XenoSotaAgent: An Agent Submitted to the ANAC 2025 SCM League

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Abstract

This paper describes the design and key features of "XenoSotaAgent", an agent submitted to the ANAC 2025 SCM League. The agent aims to minimize shortfall penalties and secure stable profits through an integrated strategy that combines trust-based proposal selection, concurrent negotiation management, and early inventory acquisition to mitigate risk.

1 Introduction

One of the major challenges in the SCML environment is to maximize profit while avoiding contract violations in manufacturing and trading plans. This is especially critical in Levels 1 and 2, where the lack of raw materials in the production process often leads to shortfalls.

To address this issue, XenoSotaAgent was designed with three core strategies:

- Proposal generation based on trust levels and feasibility
- Concurrent negotiation management using offer histories and risk evaluation
- Shortfall prevention through proactive inventory acquisition in early steps

2 The Design of MyAgent

2.1 Negotiation Choices

The agent generates proposals using the `ProposalStrategy` and `OfferGenerator` modules, which score multiple candidate offers and select the optimal one based on expected profit, feasibility, and consistency with existing contracts.

The `UtilityEvaluator` assesses the value of each proposal, and makes accept/reject decisions by balancing profitability and execution feasibility. This prevents the agent from entering unsustainable contracts.

2.2 Concurrent Negotiation

The agent negotiates with multiple partners simultaneously. Proposal histories with each partner are recorded in the `OfferHistory`, which are used to compute trust scores via `PartnerScorer`. This allows the agent to mitigate the risks of contracting with unreliable partners.

Current and future contract states are managed by `AgreementsManager`, and quantities are dynamically adjusted through `SupplyDemandAllocator` to avoid excess inventory and potential shortages.

2.3 Risk Management

A notable feature is the strategy of aggressive material acquisition during the early steps in Levels 1 and 2. This avoids bottlenecks in the later production process.

Past sales and production records are tracked using `RecordManager`, which helps the agent decide whether to apply the inventory-first strategy in the early phase.

In addition, the agent restricts both the frequency and volume of proposals to low-trust partners, thereby reducing the overall probability of shortfall incidents.

3 Evaluation

Experimental Settings

Simulations were conducted with the following settings:

- Steps: `n_steps=10`
- Processes: `n_processes=3`
- Configurations: `n_configs=4`

Each simulation was run five times per configuration. In each case, 16 samples were collected, for a total of 80 samples per agent.

Evaluation Metrics

Normalized scores defined by SCML were used as evaluation criteria. The following statistical indicators were calculated:

- Mean score and standard deviation
- Minimum and maximum values
- Median and interquartile range (25%, 75%)

Results and Comparison

The table below compares statistical scores across three agents.

Agent	Mean	Std	Min–Max	Median (25%-75%)
XenoSotaAgent	1.15	0.17	0.526–1.539	1.19 (1.05–1.27)
SimpleSyncAgent	0.631	0.26	0.072–1.004	0.689 (0.582–0.849)
ProactiveAgent	0.666	0.40	-0.651–1.460	0.724 (0.512–1.018)

Table 1: Statistical score comparison of each agent (average of 5 trials)

Robustness Metrics

To further assess the stability of each agent, we computed the score range and the ratio of standard deviation to the mean, as summarized below.

Agent	Score Range (Max - Min)	Std / Mean Ratio
XenoSotaAgent	1.013	0.148
SimpleSyncAgent	0.932	0.412
ProactiveAgent	2.111	0.601

Table 2: Agent-wise robustness metrics: score range and normalized deviation

Discussion

- **XenoSotaAgent** achieved the highest mean score of 1.15, with narrower variability (0.17) and a maximum score reaching 1.539.
- It now outperforms others not only in robustness but also in peak performance across all simulations.
- **SimpleSyncAgent** showed modest performance with relatively low variance but limited upper-bound potential.
- **ProactiveAgent** exhibited the widest range and highest score deviation, indicating high scenario sensitivity despite strong median values.

These findings demonstrate that XenoSotaAgent not only performs well on average but also exhibits high robustness across diverse simulation conditions.

4 Lessons and Suggestions

Our findings show that emphasizing feasibility over the theoretical quality of proposals is key to reducing shortfalls.

In addition, using historical data and trust scoring enabled greater stability in long-term negotiations.

Future improvements include:

- Dynamic optimization of inventory strategies depending on the simulation phase
- Incorporation of learning-based proposal generation, such as reinforcement learning

Conclusions

XenoSotaAgent successfully achieved robust negotiation performance by combining proposal generation, negotiation history tracking, trust evaluation, and inventory strategies. This design philosophy is potentially applicable to other tracks and manufacturing scenarios. In the future, we aim to integrate learning capabilities and develop more autonomous, self-optimizing agents.