https://www.perplexity.ai/search/i-am-writing-a-simulation-whic-oTghHbfcRcONlJtO.LpWdA

```
I am writing a simulation which operates in timesteps and involves 3 Active
Inference agents who each try to maintain the values of the variables in their
environment (collected at each timestep as time-series variables) between each
variable's respective target constraint range. The time-series variables have
unknown relationships between one another. At each timestep, a new row of the data
is recorded and a list is created which contains one indicator for each variable
denoting whether the value of the variable is higher, lower, or within the
variable's respective target range. The agents receive these indicators as
observations to infer hidden states denoting, for each variable, whether the state
is higher, lower, or homeostatic. Each of agents which has 3 actions ("MAINTAIN",
"DECREASE", "INCREASE") to modify its respective variable. The agent strongly
prefers to see each variable within its target range. This makes the entire
simulation like a homeostasis machine, where the agents try to keep all variables
in homeostasis. Are there any similar systems, applications, or simulations
similar to my simulation?
```

Your described simulation bears similarities to several systems and applications across different domains. Let me break down the comparable systems:

Biological Homeostatic Systems

Physiological Control Systems The multi-agent homeostatic control you're describing closely resembles biological regulatory networks, particularly how the human body maintains various physiological parameters. The endocrine system, for example, uses multiple glands acting as agents to maintain hormonal balance through similar increase/decrease/maintain actions.

Artificial Homeostatic Systems Your system shares characteristics with artificial homeostatic hormone systems (AHHS), which are bio-inspired control architectures where virtual hormones regulate system parameters through decentralized control mechanisms.

Industrial Applications

Process Control Systems Industrial control systems, particularly in chemical processing plants, employ multiple PID controllers that work simultaneously to maintain different variables within specified ranges. These systems often deal with interconnected variables where changes in one parameter affect others, similar to your unknown variable relationships.

Environmental Control Systems

Building Management Modern building automation systems use multiple controllers to maintain various environmental parameters (temperature, humidity, CO_2 levels) within comfort zones, dealing with interconnected variables and multiple control points.

Key Similarities to Your System

Your simulation shares these fundamental characteristics with the above systems:

- Multiple autonomous controllers (agents)
- Homeostatic target ranges
- Interdependent variables
- Discrete action spaces
- Observation-based state inference
- Decentralized control architecture

Unique Aspects

What makes your system particularly interesting is:

- The use of Active Inference for agent decision-making
- The explicit modeling of unknown variable relationships
- The discrete tri-state representation of variables (high/low/homeostatic)
- The combination of time-series data with categorical state inference

Related Research Areas

Multi-Agent Systems Your simulation aligns with research in distributed control systems where multiple agents must coordinate without explicit communication to maintain system stability.

Homeostatic AI The field of artificial homeostatic systems, which aims to create self-regulating artificial systems inspired by biological homeostasis, is particularly relevant to your work.

Complex Systems Control Your simulation relates to research in controlling complex systems with multiple interconnected variables and uncertain relationships between parameters.

```
What is the novelty of applying this kind of system to data representing the
health and preservation of farmland for bioregional regenerative finance?
```

Based on the search results, applying an Active Inference multi-agent homeostatic control system to bioregional regenerative agriculture finance represents several novel aspects:

Integration of Monitoring and Decision Making

Automated Feedback Loops Your system could provide real-time monitoring and response mechanisms for maintaining agricultural ecosystem health, similar to how industrial control systems maintain process variables[1]. This would be particularly valuable for bioregional financing facilities (BFFs) that need to track the effectiveness of their investments[9].

Data-Driven Decision Support The system could help BFFs make more informed decisions about resource allocation by:

- Tracking multiple ecological health indicators simultaneously
- Identifying correlations between different variables
- Providing early warning signals when variables move outside target ranges[5]

Novel Financial Applications

Performance-Based Financing The system could enable new forms of financial instruments by:

- Providing reliable metrics for outcome-based funding
- Supporting real-time monitoring of conservation outcomes
- Enabling automated disbursement of funds based on achieved targets[10]

Bioregional Adaptation

Context-Specific Implementation The system could be calibrated to different bioregions by:

- Accounting for local ecological conditions and constraints
- Adapting target ranges based on regional characteristics
- Supporting coordination between multiple stakeholders[12]

Technical Innovation

Integration with Emerging Technologies The system aligns with current trends in agricultural technology by:

- Leveraging AI and digital technologies for monitoring
- Supporting geospatial analysis and planning
- Enabling rapid soil testing and program monitoring[13]

This application represents a novel bridge between computational control systems and regenerative finance, potentially enabling more efficient and effective deployment of capital for ecological regeneration.

Citations: [1] https://soilhealthinstitute.org/news-events/nationwide-study-on-30-u-s-farms-shows-positive-economic-impact-of-soil-health-management-systems/ [2] https://rsfsocialfinance.org/2024/03/18/regenerative-finance-helps-living-lands-trust-expand-biodynamic-farming/ [3] https://agfundernews.com/making-the-investment-case-for-regenerative-agriculture [4] https://www.eci.ox.ac.uk/sites/default/files/2023-12/Financing_NbS_for_Adaptation-GCAOxford2023-finalv2.pdf [5] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10643297/ [6] https://www.amazon.com/Bioregional-Financing-Facilities-Reimagining-Regenerate/dp/B0DCVYTNQS [7] https://stage.madagriculture.org/assets/files/economicsofregeneration.pdf [8] https://www.sciencedirect.com/science/article/pii/S004896972304384X [9] https://www.oneearth.org/citation/bioregional-financing-facilities-reimagining-finance-to-regenerate-our-planet/ [10] https://cbey.yale.edu/sites/default/files/2024-02/Bridging%20the%20Regenerative%20Agriculture%20Financing%20Gap_FinalRev.pdf [11] https://www.sciencedirect.com/science/article/pii/S2352550924001842 [12] https://deepscienceventures.com/content/agriculture-venture-should-focus-on-bioregions [13] https://www.weforum.org/agenda/2024/09/farms-ai-accelerate-regenerative-agriculture/ [14] https://thelandapp.com/2024/04/15/financial-benefits-of-regenerative-agriculture-for-farmers/ [15] https://practicalaction.org/news-stories/developing-market-systems-that-support-regenerative-agriculture/

```
Our agents in our simulation are Active Inference agents, which can be likened to
reinforcement learning. We would like to expand our simulation to draw from
textual domain knowledge, information and documents from stakeholders, so that our
agents' decisions are grounded in both the data generated in real-time but also
real textual knowledge about the relationships between variables in the dataset as
```

```
well as the preferences of stakeholders. This should involve the incorporation of
LLMs, building a knowledge base over time, and perhaps the methodologies in the
attached paper ("PRefLexOR: Preference-based Recursive Language Modeling for
Exploratory Optimization of Reasoning and Agentic Thinking", Buehler, 2024).
Describe how we can accomplish this goal of incorporating these dynamics into our
simulation.
```

Based on the search results and your current simulation setup, here's how you can expand your Active Inference agents to incorporate textual domain knowledge and stakeholder information:

Knowledge Integration Framework

Dynamic Knowledge Graph Construction

- Build a knowledge graph by processing domain documents, stakeholder information, and real-time data using retrieval-augmented generation (RAG)[1]
- Map relationships between variables using embeddings to create adjacent nodes representing related concepts and constraints[1]
- Continuously update the knowledge graph as new information becomes available from stakeholders or real-time data

Multi-Module Architecture

1. **Environmental Module**

- Track real-time variables and their relationships
- Evaluate natural material stocks and flows[2]
- Monitor sustainability metrics and constraints

2. **Behavioral Module**

- Model stakeholder preferences and constraints
- Incorporate decision-making rules from domain knowledge
- Update agent behaviors based on feedback loops[2]

Agent Enhancement Strategy

Knowledge-Grounded Decision Making

- Augment agent observations with relevant context from the knowledge graph
- Use LLMs to interpret textual information into actionable constraints and preferences
- Implement recursive reasoning to refine decisions through multiple passes[1]

Preference Integration

- Map stakeholder preferences to specific variable constraints
- Use preference optimization to align agent behaviors with stakeholder goals[1]
- Balance multiple, potentially conflicting objectives from different stakeholders[3]

Implementation Approach

Technical Components

1. **Knowledge Processing Pipeline**

- Implement RAG to contextualize documents and stakeholder input
- Use embedding models to map relationships between concepts
- Create structured representations of constraints and preferences

2. **Agent Architecture Updates**

- Add knowledge attention mechanisms to focus on relevant information
- Implement recursive reasoning loops for deeper decision evaluation
- Create feedback mechanisms to update knowledge based on outcomes

3. **Integration Layer**

- Build interfaces between the knowledge graph and Active Inference agents
- Implement preference optimization for multi-stakeholder alignment
- Create monitoring systems to track knowledge utilization and impact

Continuous Improvement

Adaptive Learning

- Use feedback loops to refine knowledge representations
- Update stakeholder preferences based on observed outcomes
- Evolve agent behaviors through recursive optimization[1]

This enhanced system would enable your Active Inference agents to make decisions grounded in both real-time data and domain knowledge while respecting stakeholder preferences and constraints.

Citations: [1] https://ppl-ai-file-upload.s3.amazonaws.com/web/direct-files/13022412/26f83b8b-5bf2-40ee-94ef-0f8b248850a8/2410.12375v1.pdf [2] https://pmc.ncbi.nlm.nih.gov/articles/PMC10643297/ [3] https://www.admscentre.org.au/genaisim-simulation-in-the-loop-for-multi-stakeholder-interactions-with-generative-agents/ [4] https://escholarship.org/uc/item/7r65h2t5

```
The structure of the observations our agents receive are in the form of discrete
observation categories, a.k.a. observation modalities, where each observation
modality comprises a set of discrete observations which can be received per time
step. For example, our agent might have an observation modality called "knowledge
modality" which can receive a 1 or 0 at each timestep, where a 1 denotes that the
agent's last action was a good idea based upon the information in our gathered
knowledge base while a 0 denotes the agent's last action was not a good idea based
upon the information in the knowledge base. We could have an LLM evaluate the
agent's last action relative to the information in the knowledge base, and then
have the LLM return the 1 or 0 indicator as the agent's observation. Is this a
reasonable approach for us to take to incorporate LLM feedback into agent
decision-making?
```

Based on the PRefLexOR paper and your current simulation setup, this is a reasonable approach that can be enhanced further. Here's an analysis of your proposed method and suggestions for improvement:

Current Approach Validation

Binary Feedback System Your proposed approach of using binary (1/0) observations from LLM evaluation is valid as it:

- Provides clear, discrete feedback that can be directly integrated into Active Inference agents' observation spaces
- Creates a simple interface between knowledge-based reasoning and agent decision-making
- Maintains compatibility with your existing discrete observation modalities

Enhanced Implementation Strategy

Multi-Level Feedback Instead of just binary feedback, consider implementing:

- Multiple discrete levels of feedback (e.g., -1, 0, 1 for negative, neutral, positive)
- Separate observation modalities for different aspects of knowledge-based evaluation
- Confidence scores alongside binary decisions

Knowledge Integration Pipeline

1. **Dynamic Knowledge Graph**

- Build and maintain a knowledge graph from textual information
- Use embeddings to map relationships between variables and concepts
- Update the graph continuously as new information becomes available

2. **Recursive Evaluation**

- Implement multiple passes of LLM reasoning before finalizing feedback
- Use thinking tokens to structure the LLM's evaluation process
- Allow for self-correction and refinement of assessments

Implementation Framework

Technical Components

1. **Observation Generation**

```
def generate_observation(agent_action, knowledge_base):
    # Structure LLM prompt with thinking tokens
    prompt = f"""
    <|thinking|>
    1. Analyze action: {agent_action}
    2. Compare with knowledge base
    3. Evaluate implications
    </thinking|>
    Decision: Is this action aligned with knowledge base?
    """
```

```
    # Get LLM response with recursive reasoning
    response = evaluate_with_recursive_reasoning(prompt, knowledge_base)
    return convert_to_observation(response)
```

2. **Recursive Reasoning**

- Implement multiple evaluation passes
- Allow the LLM to refine its assessment
- Aggregate multiple perspectives before final decision

3. **Integration Layer**

- Create clear interfaces between LLM evaluations and agent observations
- Implement feedback loops for continuous improvement
- Monitor and validate LLM evaluations over time

This enhanced approach would provide more nuanced and reliable feedback while maintaining the simplicity of discrete observations that your Active Inference agents can process.

Citations: [1] https://ppl-ai-file-upload.s3.amazonaws.com/web/direct-files/13022412/26f83b8b-5bf2-40ee-94ef-0f8b248850a8/2410.12375v1.pdf

```
We will also need to inform the LLM of the current state of the environment to
better infer if the actions the agents take are positive, neutral, or negative
within the temporal context as well. This will best be represented by the values
in the dataset, but because LLMs work better with reasoning rather than raw
numbers, what are sophisticated yet concise ways that we could prompt the LLM with
summarized information about recent patterns in the data?
```

Based on your simulation setup and the PRefLexOR framework, here are sophisticated ways to prompt the LLM with temporal context and data patterns:

Pattern-Based Context Generation

Trend Indicators Create concise trend descriptions that summarize recent variable behaviors:

```python
def generate_trend_context(time_series_data, window_size):
    trends = {
        'increasing': '↑',
        'decreasing': '↓',
        'stable': '→'
    }
    context = "Recent patterns: "
    for var in variables:
        direction = analyze_trend(time_series_data[var][-window_size:])
        context += f"{var}: {trends[direction]} | "
    return context
```

State Transitions Track recent state changes to provide temporal context:

```
def generate_state_context(state_history):
    transitions = []
    for var in variables:
        states = state_history[var][-3:]  # Last 3 states
        transition = ' -> '.join(states)
        transitions.append(f"{var}: {transition}")
    return "State transitions: " + " | ".join(transitions)
```

Recursive Reasoning Framework

Multi-Level Context Structure the context in thinking tokens for recursive evaluation:

```
def generate_llm_context(env_data):
    context = f"""
    <|thinking|>
    1. Current State Assessment:
       - Variable positions relative to targets
       - Recent trend directions
       - State transition patterns

    2. Historical Pattern Analysis:
       - Frequency of state changes
       - Duration in each state
       - Correlation between variables

    3. Action Impact Evaluation:
       - Previous action outcomes
       - Variable response patterns
       - Cross-variable effects
    </thinking|>
    """
    return context
```

Temporal Abstraction Create higher-level abstractions of temporal patterns:

```
def generate_temporal_summary(data_history):
    summary = {
        'stability': assess_system_stability(data_history),
        'cyclicity': identify_cyclic_patterns(data_history),
        'responsiveness': evaluate_action_responses(data_history)
    }
    return format_summary(summary)
```

This approach provides the LLM with structured, reasoning-oriented context while maintaining computational efficiency and clear interpretability for decision-making.

Citations: [1] https://ppl-ai-file-upload.s3.amazonaws.com/web/direct-files/13022412/26f83b8b-5bf2-40ee-94ef-0f8b248850a8/2410.12375v1.pdf [2] https://shenghua-liu.github.io/papers/pkdd2017-beatlex.pdf [3] https://www.admscentre.org.au/genaisim-simulation-in-the-loop-for-multi-stakeholder-interactions-with-generative-agents/ [4] https://aws.amazon.com/blogs/machine-learning/techniques-for-automatic-summarization-of-documents-using-language-models/

```
Given the preceding conversation about our simulation's design principles,
describe how this kind of system can be used for the maintenance of nonequilibrium
steady state systems. For example, we are considering approaching land
preservation, e.g., maintaining local biodiversity, soil quality, carbon
sequestration, and other variables in the context of a variety of complex dynamics
between these and environmental variables, as well as in the context of finite
resource management, climate change, and other factors.
```

Based on the search results and our previous discussion, here's how your Active Inference multi-agent system can be applied to maintaining nonequilibrium steady states in land preservation:

Theoretical Framework Integration

Nonequilibrium Dynamics Your system aligns well with nonequilibrium thermodynamics principles, where:

- The system maintains steady states far from equilibrium through continuous energy/resource flows[5]
- Multiple variables are maintained within target ranges despite external perturbations[3]
- The agents act as controllers managing the flux between different states[1]

Complex System Management The system can handle:

- Multiple interacting variables with unknown relationships[3]
- Dynamic feedback loops between environmental factors[2]
- Local and global stability considerations[4]

Practical Implementation

Environmental Module

- Track real-time variables like soil quality, biodiversity metrics, and carbon levels[3]
- Monitor natural material stocks and flows
- Evaluate sustainability metrics against target ranges

Behavioral Module

- Model stakeholder preferences and constraints[7]
- Incorporate domain knowledge about ecological relationships
- Update agent behaviors based on feedback loops

Specific Applications

Land Management Variables Your agents could maintain homeostasis for:

- Soil organic matter content

- Biodiversity indices
- Water retention capacity
- Carbon sequestration rates
- Nutrient cycling efficiency

Resource Allocation The system can help optimize:

- Distribution of finite resources
- Timing of interventions
- Balance between competing objectives

Advanced Features

Early Warning System

- Detect early warning signals for critical transitions[2]
- Identify potential tipping points
- Enable preemptive interventions

Knowledge Integration

- Incorporate traditional ecological knowledge
- Learn from successful management practices
- Adapt to changing environmental conditions

This approach is particularly powerful because it combines the mathematical rigor of nonequilibrium systems theory with practical land management needs, while accounting for the complex, interconnected nature of ecological systems.

Citations: [1] https://ppl-ai-file-upload.s3.amazonaws.com/web/direct-files/13022412/26f83b8b-5bf2-40ee-94ef-0f8b248850a8/2410.12375v1.pdf [2] https://pmc.ncbi.nlm.nih.gov/articles/PMC9945981/ [3] https://pmc.ncbi.nlm.nih.gov/articles/PMC10643297/ [4] https://link.springer.com/chapter/10.1007/978-3-319-46709-2_6 [5] https://www.nature.com/articles/s41467-022-32700-7 [6] https://journals.aps.org/prresearch/abstract/10.1103/PhysRevResearch.5.033101 [7] https://www.eci.ox.ac.uk/sites/default/files/2023-12/Financing_NbS_for_Adaptation-GCAOxford2023-finalv2.pdf [8] https://thelandapp.com/2024/04/15/financial-benefits-of-regenerative-agriculture-for-farmers/ [9] https://pubs.acs.org/doi/10.1021/jp061858z [10] https://en.wikipedia.org/wiki/Nonequilibrium [11] https://journals.aps.org/prresearch/abstract/10.1103/PhysRevResearch.3.023252 [12] https://escholarship.org/uc/item/7r65h2t5