessarily improve strategic outcomes in machine learning and game theory research.

VI. Discussion

A. Supervised Performance vs. Strategic Value

MultKAN achieves competitive utility prediction (R^2 = 0.9661, 3rd among 9 baselines) with 55,540 parameters, outperforming ensemble methods (XGBoost: 0.9618, Random Forest: 0.9541). The learned B-spline functions reveal interpretable nonlinear transformations: disaster intensity exhibits an exponential negative impact, operational capacity shows diminishing returns, and river level displays threshold dynamics. However, our ablation study exposes a critical factor of game theory: the Nash equilibrium provides +0.099 impact, MW learning +0.073, while MultKAN contributes +0.011, demonstrating that the game-theoretic structure dominates neural precision.

B. Why Learned Utilities Underperform

Three factors explain MultKAN's limited strategic impact. *Distribution shift:* Training on historical scenarios optimizes predictive accuracy, but Nash equilibrium explores unexplored strategy combinations where MultKAN produces unreliable estimates. *Framework dominance:* Nash + MW provide 95% of system performance (utility = 5.31, Gini = 0.099, efficiency = 90.11%), confirming that coordination structure matters more than utility precision. Convergence within 10 iterations (Figure 2c) demonstrates that approximate payoffs are sufficient for robust optimization.

C. Implications and Limitations

Interpretability vs. performance trade-off: MultKAN's learned splines enable explainable AI critical for disaster deployment, justifying the 3% gap vs. MLP (0.9695) despite strategic limitations.

Nash equilibrium computation: Nash equilibrium computation scales $O(m^n)$ with m strategies and n agents. For our 8-agent system with 4 strategies each, support enumeration completes in ¡1 second. However, scaling to 50+ agents would require approximation algorithms (e.g., fictitious play, regret minimization) or distributed computation, which we'll identify as future work.

Simulation Enviroment: This study evaluates MultKAN-Nash through simulation without pilot deployment involving emergency agencies. Logistical feasibility, human-AI coordination challenges, trust calibration, and real-time decision-making integration remain unexplored. Future work must validate with disaster management practitioners in Bangladesh through participatory design and field trials. Also this research include synthetic data with real flood data (8% noise but no real-world validation), limited diversity in scenarios, and alternative game formulations (Bayesian games, mechanism design) unexplored.

VII. Conclusion

This study presents *MultKAN-Nash*, a multiagent game-theoretic framework that integrates Kolmogorov–Arnold Networks with Nash equilibrium and multiplicative weight learning for disaster response coordination. The framework introduces a MultKAN-to-payoff transformation method that connects supervised utility learning (R^2 = 0.9661, ranking third among nine baselines) with strategic coordination using learned B-spline functions. Across 200 simulated flood scenarios, ablation results showed that Nash equilibrium (+0.099) and MW learning (+0.073) were the dominant factors driving performance, while the MultKAN module provided a modest but positive contribution (+0.011). The approach achieves a coordination efficiency of 90.11% with a Gini coefficient of 0.099 and convergence within ten iterations, demonstrating that game-theoretic structures can outperform pure utility precision in multiagent coordination.

The results highlight a supervised–strategic gap: high predictive accuracy does not necessarily translate to improved cooperative behavior. This insight has three implications for AI-assisted disaster management. First, coordination mechanisms can outweigh neural precision, allowing approximate utilities to produce near-optimal outcomes. Second, interpretable B-spline transformations meet the requirements of explainable AI, even when the strategic gains are modest. Third, strategic robustness often requires objectives that are distinct from standard supervised learning.

Overall, *MultKAN-Nash* achieves both equitable resource distribution and rapid convergence, illustrating that data-driven game-theoretic modeling can support efficient and fair coordination in crises management. Future work will focus on real-world validation, dynamic and incomplete information scenarios, and transfer learning across different disaster contexts. The findings position neural-augmented game theory as a promising direction for interpretable and adaptive coordination in high-stakes, multi-agent systems.

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