Network Agency: An Agent-based Model of Forced Migration from Ukraine

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ABSTRACT

Individuals in social systems are embedded in collective decision-making hierarchies, such as households, neighborhoods, communities, organizations, etc. The locus of agency in such systems is dispersed across the system, and can variously be viewed as individual, distributed, and shared agency. Here we propose a general notion of network agency that subsumes these descriptions and also allows for integrating related notions, such as peer influence. In our view, the social system can be seen as a multi-layer network, where each layer corresponds to different aggregations of the underlying units, representing different kinds of perception and decision-making. We illustrate this general framework with an agent-based model of the ongoing forced migration from Ukraine. In our model, individuals perceive hazards (conflict events), but decisions to migrate are taken at the household level, where peer influence from other households in the neighborhood is also taken into account. We present this model in detail to elucidate our concept of network agency. We also calibrate the model with data on daily refugee flows and show that our model is able to estimate the scale of the daily refugee flow from Ukraine for the first two months with a Root Mean Squared Percentage Error (RMSPE) of 0.24, outperforming state-of-the-art, which had an RMSPE of 0.77. Moreover, our model also captures the daily trend of outflow with a Pearson Correlation Coefficient (PCC) of 0.98. We also perform sensitivity analysis of the model and analyze the significant parameters of the model, which in turn tells us how different agencies are significant in different contexts.

Proc. of the 23rd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2024), N. Alechina, V. Dignum, M. Dastani, J.S. Sichman (eds.), May 6 – 10, 2024, Auckland, New Zealand. © 2024 International Foundation for Autonomous Agents and Multiagent Systems (www.ifaamas.org).

KEYWORDS

Agency; Ukraine; Migration; Agent-based Model, Forced Migration; Sensitivity Analysis; Network

ACM Reference Format:
Zakaria Mehrab, Logan Stundal, Samarth Swarup, Srinivasan Venkatramanan, Bryan Lewis, Henning Mortveit, Christopher Barrett, Abhishek Pandey, Chad Wells, Alison Galvani, Burton Singer, David Leblang, Rita Colwell, and Madhav Marathe. 2024. Network Agency: An Agent-based Model of Forced Migration from Ukraine. In *Proc. of the 23rd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2024), Auckland, New Zealand, May 6 – 10, 2024*, IFAAMAS, 9 pages.

1 INTRODUCTION

Agency refers to the capacity of individuals to plan and act effectively, given their environmental and social context. Depending on the structural context of these agents in the overall larger social network and the loci of the decision-making task, different forms of agencies emerge. When decision-making is performed by a single individual based on their own perception of the events, it is known as *individual agency* [41]. However, sometimes individuals perform decision-making based on their own perception as well as that of other agents related to them through some social relationship. For example, when someone is performing in a team play, they have to perceive their stage presence and memorize lines as well as synchronize with others' acts. Actions generated from such *shared intention* can be attributed to *shared agency* [11]. Alternatively, during evacuation or migration situations, agents often migrate as a single household unit [40]. So, here decision-making happens through households instead of single individuals. Nevertheless, when making such decisions households also account for the individuals associated with that household. Such a form of agency can be attributed to *distributed agency* [26].

With regard to these various forms of agents and agencies in different contexts, a unified approach is necessary that allows one to integrate the notion of agents and agencies at any layer of the larger hierarchical social structure [24]. This translates to the necessity of a computational framework that allows for designing an agent-based model from the perspective of agents and their corresponding actions along with related notions. However, such a framework is absent from the literature. In this work, we present a practical framework for agent-based modeling, based on the idea of network agency, which subsumes individual, group, and shared agency, and also integrates peer influence.

To demonstrate the efficacy of this framework, we develop an agent-based model (ABM) in the context of the ongoing crisis of *forced migration* caused by the Russian invasion of Ukraine. As of September 2023, Around 5.8 million people have taken refuge in different European countries and another 5.09 million have migrated to different parts of Ukraine as internally displaced persons (IDP). As assessed by UNOCHA, almost 17.6 million people are in need of some form of assistance from humanitarian groups [57].

1.1 Summary of contributions and significance

In this paper, we propose a framework using the notion of *network agency*, which captures the hierarchical relationship structure between different forms of agents, interaction across these hierarchies, and network influence across agents. The notion of *network agency* is prevalent in social science that studies the decision-making of agents not only from an individualistic perspective but also their structural position in the complex multi-layered social network [17, 30, 35, 37]. Our framework conceptualizes the social system as a multi-layer network, where each layer represents agents of some aggregated form of their descendant layer agents. Moreover, agents in the same layer are connected to one another, which allows for the incorporation of peer-influenced decision-making. Consequently, this framework enables defining perception and action at different layers, allowing for different forms of agencies.

Case study. Our ABM utilizes a *synthetic population* containing synthetic individuals and their household information to create a two-layered representation of the social structure of agents. We calibrate our model using real-world data and observe that the model outperforms current state-of-the-art methods in capturing different aspects of migration dynamics. We also perform a counterfactual scenario study where the model estimates migration under events of varying intensity. The study reveals that although initially the migration is *event-driven*, later on it becomes more *peer-driven*. We also perform sensitivity analysis of the model to demonstrate the significant parameters, and consequently, the significance of different components of the proposed *network agency* framework.

2 NETWORK AGENCY

Formal conceptions of social action that are aligned with the BDI framework [10, 12] have been established for a while [15, 28]. These early works laid the foundation for modeling distributed and shared agency by articulating the basic principles of coordinated, contextualized hierarchical social action [28] and the predicates or primitives, such as *Goal Delegation* and *Goal Adoption*, needed for a computational formalization [15].

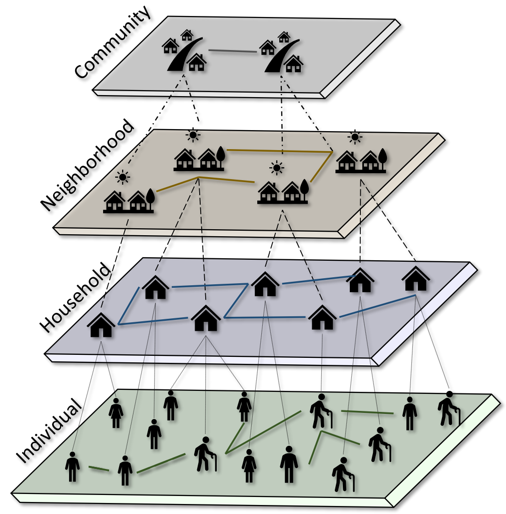


Figure 1: Proposed framework of Network Agency. A conceptual four-layered hierarchical representation of social structure where individuals form households, households form communities and communities form neighborhoods. The nature of agency will depend on where the *loci of perception* and the *loci of action* reside.

However, there are multiple important aspects of agency in organized social systems that are still debated, or even largely unaddressed. One important example in this regard is the notion of a group agent. What makes a group a group *agent*? Lewis-Martin identifies individuality, interactional asymmetry, and normativity as three necessary conditions, in addition to the existence of group goals [39]. He particularly emphasizes individuality (meaning discreteness of a group), but this conception is not fully congruent with notions of distributed agency, e.g., as described by Gasser [28].

Other important aspects of social agency, which have also received limited attention, as shown by recent surveys [3, 21], have to do with the role of network structure and information flow. These aspects have empirical support, but not a proper computational formalization in a theory of agency yet. For example, Landis et al. [37] studied agency from the context of brokerage opportunity. Through a role-based study they found that participants tend to relay information through the network more if they perceive themselves to be structurally relevant in the overall network. Clement et al. [17] studied agents in the form of network hubs, and found that these hubs can exert either positive or negative influence more significantly than other nodes. This reveals that not only the structural position of (human) agents matters in the network, but also they are aware of this and their behavior is affected accordingly.

On the other hand, alternative conceptions of agency from social science have emphasized the primary role of relations between agents [13, 25]. This relational perspective shows that crucial aspects of agency, largely unaddressed by the BDI model, such as social perception and goal selection, depend on network structure and information flow. Our goal here is to take the first steps towards reconciling and combining these formulations by taking a "network-first" perspective. The benefit of this approach is that it doesn't get bogged down in definitions of group or shared agency. The focus is on how individuals are connected in a hierarchical social network and how state updates (including constraints and commitments) and information flow occur in this network. This also allows us to naturally bring in peer influence, known to be a very important factor in social decision-making, but has not traditionally been included in discussions of agency or social action. It should be noted that although We have used peer influence as a simple example to demonstrate this network effect, but our framework is general enough to include any other kinds of network influences. This leads to a blurring of the traditional dichotomy of agency and structure, which is why we have chosen a *network-first* approach.

Additionally, we acknowledge the existence of discussion surrounding agency-structure distinction and metamodels in literature in different forms. *Recursive agents* [23, 60] require a payoff matrix with possible actions for each agent, which is not feasible in most social simulations. The *agentified group* [46] framework describes relationships between agents and their roles and how different collections of agent-role combinations form groups to perform tasks as a collective. However, there is no clear specification of how external events or peer influence can affect the dynamics. *Holonic agents* [1, 29] describe how agents can work both as collectives and individuals in different contexts. In network agency, we capture this notion in social context, since a single agent can act individually or as a collective in an upper hierarchy, while also incorporating their perceptions of external events and peer influence.

2.1 Proposed Framework

Our proposed framework assumes a multi-layered network of social structure, where agents in adjacent layers are connected. Consider the example structure shown in Figure 1. Group of individuals at the bottom-most layer may be part of a single household. Actions arising from the level of household in the form of *distributed agency* will also affect the individuals associated with it. The decision of households is constrained by the associated individuals, and simultaneously, the individuals are committed to complying with the decision of the households. Consequently, households and community may another level of similar relational structure. In this way, the notion of *constraints* and *commitments* exists across the consecutive layers of the agents [14, 53]. We also assume that there are connections between agents within the same layer. These connections drive peer influence and are an essential part of *network agency*, which dictates that decision-making is often affected by local information in the network; a construct that also arises in many social theories of human behavior [5, 7].

In order to develop a model with this framework, one needs to define the following steps:

Define the hierarchy: The first step is to consider how many hierarchies of agents should exist in the model and the nature of the relationship between agents across different hierarchies.

Define the loci: Second, one needs to define the loci of perception and action. It can exist across the same layer or different layers.

Define the peer network: To capture the peer influence, one needs to define the peer networks at different hierarchies.

Define the functions: There are generally four kinds of functions one needs to define. *First*, the perception function through which agents interact with the events. *Second*, the representation function through which the transfer of information happens across different hierarchies of agents. *Third*, the peer influence function through which agents gather local information from their peers and adjust their actions accordingly. *Fourth*, the action function through which the agents at the *loci of action* carries out their actions.

Taken together, these steps constitute a practical recipe for the design of agent-based models guided by the novel unifying perspective of network agency. In Section 3, we demonstrate how these steps are instantiated in an ABM of forced migration from Ukraine.

2.2 Related Work on Forced Migration

There have been multiple ABM efforts to study forced migration due to conflict events. Nelson et al. [45] studied how Somalian shepherds migrate due to civil war. They found that the agents consider access to vegetation as a key factor in choosing their destination. Hebert et al. [33] proposed an ABM to study migration from Syria using a simple method of using the death toll as an indicator of how dangerous a conflict zone is. Collins et al. [18] studied group formation and deformation amongst refugees under different urgency situations using an ABM. Suleimenova et al. [54] developed FLEE, a generalized ABM simulation model to estimate migration destination from a conflict-induced region assuming out-migration from the conflict-induced migration is given as input. Pandey et al. [47] studied forced migration from Ukraine in the context of how the migration situation contributes to the disease dynamics in the destination countries using ABM. They proposed a model where agents decide to migrate based on the number and spatial proximity of the events. However, in all these models, the hierarchical nature of decision-making is not considered, nor do the agents consider peer influence.

3 ABM OF FORCED MIGRATION

As stated in the previous section, the development of a model based on our proposed framework requires four steps. We describe the four steps below in the context of our ABM.

Hierarchy: Assuming a two-layered hierarchy of agents with individuals in the bottom layer and their household at the top layer, our framework assumes the following inputs.

(1) $A = \{a_1, a_2, ..., a_i, ...\}$: Set of individual agents, where a_i represents the i^{th} individual agent.
(2) $H = \{h_1, h_2, ...h_k, ...\}$: Set of household agents, where h_k represents the k^{th} household agent.
(3) $\eta : A \rightarrow H$: Mapping, where $\eta(a_i) = h_k$ means that a_i lives in house h_k.
(4) $C = \{c_1, c_2, ..., c_j, ...\}$: Conflict events in the conflict induced region. We assume that each event c_j is associated with a severity s_j, and a location y_j. Also, let $C(t) \subseteq C$, be the subset of events observed at time t.

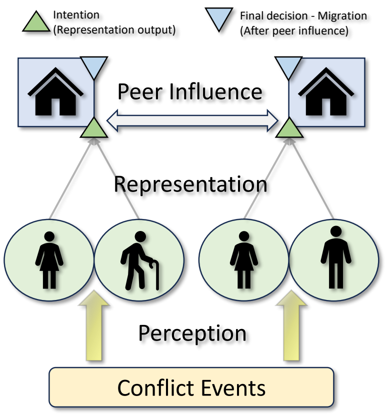


Figure 2: The dynamics of our ABM based on the Network agency framework. Individuals interact with events using *perception* function. Households compute intention based on individuals' perception through *representation* function. Final decision after gathering local information of other households through the *peer influence* function.

Loci of perception and action: Our model assumes that migration is a household-level phenomenon, following prior literature [8, 52]. This means that when a household migrates, all associated individuals of that house migrate. However, perception of events happens at the individual level [48]. Following this, the *loci of perception* is the individual layer but the *loci of action* is the household layer.

Throughout the perception-action loop, we assume the following states are updated for the agents at each timestep t. Each individual agent a_i is associated with a *fear level* $F_i(t) \in \mathbb{R}$ ($F_i(t) > 0$), representative of their perception of the events. Subsequently, each household agent h_k is associated with two different states. First is a *migration* state, $M_k(t) \in \{0, 1\}$ (0 = Not migrated, 1 = migrated). The other is *intention*, $P_k(t) \in [0, 1]$, denoting the intention of household h_k to migrate when $M_k(t) = 0$. It has to be noted that the difference between $P_k(t)$ and $M_k(t)$ is that, $P_k(t)$ does not account for peer influence while $M_k(t)$ does. Therefore, the final decision or action is generated from $M_k(t)$.

Network: In order to capture the peer influence of *network agency*, we construct a network between the agents. While peer influence can also exist at the *loci of perception*, we only consider a network at the *loci of action* in our model. Since The households are geospatially located entities, we use a variant of Kleinberg's Small World Model (KSW) [36] to generate our model. We start by creating a ball of radius r around each household. Among the household pairs within this ball, we add edges between each household if their distance is below a *short-edge threshold* p. Among other pairs, we add at most Q edges from household u with probability $dis(u,v)^{-\alpha}$ where $dis(u,v)$ is the distance between household h_u and h_v and α is an exponent ($\alpha > 0$). The ball of radius r imposes an additional constraint on the distance of the long edges in the network, to put a threshold on the longest communication distance during wartime. The algorithm is outlined in the Supplementary material[1].

[1]Supplementary material available at https://github.com/dmehrab06/Network_agency

Function definition: In this section, we define the *perception*, *representation* and *peer influence* functions. While there could be many forms of functions for capturing these concepts, our functional forms are mostly motivated by social theories, since they have a solid foundation to capture the dynamics of human behavior.

Perception function: The push-pull theory [22] is a prevalent theory in the study of migration. In the context of *forced migration*, push factors become significantly more important than pull factors [59]. The perception function essentially captures this *push factor* by calculating their fear value at each timestep. We propose the following functional form for updating $F_i(t)$.

$$F_i(t) = \begin{cases} \sum_{\hat{t}=0}^{t} f(t-\hat{t})\, g(C(\hat{t}), a_i) & \text{if } M_k(t) = 0 \\ F_i(t-1) & \text{otherwise} \end{cases} \tag{1}$$

The functional form is known as the function of discounted utility. It describes total utility as a result of perceived weights (e.g. rewards, risks) at different points of time from the standpoint of current timestep and has been used in ABM [16, 27]. Here, $f(t-\hat{t})$ is the discount function which should have a negative first-order derivative, and $g(a_i, C(\hat{t}))$ is the risk consumption of agent a_i at time $\hat{t}$ from the events $C(\hat{t})$. For our model, we choose exponential discounting as the *discount function*. Thus, the discount function $f(t-t') = \theta^{t-t'}$, where θ is the discounting factor ($0 < \theta < 1$).

As for the choice of the *risk function*, we consider the following factors in guiding our choice for a function. First, Spatiality, since events in close proximity are likely to affect the agents more. Second, Severity, where perception depends on the nature and impact of the event. Finally, perception of the same event varies across individuals owing to various personality and other factors (e.g. demography, economy) [19]. This notion is also stated in the Theory of Planned Behavior theory [5], a popular social theory of human behavior. We assume that each agent is associated with its own risk-perceivedness b_i which we take into consideration in this function. With these considerations in mind, our *risk function* is as follows:

$$g(C(t), a_i) = \sum_{c_j \in C(t)} \beta \frac{s_j \times b_i}{dis(y_j, x_i^t)^{\delta}} \tag{2}$$

The function is motivated by the Gravity Model [61] which takes distance into account in calculating the attraction between two objects. In order to account for the other factors, we put the severity of the event s_j and the risk-perceivedness b_i of the agent in the nominator. Here, x_i^t is the location of agent a_i at time t, δ is the distance decay parameter ($\delta > 1$) and β is a fear-scaling parameter.

Representation function: The representation function computes $P_k(t)$ for each household, and their intention to migrate based on the perception of the associated individual agents. The model does so through the following functional form.

$$P_k(t) = \begin{cases} \underset{a_i \in \eta^{-1}(h_k)}{\mathbb{I}} \{\sigma(F_i(t))\} & \text{if } M_k(t) = 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Here, the activation function $\sigma(\cdot)$ takes the *fear level* and transforms it into a probabilistic form. Second, the aggregation function $\mathbb{I}$ aggregates a set of values into one single representative *migration intention probability* of the household. We propose this functional form because it provides a straightforward way to transfer information between two hierarchies of agents, similar to how neural networks often capture representations of values at lower layers into the upper layers [38].

In our model, we use *Average* as the aggregation function $\mathbb{I}$. As our choice of *activation function*, we choose the sigmoid function (S) of the form $\sigma(x) = (1+Qe^{-\tau x})^{-1}$. Here, Q is the No-fear control parameter, which essentially controls the intention probability of an agent when they have a fear of 0. On the other hand τ is the growth rate parameter.

Note that, one could have defined the action at this locus, where the household agents would migrate based solely on their intention. However, in that case, it would be more similar to *distributed agency*. In *network agency*, we go one step further and take into consideration the peer-influence before taking the final decision.

Peer influence function: The effect of peer influence on human behavior is prevalent in both *Herd Behavior* and the *Theory of Planned Behavior*. Based on these theories, intention might change depending on how the peer is acting. In our context, the peer influence function dictates whether household will retain their *intention* state or update them due to peer pressure.

The peer influence function is defined over $\mathcal{G}(H, E)$, the network of households constructed by the network generation model described previously. An edge $(h_u, h_v) \in E$ denotes that h_u and h_v are neighbor households. Let $\mathcal{N}_k$ denote the neighborhood of household h_k. We employ a threshold function [32, 49, 58] over $\mathcal{G}$ to capture peer influence as follows.

(i) *Inside Peer Influence*: Let $\psi_u^1(t-1) \in [0, 1]$ be the fraction of h_u's neighbor intending to migrate at time $t-1$. This can be obtained from the average $P_k(t-1)$ values ($h_k \in \mathcal{N}_u$).
(ii) *Outside Peer influence*: Let $\psi_u^2(t-1) \in [0, 1]$ be the fraction of h_u's neighbors who have migrated upto time $t-1$. This can be obtained from the average $M_k(t-1)$ values ($h_k \in \mathcal{N}_u$).

Based on this, each household h_u updates its migration decision based on the threshold function as follows:

$$M_u(t) = \begin{cases} 1 & \text{if } M_u(t-1) = 1 \\ 1 & \text{if } M_u(t-1) = 0 \text{ and } \lambda\psi_u^1(t-1) + (1-\lambda)\psi_u^2(t-1) \geq \pi \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Essentially, this function denotes that a household agent would migrate only under the conditions that a certain threshold of their peer is also considering migration or has already migrated. This function is computed synchronously for all household agents. Here, λ is a parameter that controls how much weight is given to inside peer influence compared to outside peer influence and π is the threshold parameter. This function essentially considers the structural position of the household agent and by gathering local information from peers before taking the final decision, it brings the essence of *network agency* to a full circle.

Action function: The action function is somewhat straightforward and integrated into the *migration* state value. If $M_k(t) = 1$, the household agent migrates and if $M_k(t) = 0$, the household stays and goes through the *perception-action* loop for another round. Note that, although an agent who has migrated does not participate in the *perception-action* loop, they still exert outside peer influence on the agents who did not migrate.

Table 1: Summary of ABM

Layer	Social Theories	Function choices	Parameters
Individual	Push-pull theory, Perceived Behavior Control	Discounted Utility as perception function	Discounting factor θ
			Distance decay δ
			Fear scaling β
Household	Herd Behavior, Subjective Norm	Aggregated activation as representation function	No fear control Q
			Growth rate τ
		Threshold model as peer influence function	Peer threshold π
			In Peer weight λ

One additional layer we account for in the action phase is as follows. Among the agents forcibly displaced, a portion of them becomes refugee, while other becomes internally displaced (IDP) [47]. Following this, the household agents employ the following actions based on their $M_k(t)$ value at timestep t.

- If $M_k(t) = 0$, the agent stays in the conflict-induced region.
- If $M_k(t) = 1$, the agent becomes refugee with γ probability or becomes IDP with probability $1 - \lambda$

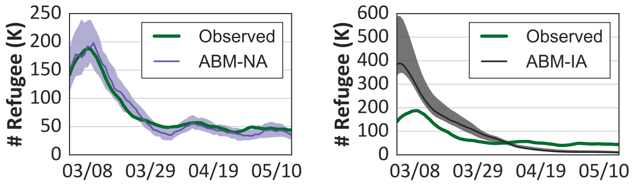
The dynamics of the ABM is conceptualized in Figure 2 and the functions along with associated parameters are tabulated in Table 1. The pseudocode is given in the Supplementary material. One key point about our ABM is that there are other alternatives for the different kinds of functions defined for the *network agency* framework. However, our proposed functional forms are motivated by social and economic models of human behavior. Thus, these functions are suited to be good representations of modeling and simulating how societies evolve under such phenomena.

3.1 Implementation

In this section, we outline dataset collection and some other adjustments we made in our implementation of the ABM. For agent data, we use the synthetic population of Ukraine developed by the Biocomplexity Institute [44] containing information about synthetic individuals (e.g. age, gender) and their corresponding households (e.g. location). For simplicity, we assume the location of the individuals to be the same as their household for Equation 2. Based on age and gender, we consider four different demographic groups of agents, each having a unique value of b_i for Equation 2. The corresponding values are given in the Supplementary material.

As for the conflict data, we utilize the dataset from Armed Conflict Location & Event Data Project (ACLED) [2]. This dataset contains various information about the different types of conflict events. It specifies the time of the event at a daily resolution. Considering each timestep of our simulation corresponding to one day, this allows us to specify $C(t)$ for each simulation timestep t. The locations are also provided as geographical coordinates, allowing us to use that information directly in Equation 2. The severity of each event is calculated based on the fatality and the type of the event. For details, please refer to Supplementary material.

Ukraine is divided into 27 oblasts (Administrative level 1 regions) and 139 Raions (Administrative level 2 regions). For fast and scalable simulation, we parallelized the ABM model by partitioning agents and events by Raion. During the network generation, we choose $p = 40$ meter, $\alpha = 2.3$, and $q = 16$, motivated by literature [31]. We empirically selected $r = 1$km. We also created a 10 km buffer around each Raion so that they are exposed to surrounding conflict

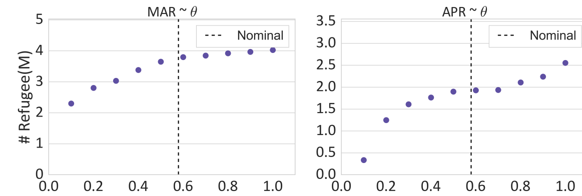


(a) ABM-Network Agency (b) ABM-Individual Agency

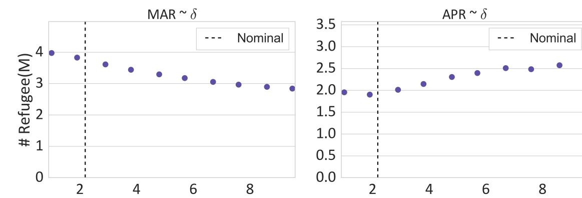
Figure 3: Daily refugee estimation comparison of two models.

Table 2: Comparison of %IDP origin estimation.

	% IDPs origin per Macro-Region		
Macro-Region	IOM Report	ABM-NA	ABM-IA
Center	3.4	3.7	5.4
East	36.2	38.1	47.4
Kyiv	29.9	25.7	12.3
North	20.1	19.2	18.7
South	7.5	9.6	11.2
West	2.9	3.8	4.9



(a) Effect of Discounting Factor Parameter θ



(b) Effect of Distance Decay Parameter δ.

Figure 4: Local sensitivity analysis of two parameters associated with the perception function.

events beyond their border. Finally, we chose γ to be normally distributed with a mean of 0.33 and a standard deviation of 0.05 based on historical data from UNHCR [56] on conflict-induced displacement. This estimation coincides with previous work [47]. The pipeline was implemented with Python 3.7 and executed in an HPC cluster with 40 computing nodes and 384 GB memory using SLURM scheduler[2].

3.2 Calibration

Calibration of the ABM parameters (outlined in Table 1) is necessary so that the model can behave realistically. Utilizing the daily border crossing data from Humanitarian Data Exchange [34] as observation, we use the Bayesian Optimization strategy [43] for calibration of the model. Let us assume that $z(t)$ and $\hat{z}(t)$ are the estimated refugee and the observed refugee, respectively. Let $T_S = \{t_1, t_2, ...t_S\}$ be the sample of several timesteps. With this, our objective function in Bayesian Optimization is to minimize the mean squared error (MSE) between the refugee estimation of the model and the observed data along the samples. The dataset used for calibration contains reports of border crossing for 90 days. To avoid overfitting and separate some data for validation purposes, we used 15 data points for calibration.

4 EVALUATION

We now demonstrate the performance of the ABM extended from the proposed framework in the context of migration from Ukraine due to conflict events. Since the ABM perceives at the individual level and takes action at the household level, it is able to produce various estimates at very fine resolution. However, real data to validate all these different estimates are usually difficult to obtain. Here, we choose two data sources to compare our ABM with the state-of-the-art (SofA) method [47] which proposes an agent-event interaction model. Since their model does not consider any peer effect, we accommodate their model across the individual layer where agents decide to migrate or not solely based on their perception of the events. We refer to this SofA as *ABM-Individual Agency* or *ABM-IA* for short since the loci of action is at the individual level. We refer to our model as *ABM-Network Agency* or *ABM-NA*.

Daily Refugee Estimation: The first data source we used to compare the performance of our model is the daily border-crossing data from Humanitarian Data Exchange (HDX). We consider the time interval from February 24, 2022, to May 15, 2022 as this date range encompasses the shock period of the war. However, the models can also estimate migration for future timesteps. Estimates over longer time horizons will likely suffer greater error without considering *return migration* and other uncertainty factors. Therefore, estimation over the shorter period represents a conservative estimation strategy. Additionally, the conflict shock period represents a period of greatest uncertainty from a policy-making standpoint since policymakers will lack reliable estimates of the dynamics and intensity of conflict-induced refugee flows over this period. We leave estimation of displacement over longer time horizons which incorporates *return migration* for future research.

In Figure 3, we show the daily refugee estimations from the two models, smoothed by a rolling average of seven days to correct for noises inherent in the observed data. Visually, *ABM-NA* captures both the scale and temporal pattern of the daily refugee flow very precisely. On the other hand, *ABM-IA* overestimates the refugee flow initially and underestimates afterward. The underestimation can be attributed to the quick depletion of potential migrants within conflict-induced regions due to the initial overestimation as well as the incapability to migrate other individuals through peer influence. Quantitatively, the Root Mean Squared Percentage Error (RMSPE) of *ABM-NA* is 23% compared to the 77% RMSPE of *ABM-IA*. Both methods are comparable in terms of capturing the daily trend based on the Pearson Correlation Coefficients (PCC) values.

[2] Scripts available at https://github.com/dmehrab06/Network_agency/

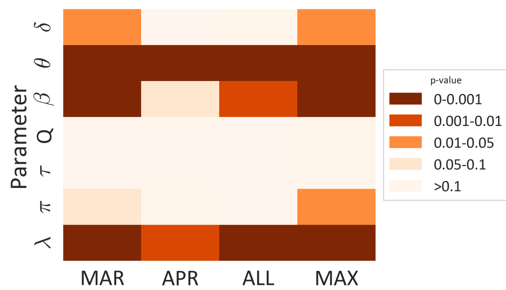


Figure 5: p-values of model parameters on different outputs of interest obtained from global sensitivity analysis.

IDP Estimation: As an alternative source of validation, we collect the Round 1 general survey report conducted by the International Organization of Migration (IOM). Among other statistics, it includes the percentage of Internally Displaced Persons (IDPs) based on their origins across six different Macro-regions of Ukraine (North, South, East, West, Center, Kyiv). The first round contains these estimates up to March 16, 2022. We report the median estimated percent of IDPs from each macro-region origin for both models in Table 2. Results indicate that the percentage estimates of *ABM-NA* more closely map to the IOM reported values than *ABM-IA*, demonstrating *ABM-NA* model's capacity to accurately identify the spatial geography of internal displacement in response to armed violence. Access to high-quality internal displacement data represents a great challenge for political leadership and humanitarian organizations in conflict zones [51] and this accuracy therefore underscores the policy value of *ABM-NA*. Maps corresponding to the tabulated results are provided in the Supplementary material.

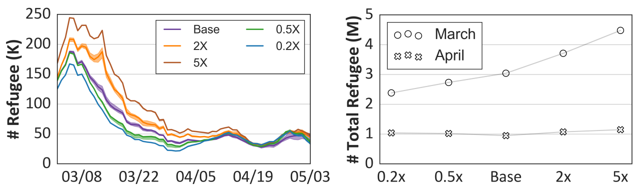
4.1 Sensitivity Analysis

In order to understand the significance of the parameters associated with the ABM, which consequently can reveal important information about the different kinds of functions employed throughout the *network agency* framework, we conduct a sensitivity analysis of our model. We follow the six-phase protocol suggested by Borgonovo et al. [9] to conduct the sensitivity analysis in our context as follows.
Output of Interest: Our model is calibrated against the daily border-crossing data. However, comparison between such daily curves is challenging during sensitivity analysis [6]. Therefore, we choose the following summary outputs as the outputs of interest: total refugee (ALL), total refugee in March (MAR), total refugee in April (APR), and maximum refugee in one day (MAX). Aside from ALL, MAX is also important from a policy standpoint since it reveals when a surge in refugee inflow can be expected in different destination countries. Moreover, MAR and APR will provide better insight to the seasonal significance of the parameters.
Goal: Our goal is twofold. *First,* relative importance of the parameters across various outputs of interest (Factor prioritization) and *Second,* variation of outputs by varying different parameters (Direction of Change).
Elements: Apart from the model parameters, other elements of the model can be varied. For example, the choice of the network generation model is a design principle that can essentially affect the outputs of interest. However, for this study, we focus only on the ABM parameters as the elements to examine.
Analysis Method: For *factor prioritization*, we conduct the partial rank correlation coefficient (PRCC) analysis leveraging the Latin Hypercube Design sampling (LHS) method [42]. To understand the direction of change, we use the One Factor at a Time (OFAT) analysis technique [55]. Following Ten et al. [55], we first perform OFAT since it is less computationally extensive and PRCC afterwards.
Assignment of Values: For each parameter, we fix a range of values within which they can be varied. During OFAT, we fix each value to their nominal settings obtained after calibration and change one parameter within that range. The nominal value for each parameter is given in the Supplementary material. Afterward, we sample the parameter space defined by the ranges using LHS.
Result visualization: Following Alam et al. [6], visualization of the sensitivity of the parameters is captured with main effect plots (for local sensitivity analysis) and heatmap (for global sensitivity analysis). We describe the results next

4.1.1 Local Sensitivity Analysis. Figure 4 shows main effect plots for two outputs of interest for two parameters. Main effect plots for other parameters are present in the Supplementary material. Figure 4a shows the monotonic increment of the outputs θ is increased. This is intuitive since a higher discounting factor (lower discount rate) makes agents perceive less recent events with more weight, accumulating greater fear as time progresses. This causes people to be more inclined towards migration. Moreover, the monotonic nature of the main effect plots tells us that the model is likely to be sensitive to the parameter [6]. While figure 4b also reveals a monotonic nature, the effect is different across the two outputs. As δ increases, perception of fear decreases. Therefore, naturally, the number of migrants goes down in March. However, the opposite behavior in the main effect plot for April is because when there are fewer migrations in March, more people are left to be peer-influenced, generating a higher total migration during April. In other words, this main effect plot reveals the effect of peer influence indirectly.

4.1.2 Global Sensitivity Analysis. Figure 5 shows the p-values of the partial correlation coefficients between each parameter-output pair. From this figure, the discounting factor parameter θ is found to be significant across all outputs of interest. The risk scaling parameter β and the distance decay parameter δ are also significant across a subset of the outputs. Note that, these parameters are associated with the *perception function.* Interestingly, the parameters Q and τ, associated with *representation function*, did not prove to be significantly correlated to any of these outputs. Further investigation is required regarding whether other choices of activation or aggregation functions demonstrate similar behavior.

Among the remaining parameters, λ is significant across all the outputs. In fact, it is the only parameter apart from θ, which is significant across all output types and it would be the second most significant parameter if we were to rank the parameters based on their average p-values, as suggested by [6] as a ranking method. Another key observation is that λ is found to be significant in the context of total migration during April. Apart from the discounting factor θ, no other parameters were significant for this output type. Therefore, at a constant discounting factor, *peer influence* is



(a) Daily Trend (b) Monthly Migration

Figure 6: ABM estimation under different event intensity

significant in capturing migration after the initial wave has subsided. While an individual's own perception is certainly important, once some form of migration has happened, peer influence starts becoming more important in driving subsequent migration.

4.2 What-If Scenario

This section presents one counterfactual analysis where we estimate the migration shift that would have been observed if the Russian forces had invaded with more (or less) intensity. By scaling the fatality of the events in the event dataset by different magnitudes, we were able to observe interesting insights. Figure 6a presents daily refugee flows estimated using conflict events scaled across four intensity levels with each scenario computed over 10 simulations to allow for stochasticity. Interestingly, although the resulting shift is quite noticeable in the early period, it diminishes over time converging back to base-level estimates by April. Figure 6b compares how the scale of conflict-intensity maps to the scale of cumulative migration estimated by the model in March and April. In March, a 2x increase in event intensity corresponds to a 23.4% increase in refugee flow (from 3.04 million to 3.71 million) while a 5x increase results in a nearly 50% increase in refugees (from 3.04 million to 4.5 million). Refugee flows in response to conflict intensity shifts in April result in smaller magnitude refugee flow increases of 25% (14%) for the 5x (2x) conflict scenarios.

As event intensity increases, most people affected by the events already migrate in the first month. However, since the spatial distribution of violence does not change, the increasing intensity does not affect the remaining agents. Consequently, peer influence plays a greater role in the migration choices of those leaving later. In fact, in the lower-intensity conflict scenarios, refugee flows marginally increased in April due to outflows of individuals who remained after March due to the peer influence of their social networks. Social science conflict scholarship has identified the role of social networks to influence both the timing [20, 50] and migration decisions [4] of individuals proximate to violence. These counterfactual results map onto the micro foundations of migration choices identified by conflict scholars and therefore lend additional credibility to the modeling approach. In summary, the what-if analysis demonstrates the model's capacity to capture the role of peer effects on the timing of migration with the agent's decisions to migrate being *event-driven* at the beginning of hostilities but becoming *peer-driven* as time progresses, in line with the observations we made from sensitivity analysis. Future research can extend upon this by allowing for variation in the spatial location of events in addition to intensity to evaluate how informed variation in the location of violence interacts with peer networks to drive downstream changes in refugee flows in response to violence.

5 DISCUSSION AND CONCLUSION

We have developed a data-driven agent-based simulation of forced migration from Ukraine not just as a demonstration of the idea of network agency, but also because it is an important current issue where ABM can be used to help understand refugee dynamics. We have shown that our model reproduces refugee flow quite accurately. We validated it using published estimates of counts of internally displaced persons. The sensitivity analysis suggests that the dynamics of evacuation have shifted from being event-influenced to peer-influenced. The model also allows studying policy-relevant what-if scenarios, such as the effects of changes in event intensities.

The approach is general enough to be applied to other conflict scenarios and highlights the need to develop a theoretical and computational understanding of how agency functions in complex hierarchical social systems where agency can be distributed and shared and emerges through the interactions between individual perceptions, information flow, social norms, and peer influence. As a simple example, the model could potentially be used to identify migration routes with different choices of functional forms. As one possibility, instead of a binary decision of whether to migrate or not, the action function should select from a set of possible destinations and choose a route from possible routes toward that destination. Currently, our approach serves as a practical recipe for the development of agent-based models in a way that sidesteps definitional questions of group and shared agency, while allowing the modeler to account for these phenomena. Much work remains to be done in formalizing the classes of functions that are valid agent descriptors. This is an important direction for future research.

A formalization of this approach will also allow bringing to bear network science to the understanding of agency. Network structure can both constrain and facilitate information flow and decision-making, potentially providing locational power to some agents over others. This is especially important in modern contexts where much social coordination happens over social networks and organizations are often spatially distributed. We believe that the network agency perspective will help in moving forward on the longstanding debate in social science between agency and structure and in computer science between distributed and group agency.

ACKNOWLEDGMENTS

This work was supported in part by NSF grant #2053013 Focused CoPe: Building Capacity for Adaptation in Rural Coastal Communities, DTRA contract HDTRA1-19-D-0007, NSF grant OAC-1916805 CINES: A Scalable Cyberinfrastructure for Sustained Innovation in Network Engineering and Science, NSF Expeditions in Computing grant CCF-1918656. We thank the reviewers for their careful reading of our manuscript and their many insightful comments and suggestions.

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