Modeling and Optimizing Agent-Based Model of Conflict-Induced Forced Migration

Doctoral Consortium

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ABSTRACT

Conflict-induced forced migration leads to large-scale displacement of populations, causing social and economic disruption. The recent Russian invasion of Ukraine serves as a stark example, resulting in millions of internally and internationally displaced people. Aiding them requires an understanding of the various dynamics of forced migration, including pre-migration intentions and post-migration outcomes such as return migration. However, existing computational approaches in the literature lack a cohesive framework that integrates these multi-dimensional aspects of forced migration using social and behavioral theories as foundational elements. My dissertation focuses on developing an a) end-to-end generalized agent-based model (ABM) of forced migration that captures these multi-phased dynamics, b) uses social and behavioral theory in modeling agent behavior, and c) applies various optimization and non-differentiable techniques to jointly optimize these multi-dimensional dynamics of forced-migration. I also perform various case studies that highlight the policy relevance of the model.

KEYWORDS

Agent-based modeling; Forced migration, Optimization; Ukraine; Displacement; Calibration; Differentiable ABM

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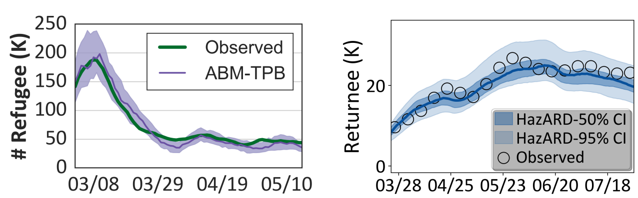
1 INTRODUCTION

Migration has been studied extensively by researchers of various backgrounds (e.g., political scientists, economists, geographers) [5, 11, 18, 28] with differing perspectives. These studies primarily focus on *planned* or *voluntary migration*. In contrast, *forced migration* has been studied less extensively; where migration is triggered by some *shock* event (e.g., conflict, natural disaster). The 2022 Russian invasion of Ukraine represents one such shock event that has caused the largest forced migration in Europe, apart from World War II [30]. Based on the reports of August 2024, around 3.7M people are internally displaced (IDP) [14], 6.8M are displaced as refugee [31] and 12.7M people require various humanitarian aid. Policymakers require understanding different dimensions of migration dynamics for making resource planning and logistic staging decisions to aid these people in need of assistance [3]. Therefore, a framework for modeling different dynamics of forced migration due to underlying geopolitical or environmental shock is critical.

Forced migration encompasses several interconnected stages: pre-migration (intention to migrate), during-migration (the movement to a host destination), and post-migration (decision to return home or relocate elsewhere) [15]. Each stage is influenced by unique social, political, and environmental factors, creating complex dynamics that are challenging to model comprehensively. Existing studies often treat these stages in isolation, which limits their ability to capture the broader migration continuum. Furthermore, many of these stages has not been explored in the context of forced migration. Thus, there is a growing need for integrated models that connect these phases, enabling policymakers to anticipate forced migration patterns and allocate resources more effectively.

In my first part of PhD research, I developed a data-driven, social theory-guided, agent-based framework to model pre-migration dynamics [19–21]. In the second part, based on the hazard function, I extended the framework to model post-migration dynamics. In the final part, I plan to explore various optimization techniques for calibrating the model to produce realistic migration estimates.



(a) ABM-TPB **(b) HazARD**

Figure 1: Temporal evaluation of proposed agent-based models. Figure 1a shows the forced migrant outflow estimate from Ukraine by ABM-TPB model against observed estimate. Figure 1b shows the number of daily return migrants from Poland to Ukraine compared to the observed estimates.

2 ABM-TPB: MODELING THEORY-GUIDED PRE-MIGRATION DYNAMICS (INTENTION)

Multiple theories explain migration intention in the context of *planned migration*. Though these theories have not been computationally applied in the context of *forced migration*, it has been

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suggested that social-theory driven models can be useful in data-inadequate situations [17], something often observed during *forced migration*. Motivated by this, we propose *ABM-TPB*, where we computationally formulate *Theory of Planned Behavior* [2] to model migration intention under the hood of an agent-based model. We apply a discounted utility model [7, 10] to capture evolving perception from the conflict events and a threshold model [12, 25, 32] to capture peer influence. Leveraging the digital twin of the country's population, we model the migration decisions of agents as a direct consequence of the perception of events and peer influence.

Comparison of our model with the State-of-the-Art (SofA) proposed by [24] shows that our model excels in capturing both the temporal and spatial migration outflow from Ukraine. The model was also applied to two other conflict settings, the 2012 Northern Mali conflict and the 2015 Burundi conflict, which underscored its generalizability. Additionally, we conduct two case studies with our model to highlight the policy use cases. The first scenario studies *entrapped population* and the second scenario studies what-if migration patterns under *counterfactual conflict* settings. Additionally, sensitivity analysis shows that parameters pertaining to event perception and peer influence are the most important in capturing the pre-migration dynamics [19].

3 HazARD: MODELING THEORY-GUIDED POST MIGRATION DYNAMICS (RETURN)

Systematic literature in the area of return migration is scarce [1, 27, 29, 34] despite its high priority. Although high priority [6]. Thus, in the second part of my PhD research, I attempt to model the return decision of displaced refugees of a particular host country.

Based on the concept of *hazard functions* [9], we propose HazARD (Hazard based ABM to model return migrants from destination), a collection of models that consider relevant contexts (i.e., social and political), to calculate the return intentions of the refugee. We also propose surrogates to these ABMs which can generate lower-resolution output with lower computational overhead. Our simplest ABM improves the accuracy of the return estimate by 42% over baseline, whereas the best model has an improvement of 57%. Consequently, our best surrogate model has an improvement over baseline by 51%. We also conducted two case studies to highlight the utility of these models in generating policy-relevant information, similar to the previous research. The first scenario studies the length of displacement of the refugees, an emergent output of the ABMs, which was validated against the ground truth estimate of subsidiary reports [13]. The second case study disaggregates migrants into six demographic groups and analyzes their return patterns. We observe that single-male households are more likely to return than other demographic groups.

4 OPTIMIZATION OF MIGRATION DYNAMICS

Computational models (e.g., Agent-based Models (ABM), Machine-learning (ML) based models), once designed, undergo an optimization step where they learn the parameters that would best fit real-world observations [22]. For ML models, these parameters correspond to the weights across different layers of the model. The number of parameters can be quite large and they are usually learned by gradient-based optimization method (e.g., backpropagation) [26]. On the other hand, for ABMs, these parameters are comparatively small in number and they are usually trained using gradient-free optimization techniques [16, 23, 33] (e.g., bayesian optimization).

Table 1: Objective functions of different modalities at different stages of migration.

Migration Stages	Modalities: Temporal	Spatial	Demographic
(Pre) Intention	Daily IDP outflow	Originating Raion of migrants	Ratio of adult female migrants
(During) Destination	What is the daily refugee inflow to a particular country?	Where are the refugees sheltering?	What percentage of single male refugees entered a particular country?
(Post) Return	What is the mean length of displacement?	Where are they returning?	What percentage of elderly returned?

In my previous works where I attempted to model pre-migration and post-migration dynamics, I used gradient-free methods to optimize the models. While they produced good estimates, it was computationally extensive to optimize these models. However, crises like forced migration require the deployed system modeling forced migration dynamics to be scalable in producing reasonable dynamics. In recent years, researchers have explored differentiable ABMs [4] in crisis situations like epidemiology [8]. These ABMs can utilize gradient-based optimization techniques to learn the parameters. It also offers the possibility of deploying these models in GPU, making this learning process scalable. Motivated by this, in the last part of my thesis, I want to rethink the models of forced migration under the hood of a differentiable ABM framework.

Consequently, similar to migration being a multi-staged phenomenon, there are multiple modalities of estimates of interest to policymakers. Table 1 outlines some of the possible modalities of objectives which would be of interest to policymakers. While my previous works have focused on only the temporal modality, I want to explore the possibility of optimizing the model using the joined objective function of multiple dimensions and modalities.

Broadly, in the final part of my research, I want to answer the following research questions.

- RQ1. Is it possible to develop a differentiable agent-based model of forced migration?
- RQ2. Is the gradient-based approach comparatively better than the gradient-free approach in optimizing an agent-based model of forced migration?
- RQ3. How can an agent-based model be optimized over objective functions defined for multiple modalities at multiple stages of forced migration?

In general, my thesis aims to build a scalable generalized end-to-end agent-based framework to model all aspects of conflict-induced forced migration that policymakers can use for case studies and provide affected people with the proper humanitarian support.

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