# A Discrete-Time Agent-Based Simulation of Market Shocks in the Oil Industry

ADRIAN EDWARDS

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## 1 Project Proposal

### Domain

This project focuses on the oil market as a representative example of a scarce resource industry. The simulation examines fundamental supply and demand interactions within commodity markets and explores how disruptive events impact system behavior over time.

### Problem Statement

Commodity markets that rely on scarce resources, such as oil, often operate in semi-stable states that can be abruptly disrupted by sudden supply or demand shocks. These shocks may arise from events such as production outages, geopolitical conflicts, or unexpected demand changes. Analytical models frequently struggle to capture the resulting transient dynamics, particularly when individual market participants act independently and under uncertainty.

The primary objective of this simulation is to investigate how a semi-stable oil market responds to a sudden disruptive shock that significantly alters supply or demand. Specifically, the simulation seeks to answer how prices, resource availability, and unmet demand evolve over time when no external corrective intervention is applied following the shock.

### Scope

The simulation models an oil market consisting of multiple seller agents and a large population of buyer agents that interact over discrete time steps. Buyers follow simple decision rules and are characterized by trait-based willingness-to-pay (WTP) values that are assigned at initialization and remain fixed throughout a simulation run. Sellers operate with limited production capacity and inventory and employ adaptive pricing rules in response to observed market conditions.

Randomness in the simulation arises from stochastic buyer demand and predefined WTP traits, with each simulation run initialized using a unique random seed to ensure both variability and reproducibility. The model intentionally excludes advanced market intelligence, artificial intelligence techniques, and strategic global knowledge. Market

Author's Contact Information: Adrian Edwards.

participants act solely on local information and predefined behavioral rules, allowing market-level behavior to emerge organically from agent interactions.

### 1.1 System Description

#### System Components

The simulation consists of four primary components: buyers, sellers, a market mechanism, and shock events. Together, these components define the structure and behavior of the modeled oil market.

*Buyer Agents.* Buyers represent aggregate consumers or consumer groups within the oil market. Each buyer is characterized by a fixed willingness-to-pay (WTP) trait assigned at simulation initialization, representing persistent economic characteristics such as budget constraints or consumption tolerance. Buyers generate demand stochastically over time and follow simple decision rules when selecting sellers. Buyers do not possess global knowledge of the market and make purchasing decisions based solely on local information such as price and availability.

*Seller Agents.* Sellers represent oil producers operating within the market. Each seller is defined by production capacity, inventory level, and a dynamically adjusted price per unit. Sellers replenish inventory over time subject to capacity constraints and employ adaptive pricing strategies based on observed sales performance. Unlike buyers, sellers exhibit more complex behavior by responding to market conditions through price adjustments, while still lacking global system awareness.

*Market Mechanism.* The market component is responsible for facilitating interactions between buyers and sellers. It processes buyer demand, matches buyers to available sellers according to predefined allocation rules, and enforces transaction constraints such as inventory availability and willingness-to-pay limits. The market does not optimize outcomes but instead applies consistent rules that allow market-level behavior to emerge from individual agent interactions.

*Shock Events.* Shock events represent sudden disruptive changes to the market, such as the partial or complete loss of a major seller's production capacity. Shocks are introduced at predefined simulation times and are modeled as discrete events that alter seller availability or production rates. These events are intended to simulate real-world disruptions and to observe the resulting transient and long-term effects on market behavior.

#### System Dynamics

The simulation progresses in discrete time steps, with each timestep representing a fixed unit of time (e.g., one day). This discrete-time structure simplifies state tracking, logging, and analysis while remaining appropriate for modeling market-level dynamics.

At the beginning of each timestep, seller agents replenish their inventories according to fixed production rates subject to capacity constraints. This replenishment represents ongoing oil production and ensures that supply evolves gradually over time rather than instantaneously responding to demand.

Buyer agents then generate demand stochastically. Each buyer's demand quantity for the timestep is determined probabilistically, while their willingness-to-pay (WTP) remains fixed as a trait assigned at initialization. Buyers attempt to fulfill their demand by selecting sellers whose prices do not exceed their WTP and who have sufficient inventory available.

Buyers evaluate sellers sequentially according to their decision rules and place purchase requests until their demand is satisfied or no eligible sellers remain. If a buyer is unable to fulfill their demand due to price constraints or insufficient supply, the unmet portion of demand is recorded, and the buyer exits the market for the remainder of the timestep.

Following buyer transactions, sellers update their internal state based on observed sales outcomes. Sellers adjust prices adaptively in response to inventory levels and sell-through rates, allowing pricing behavior to evolve dynamically over time without requiring global market awareness.

Shock events are introduced at predefined timesteps and are modeled as discrete disruptions to the system. These events typically affect one or more major sellers by reducing or eliminating production capacity, thereby altering available supply. After a shock occurs, no external intervention is applied; the system is allowed to evolve naturally according to the established agent rules.

Throughout the simulation, key metrics such as prices, transaction volumes, inventory levels, and unmet demand are recorded at each timestep. Each simulation run is initialized with a unique random seed to ensure reproducibility while allowing variability across multiple executions.

### Assumptions

To maintain tractability and focus on core market dynamics, the simulation operates under the following assumptions:

**Single-Product Market** The market models a single homogeneous commodity (oil). Product differentiation, substitutes, and cross-market interactions are not considered.

**Trait-Based Buyer Behavior** Each buyer is assigned a fixed willingness-to-pay (WTP) value at simulation initialization. This trait remains constant throughout a simulation run and represents persistent economic characteristics such as budget constraints or consumption tolerance. Buyers do not adapt or learn over time.

**Stochastic Demand Generation** Buyer demand is generated stochastically at each timestep. While demand quantities vary probabilistically, the underlying buyer population and WTP distribution remain fixed within a run.

**Local Decision-Making** Buyers and sellers act solely based on local information, such as current prices, available inventory, and individual demand. No agent possesses global knowledge of the market state or future events.

**Adaptive but Non-Strategic Sellers** Sellers adjust prices using simple feedback rules based on inventory levels and sales outcomes. Sellers do not perform forecasting, optimization, or strategic coordination and do not anticipate shock events.

**Discrete Time Progression** Market activity occurs in fixed discrete time steps. All production, demand generation, transactions, and price updates occur once per timestep.

**No External Intervention** Following the introduction of a shock event, no external regulatory or corrective intervention is applied. The market is allowed to evolve solely according to agent rules and resource constraints.

**Reproducibility Through Seeding** Each simulation run is initialized with a unique random seed. This ensures that stochastic behavior is reproducible while allowing statistical analysis across multiple runs.

These assumptions intentionally simplify real-world oil market complexity in order to isolate and analyze the effects of demand uncertainty, adaptive pricing, and supply disruptions within a controlled simulation environment.

### Core Models and Algorithms

The simulation is structured around a small set of formal models and rule-based algorithms that collectively govern market behavior. These models are intentionally simple, interpretable, and well-aligned with established simulation practices, allowing complex system-level dynamics to emerge from local interactions.

*Agent-Based Market Model.* The simulation follows an agent-based modeling (ABM) paradigm in which buyers and sellers are represented as autonomous agents. Each agent maintains its own internal state and operates according to predefined local rules without access to global market information. Market-wide behavior, such as price volatility, shortages, and recovery following shocks, emerges from repeated interactions between buyers and sellers over time rather than from centralized control or optimization.

*Stochastic Demand and Trait-Based Willingness-to-Pay.* Each buyer $i$ is assigned a fixed willingness-to-pay (WTP) trait $w_i$ at simulation initialization, sampled from a probability distribution such as a truncated normal distribution:

$$w_i \sim \mathcal{N}(\mu_w, \sigma_w), \quad w_i \geq 0.$$

This WTP trait remains constant throughout a simulation run and represents persistent buyer characteristics such as budget constraints or consumption tolerance.

At each timestep $t$, buyers generate demand quantities probabilistically to reflect uncertainty in consumption behavior. Demand may be modeled using a discrete stochastic process such as:

$$q_i(t) \sim \text{Poisson}(\lambda_i),$$

where $\lambda_i$ represents the average demand rate for buyer $i$. This formulation introduces stochastic variability in demand while preserving stable long-run consumption behavior.

*Buyer Purchase and Market Allocation Algorithm.* Given seller prices $p_j(t)$ and inventory levels $I_j(t)$, a buyer attempts to satisfy demand by identifying eligible sellers that meet the following conditions:

$$p_j(t) \leq w_i \quad \text{and} \quad I_j(t) > 0.$$

Buyers select among eligible sellers according to a simple decision rule, such as choosing the seller with the lowest price. Purchases continue until buyer demand is satisfied or no eligible sellers remain. If demand cannot be fulfilled, the unmet portion is recorded and the buyer exits the market for the remainder of the timestep.

*Seller Inventory Replenishment and Adaptive Pricing.* Each seller $j$ operates with a fixed production rate $r_j$ and replenishes inventory at each timestep subject to capacity constraints:

$$I_j(t+1) = I_j(t) + r_j - \text{units\_sold}_j(t).$$

Sellers adapt prices using simple feedback rules based solely on recent sales outcomes. One possible formulation adjusts prices proportionally based on utilization:

$$p_j(t+1) = \max\left(p_{\min},\ p_j(t) \cdot \left(1 + k \cdot (u_j(t) - u^*)\right)\right),$$

where $u_j(t)$ represents seller utilization, $u^*$ is a target utilization level, and $k$ controls responsiveness.

*Utilization Definition.* Seller utilization is defined as the fraction of per-timestep production cleared through sales:

$$U_j(t) = \frac{units\_sold_j(t)}{r_j(t)}$$

Here, $units\_sold_j(t)$ and $r_j(t)$ are measured in identical units per timestep, so $u_j(t)$ is dimensionless and directly comparable to the target utilization $u^* \in (0, 1)$. During a supply shock, $r_j(t)$ reflects the shock-adjusted production rate.

To avoid extreme one-step price swings under rare high-demand realizations, utilization used in the pricing rule may be capped using $u_m$ as the max $u$:

$$\hat{u}_j(t) = min(u_j(t), u_m)$$

and $\hat{u}_j(t)$ replaces $u_j(t)$ in the price update.

*Discrete Supply Shock Modeling.* Supply disruptions are modeled as discrete exogenous shock events introduced at predetermined timesteps. A shock may reduce production capacity for a major seller for a specified duration:

$$r_{\text{top}} \leftarrow (1 - \beta)\, r_{\text{top}} \quad \text{for } t \in [t_s, t_s + d],$$

where $\beta$ represents shock severity and $d$ represents duration.

These formulations are representative rather than empirically calibrated and are intended to support qualitative analysis of system behavior under uncertainty.

Together, these models form a cohesive simulation framework that emphasizes decentralization, uncertainty, and emergence.

### Implementation Approach

**Programming Language** The simulation will be implemented in Python, selected for its suitability for rapid prototyping, data analysis, and experimentation. Python's support for numerical computation, random number generation, and data logging makes it well suited for iterative simulation studies and Monte Carlo experimentation.

**Simulation Type** The system will be implemented as a discrete-time, agent-based simulation. Time advances in fixed increments, with all production, demand generation, transactions, and price updates occurring once per timestep. This structure simplifies state management, enables straightforward logging of system evolution, and supports reproducible multi-run analysis.

**Development Approach** The simulation will be developed using a lightweight, custom implementation rather than a pre-built simulation framework. Core functionality will rely on standard Python libraries, with optional use of numerical or data-processing libraries (e.g., NumPy or pandas) for random sampling, aggregation, and analysis. This approach ensures transparency of model logic and direct correspondence between the conceptual model and executable implementation.

**Data Collection and Output** Simulation output will be collected at each timestep and written to structured log files (e.g., JSON or CSV format). Collected metrics will include seller prices, inventory levels, transaction volumes, unmet demand, and system response following shock events. Each simulation execution will be initialized with an explicit random seed, enabling reproducibility and controlled comparison across multiple runs.

**Analysis Strategy** The resulting dataset will support both single-run inspection of system dynamics and aggregate statistical analysis across many runs, allowing evaluation of stability, recovery behavior, and sensitivity to demand uncertainty and supply disruptions.

## 2 Literature Review

### Core Models and Algorithms

*Zeigler, Muzy, and Kofman.* Zeigler, Muzy, and Kofman present a foundational framework for modeling and simulation that emphasizes the separation between conceptual models and executable implementations [6]. Their work highlights the importance of abstraction, system boundaries, and controlled assumptions when modeling complex systems. This perspective directly informs the structure of the proposed simulation, which prioritizes a clear conceptual model of buyers, sellers, and shocks before defining executable rules. By deliberately limiting agent knowledge and excluding strategic optimization, the simulation follows established guidance for maintaining interpretability while still allowing emergent system behavior to arise.

*Banks, Carson, and Nelson.* Banks, Carson, and Nelson provide a comprehensive treatment of discrete-event and discrete-time simulation, with particular emphasis on stochastic inputs, time advancement mechanisms, and experimental execution across multiple runs [1]. Their discussion of random processes and controlled seeding supports the use of stochastic demand generation and repeated simulation runs in this project. The discrete-time progression used in the oil market simulation aligns with their recommendations for systems where state changes occur at regular intervals and where logging and statistical comparison across executions are required.

*Garrido.* Garrido's object-oriented approach to simulation motivates the use of encapsulated buyer and seller agents with independent state and behavior [3]. Treating market participants as objects with internal attributes such as inventory, production rate, and willingness-to-pay enables modular design and clear mapping between conceptual entities and executable components. This approach directly supports the agent-based structure used in the proposed simulation and reinforces the choice to model buyers and sellers as autonomous entities governed by local rules.

*Choi and Kang.* Choi and Kang explore modeling techniques for discrete event systems and emphasize the role of events in altering system state [2]. Their treatment of externally triggered events informs the modeling of supply shocks as discrete disruptions introduced at predetermined simulation times. By representing shocks as exogenous events rather than endogenous agent behavior, the simulation remains consistent with established event-driven modeling practices while enabling focused analysis of system response and recovery dynamics.

*Sokolowski and Banks.* Sokolowski and Banks discuss the tradeoff between realism and tractability in modeling and simulation, arguing that overly complex models may obscure causal relationships [5]. This principle directly motivates the simplifications made in the proposed oil market simulation, including the use of non-strategic agents, fixed willingness-to-pay traits, and feedback-based pricing rules. These simplifications allow the simulation to isolate the effects of demand uncertainty and supply disruption without introducing unnecessary behavioral complexity.

### Related Work and Educational Influences

*Primer.* Educational simulations of supply and demand, such as those presented in Primer's visual and agent-based market models, demonstrate how simple local rules can generate intuitive and informative system-level behavior [4]. While these models are not academic in nature, they influence the design philosophy of the proposed simulation by emphasizing clarity, interpretability, and emergent dynamics. The proposed project extends this educational modeling style into a more formal simulation context by incorporating stochastic processes, controlled experiments, and structured data collection.

## 3 UML Diagrams

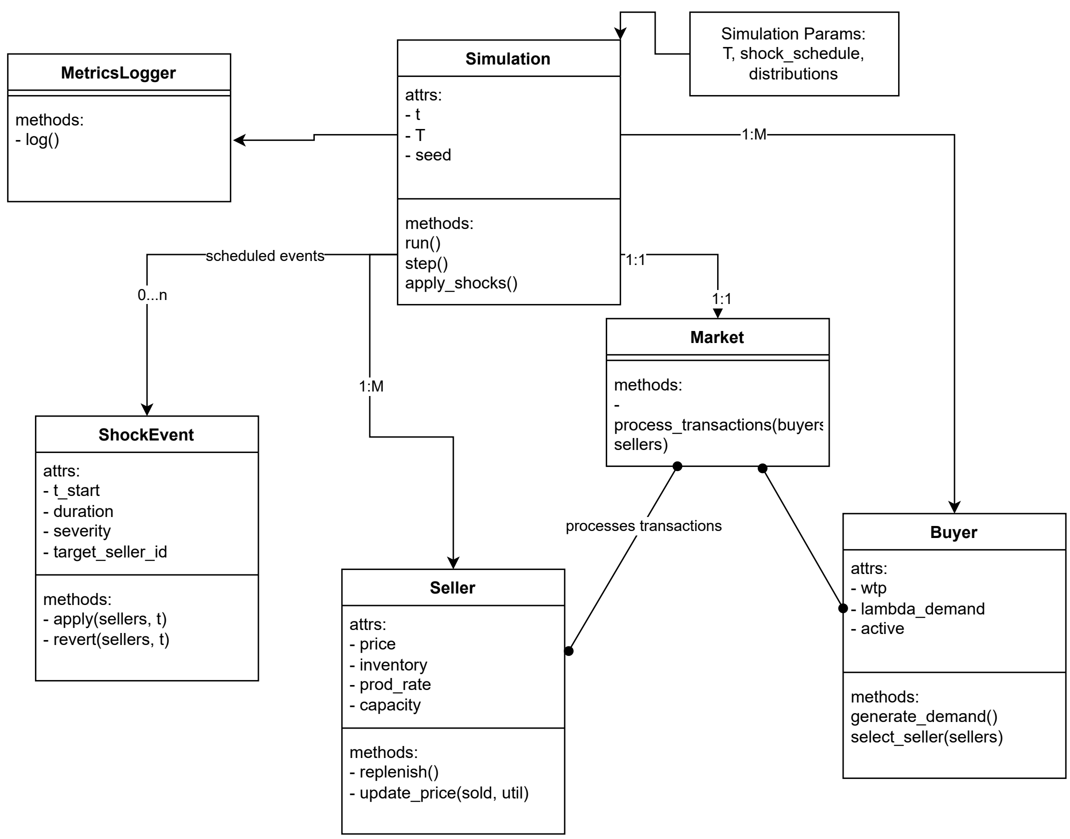


Fig. 1. UML Class Diagram for the Oil Market Simulation.

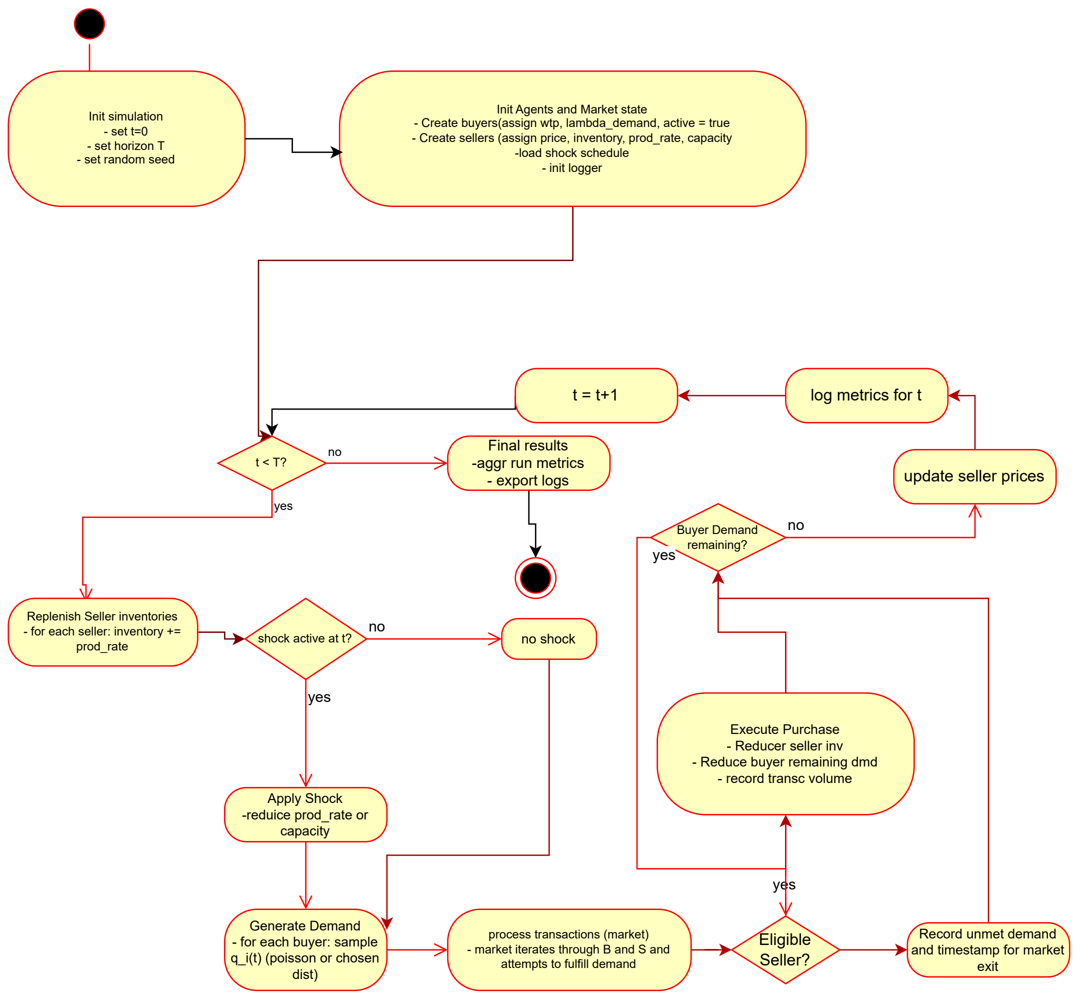


Fig. 2. UML Activity Diagram for a Single Simulation Execution.

## Project Repository

The project repository containing implementation scaffolding, UML artifacts, and documentation is available at: https://github.com/netEdwards/oil-market-simulation

## References

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[5] John A. Sokolowski and Catherine M. Banks. 2009. *Principles of Modeling and Simulation: A Multidisciplinary Approach.* Wiley, Hoboken, NJ.
[6] Bernard P. Zeigler, Alexandre Muzy, and Ernesto Kofman. 2000. *Theory of Modeling and Simulation* (2nd ed.). Academic Press, San Diego, CA.