



Visvesvaraya National Institute of Technology Nagpur

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Advancing State-of-the-Art of Digital Twins: Introducing Dynamic Actors with Orchestration (Indian Traffic and Transportation DT)

Final Year Project - Phase 1 : Eval 2

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Large Population Models

Chopra, A. (2025). Large population models. arXiv preprint arXiv:2507.09901. <https://arxiv.org/abs/2507.09901>

What are LPMs?

- **Simulations** of entire societies, not just individuals.
- They model how **millions of individual choices create large-scale outcomes** (e.g., a pandemic).
- Think of them as "**digital societies**" that show us emergent behavior.

Three Core Innovations:

- **Scale & Speed:** Can simulate millions of agents efficiently on normal computers.
- **Learns from Data:** Uses a "differentiable" framework to quickly learn from real-world data streams.
- **Privacy-Preserving:** Can securely connect with real-world systems without centralizing sensitive data.

This is all powered by the **open-source Agent Torch framework**.





The Driving Factor: Why LPMs?

Three Main Reasons:

1. The Scale vs. Detail Problem:

- a. **Old Way:** You could have many simple agents, or a few smart agents. You couldn't have both.
- b. **LPM Solution:** Achieves both population scale and behavioral realism simultaneously.

2. The Data Problem:

- a. **Old Way:** Models struggled to learn from today's massive and diverse datasets. Calibration was slow and manual.
- b. **LPM Solution:** Automatically and rapidly calibrates to real-world data, keeping the model relevant and accurate.

3. The Simulation vs. Reality Gap:

- a. **Old Way:** Simulations were disconnected from the real world due to privacy barriers and data delays.
- b. **LPM Solution:** Securely bridges this gap, allowing the model to interact with real-time information in a privacy-preserving way.





Major Contributions by Ayush Chopra from the paper

1. The Engine: FLAME (Differentiable Simulation)

- **What:** GPU-accelerated, modular simulation.
- **Impact:** Enables massive **scalability** and **gradient-based calibration** by making the environment differentiable.

2. The Actors: LLM Archetypes (Adaptive Behavior)

- **What:** Models population behavior using a few LLM-driven "archetypes" ($K \ll N$).
- **Impact:** Achieves **rich, adaptive human behavior** at a fraction of the computational cost.

3. The Calibrator: Online Variational Inference (Real-Time Learning)

- **What:** An in-simulator neural network that learns parameters on the fly.
- **Impact:** Achieves **real-time self-calibration** against live data, eliminating slow surrogate models.





Major Contributions by Ayush Chopra from the paper

4. Federated & Multi-Modal Calibration

- **What:** A data-conditioned learner (DNN_Q) trained on diverse, distributed data sources (clinical, mobility, etc.).
- **Impact:** Privacy-preserving, cross-domain calibration via federated learning.

5. End-to-End Interpretability

- **What:** Uses automatic differentiation across the entire simulation graph.
- **Impact:** Real-time, exact sensitivity analysis (interpretability) for all parameters.

6. Secure Live-Data Integration (MPC)

- **What:** Uses secure multi-party computation (MPC) to run simulations on decentralized, private data.
- **Impact:** Bridges the simulation-reality gap by securely using live data.





Why Indian Traffic? A "Stress Test" for Next-Gen Digital Twins

A Clear Research Gap:

- These models are fundamentally built on **homogeneous traffic** (mostly cars/buses) and **strict lane discipline**.

The Indian Traffic Challenge: "Organized Chaos"

- **Extreme Heterogeneity:** A dense, high-volume mix of two-wheelers (motorcycles), three-wheelers (auto-rickshaws), cars, buses, and pedestrians, all competing for the same space.
- **Emergent & Non-Linear Behavior:** Traffic flow isn't just a set of rules; it's a complex, emergent "negotiation" between diverse agents.

Our Project's Core Motivation:

- This environment provides the perfect "stress test" and high-impact use case for our core thesis: **proving that Dynamic Agents are essential** for building a realistic, predictive Digital Twin.





1. Agent Based Modeling for Traffic Simulation

Karima, Benhamza & Ellagoune, Salah & Seridi, Hamid & Akdag, Herman. (2012). *Agent-based modeling for traffic simulation*. 51-56.

1. Traffic is modeled as an **emergent phenomenon** from individual driver–vehicle interactions rather than as a continuous flow.
2. A **microscopic simulator** with **reactive agents** is used, where agents follow simple stimulus–response rules without learning or prediction.
3. **Vehicle agents** interact with **road**, **traffic light**, and **intersection agents**, adjusting speed, lane, and direction based on surroundings.
4. The simulation reproduces **realistic traffic patterns**, including congestion, using only simple local interaction rules.
5. Results show **human-like driving behaviors** and demonstrate that complex traffic jams can emerge from basic agent rules.





2. Enhancing Traffic Flow: Multi-Agent Systems in Traffic Management

<https://smythos.com/developers/agent-development/multi-agent-systems-in-traffic-management/>

1. **Core Idea:** Smart, autonomous agents (like traffic lights or apps) collaborate in real-time to optimize the entire traffic network.
2. **Key Agents:** Specialized agents manage traffic flow, coordinate intersections, and guide drivers to available parking.
3. **Main Challenges:** Key hurdles include integrating diverse data sources, scaling the system as a city grows, and ensuring instantaneous decisions.
4. **Proven Applications:** Success is shown in Singapore (dynamic tolls), Barcelona (bus regularity), and Birmingham (adaptive signals).
5. **Future Trend:** The focus is shifting from reacting to traffic to *predicting and preventing* congestion using AI.





Moving Forward

- **Foundation:** Develop a microscopic agent-based simulation environment to model the unique properties of Indian road networks (e.g., unmarked lanes, complex intersections).
- **Level 0 (Dynamic Actors):** Define and train a diverse set of heterogeneous agents (two-wheelers, auto-rickshaws, cars, buses) to replicate complex, non-lane-based, and "opportunistic" driving behaviors.
- **Level 1 (Orchestration):** Implement a high-level "Traffic Flow Agent" that monitors the entire system, identify congestion hotspots, and perform global optimization (e.g., dynamic route suggestion, adaptive traffic light control).
- **Goal:** Integrate these two levels to create a realistic, predictive Digital Twin, demonstrating that this hierarchical, learning-based approach is superior to traditional models for complex, unstructured traffic.





Identification of Agents

Level 1: Orchestration Agent (The "Global Brain")

- **Traffic Flow Agent:** A high-level agent that monitors the entire network for congestion, and identifies hotspot

Level 0: Micro-Agents (The "Individuals")

- **Driver Agents:** The "brain" of a vehicle; a dynamic, agent that makes all tactical driving decisions.
- **Vehicle Agents:** A composite agent representing the "body" (e.g., car, two-wheeler) that consists of and is controlled by its internal Driver Agent.
- **Vulnerable Road User (VRU) Agents:** Non-vehicular agents, such as pedestrians, who interact with, and are affected by, the road network.
- **Infrastructure Agents & Objects (The "Environment"):** Agents and objects representing the environment, such as Intersections (managing flow) and Road Segments (reporting data).





Characteristics of Agents

Level 1: Orchestration Agent

- **Goal:** *Global* optimization. Minimize system-wide congestion and travel time.
- **Perception (Sensing):** *Macroscopic*. "Sees" the entire network by receiving aggregated density and avg.speed data from all Road Segments

Level 0: Micro-Agents

- **Driver Agents**
 - a. **Goal:** *Local* optimization. Reach its destination safely and efficiently, based on its "personality" (e.g., aggressive, patient).
 - b. **Perception (Sensing):** *Microscopic*. "Sees" nearby vehicles, road edges, signals, and reads route guidance from the Level 1 agents.





Characteristics of Agents

Level 0: Micro-Agents

- **Vehicle Agents**
 - a. **Goal:** None (it's a passive object).
 - b. **Perception (Sensing):** None (it is controlled by its Driver Agent)
- **Vulnerable Road User (VRU) Agent**
 - a. **Goal:** Safely cross the street or reach a destination.
 - b. **Perception (Sensing):** "Sees" oncoming traffic and identifies safe crossing gaps.
- **Infrastructure Agents & Objects**
 - a. **Intersection Agent:** Manages traffic at a *single junction* (via signals or negotiation) to maximize its local throughput.
 - b. **Road Segment Object:** A passive object that acts as a sensor, reporting its local vehicle density and avg. speed up to the Traffic Flow Agent.





Tentative Project Plan

- **Phase 1 (Define & Simulate):** Formulate the simulation environment, define all actors, agents, their properties, and behaviors, and explore existing datasets or generate using simulation.
- **Phase 2 (LLM Analysis):** Apply Large Language Models (LLMs) to identify and classify characteristic properties, such as emergent behaviors and key traffic events.
- **Phase 3 (RL Optimization):** Implement Reinforcement Learning (RL) agents within the simulation and train them to achieve specific objective targets (e.g., minimize wait time).





References

- [1] **Chopra, A. (2025)**. Large population models. arXiv preprint arXiv:2507.09901. <https://arxiv.org/abs/2507.09901>
- [2] **Karima, Benhamza & Ellagoune, Salah & Seridi, Hamid & Akdag, Herman. (2012)**. Agent-based modeling for traffic simulation. 51-56.
- [3]<https://smythos.com/developers/agent-development/multi-agent-systems-in-traffic-management/>

