

Multi-Timescale Power System Dynamics: Leveraging Large Language Models for Enhanced System Dynamics Modelling

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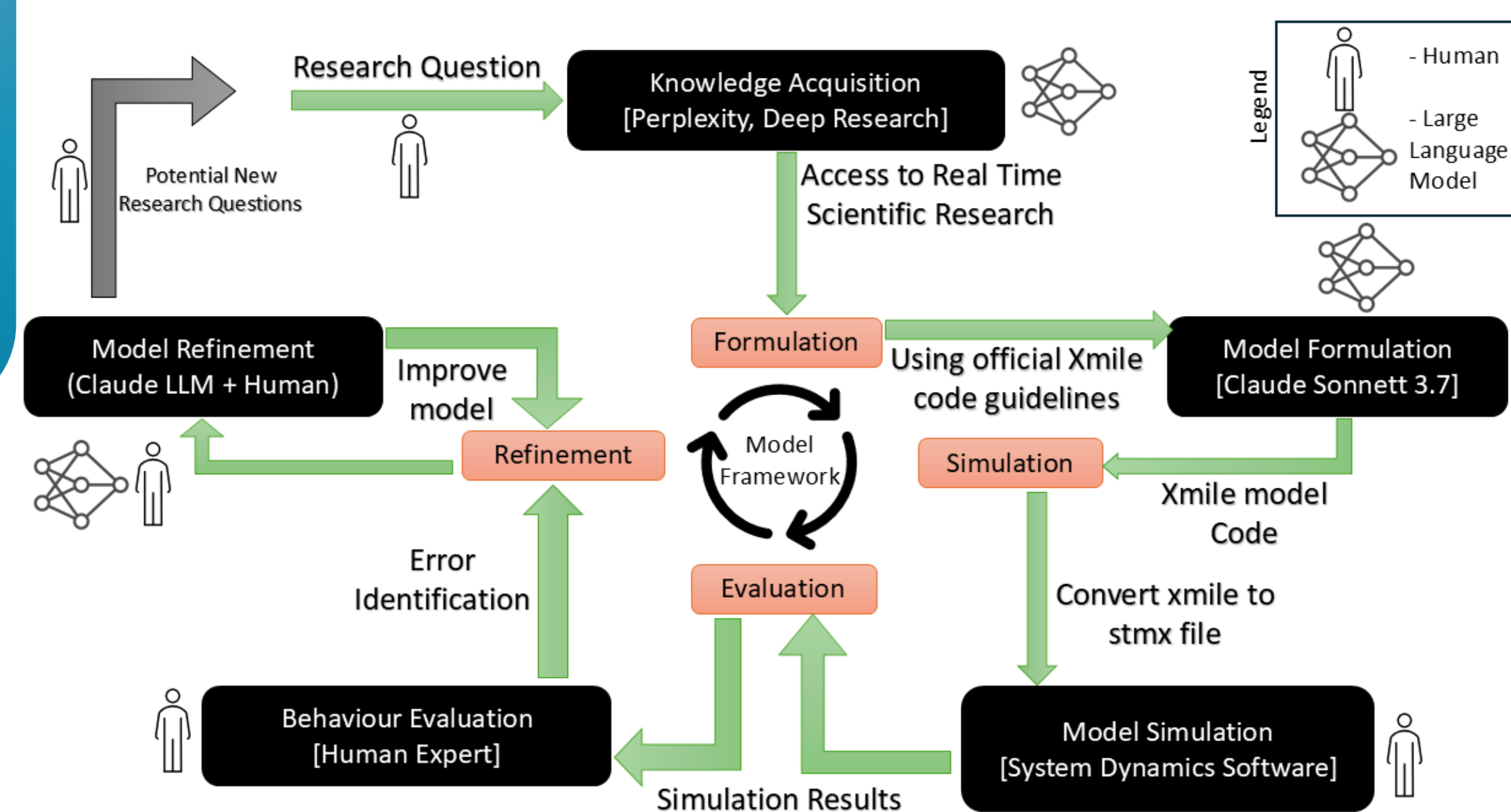
Context

- Electrical Power Systems exhibit complex dynamics across multiple timescales (microseconds to hours)
- Higher amounts of Renewable Energy requires us to revisit the models and strategies we used to navigate the complexity before:
 - Temporal coupling
 - Reduced System Inertia
 - Market-physics interactions
- Advancements in Large Language Models to that enable them to model

Objectives

- Develop three distinct system dynamics models for the multi-timescale power system dynamics
- Demonstrate how the combination of AI tools can be integrated to construct system dynamics models
- Can AI assist in finding model errors and learn about the complex power system dynamics?

Framework



Background

System Dynamics	Electro-magnetic	Electro-mechanical	Operational
Stock	Electromagnetic energy	Rotational kinetic energy	Fuel/ Energy reserves
Flow	Current/power	Mechanical power	Generation/ Demand
Auxiliary	Voltage Relationships	Frequency control	Market clearing

Artificial Intelligence Tools used:

Perplexity – Deep Research: At the time of the paper, Deep Research functionality was started which enables LLMs to search through the internet and use chain of thought to conduct research. This tech was employed to explore the different time domains of modeling in power systems.

Claude Sonnet 3.7 - This model is known for its ability to write code proficiently. It was given the XMILE guideline rules to then create the simulation in XMILE code.

Electromagnetic



The energy in this dimension fluctuates at micro-seconds and is driven by the changes in current and voltage.

$$S_{\text{flow}} = \int_{t_0}^t (I_{\text{in}} - I_{\text{out}}) dt \quad (1)$$

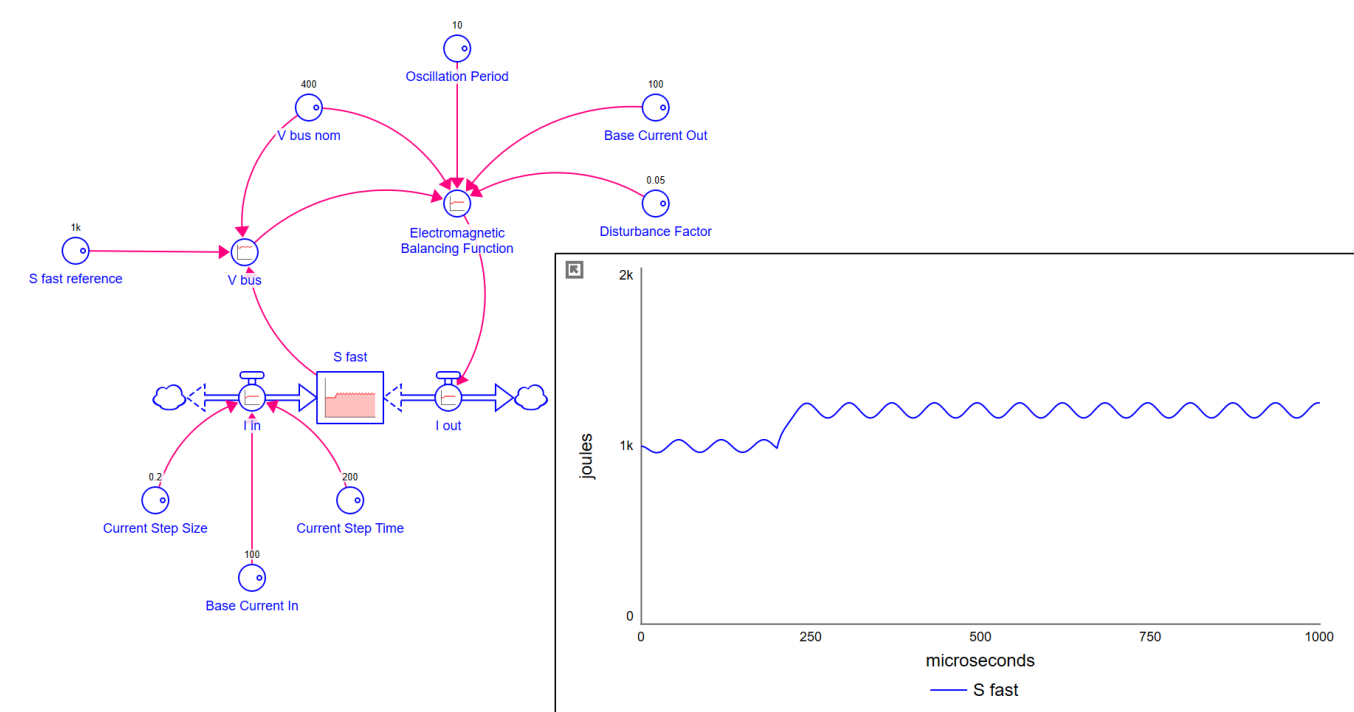
$$I_{\text{in}} = I_{\text{base}} + (1 + \text{STEP}(t_{\text{step}}, t_{\text{step}})) \quad (2)$$

$$I_{\text{out}} = I_{\text{EMD}} \quad (3)$$

$$V_{\text{base}} = V_{\text{base}}^{\text{nom}} \left(\frac{S_{\text{flow}}}{S_{\text{flow}}^{\text{nom}}} \right)^{0.5} \quad (4)$$

$$f_{\text{EMD}} = f_{\text{base}}^{\text{nom}} \left(\frac{V_{\text{base}}}{V_{\text{base}}^{\text{nom}}} \right)^2 \cdot (1 + k_{\text{EMD}} \cdot \sin(f \cdot T_{\text{osc}})) \quad (5)$$

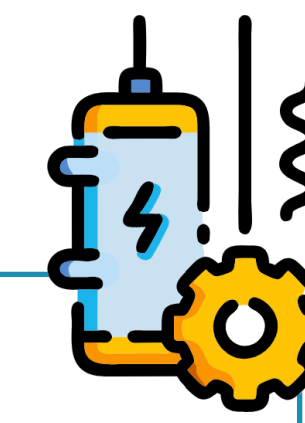
A slight increase in current shows how the energy increases and finds a new stable oscillation point



Electromagnetic Structure in Stocks and Flows

Fast: μs -ms

Electro-Mechanical



The energy in this dimension functions in seconds and stores the energy within the synchronous machines of the electricity grid.

$$S_{\text{med}} = \int_{t_0}^t (P_{\text{mech, in}} - P_{\text{mech, out}}) dt \quad (6)$$

$$P_{\text{mech, in}} = P_{\text{mech, in}}^{\text{nom}} \cdot (1 + k_{\text{med}} \cdot \text{STEP}(1, t_{\text{step}})) \quad (7)$$

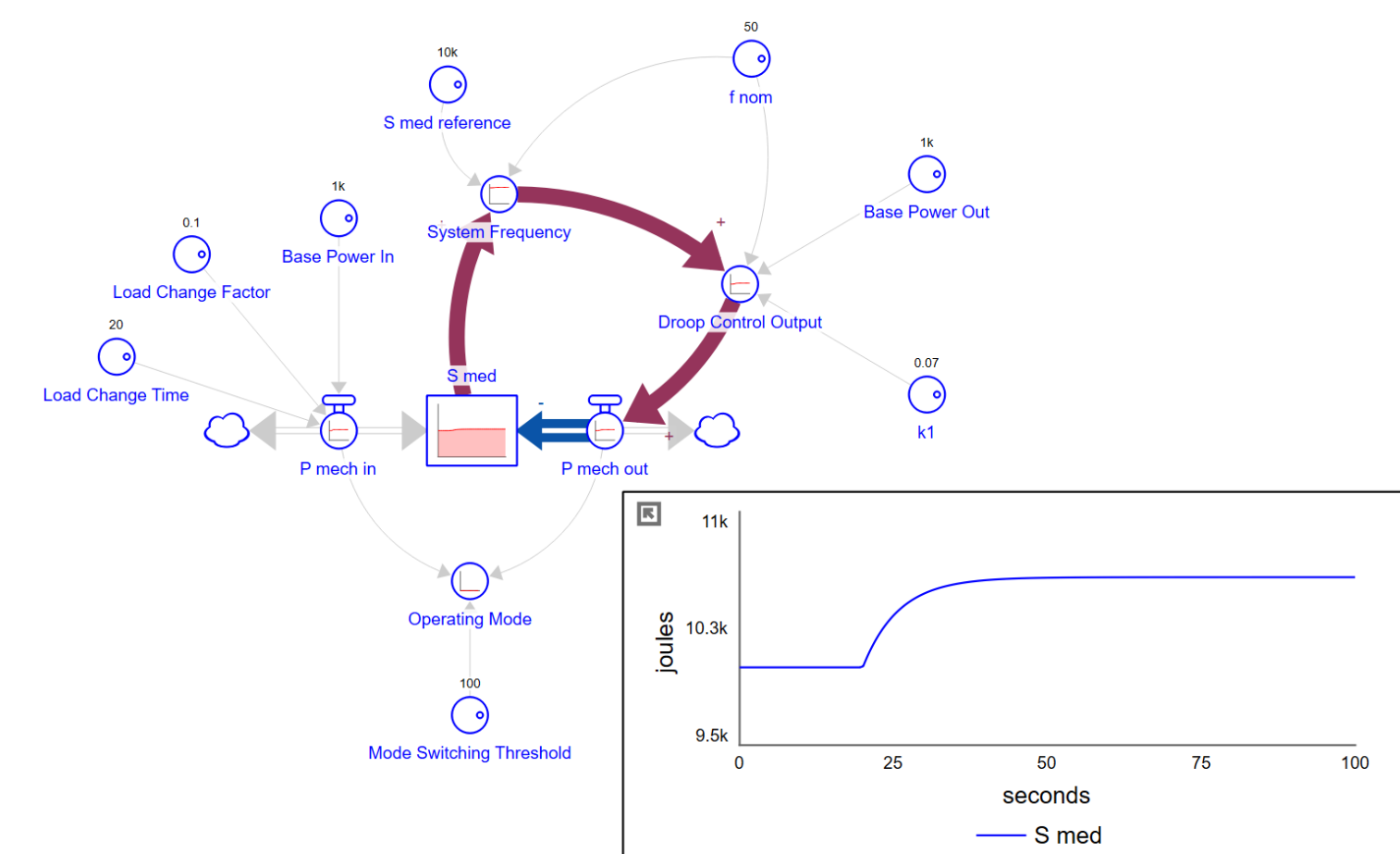
$$P_{\text{mech, out}} = P_{\text{mech, out}}^{\text{nom}} \cdot (1 + k_{\text{med}} \cdot \text{STEP}(1, t_{\text{step}})) \quad (8)$$

$$f = f_{\text{base}} \left(\frac{S_{\text{med}}}{S_{\text{med}}^{\text{nom}}} \right)^{0.5} \quad (9)$$

$$f_{\text{mech}} = f_{\text{base}}^{\text{nom}} \cdot (1 + k_{\text{med}} \cdot (1 - f_{\text{mech}})) \quad (10)$$

$$\text{Mode} = \text{IF}(P_{\text{mech, in}} - P_{\text{mech, out}} > 0, \text{"Grid-Forming"}, \text{"Grid-Following"}) \quad (11)$$

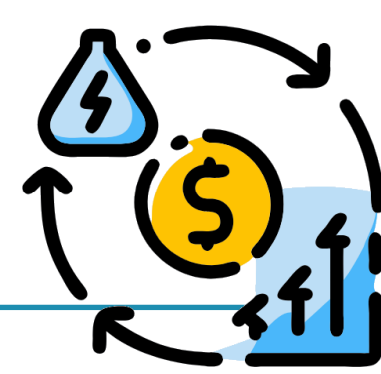
The scenario shows when the load is increased by 10 percent and how the electro-mechanical energy compensates within the system.



Electromechanical Stock and Flow Structure

Medium: 0.1-30s

Operational



Operational dynamics is related to the planning and clearing of Generation (G) and Demand (D) of electricity, taking place over hours-days.

The scenario shows how the structure is balancing G based on a fluctuating demand to reduce the energy conservation error.

$$S_{\text{slow}} = \int_{t_0}^t (G - D) dt \quad (12)$$

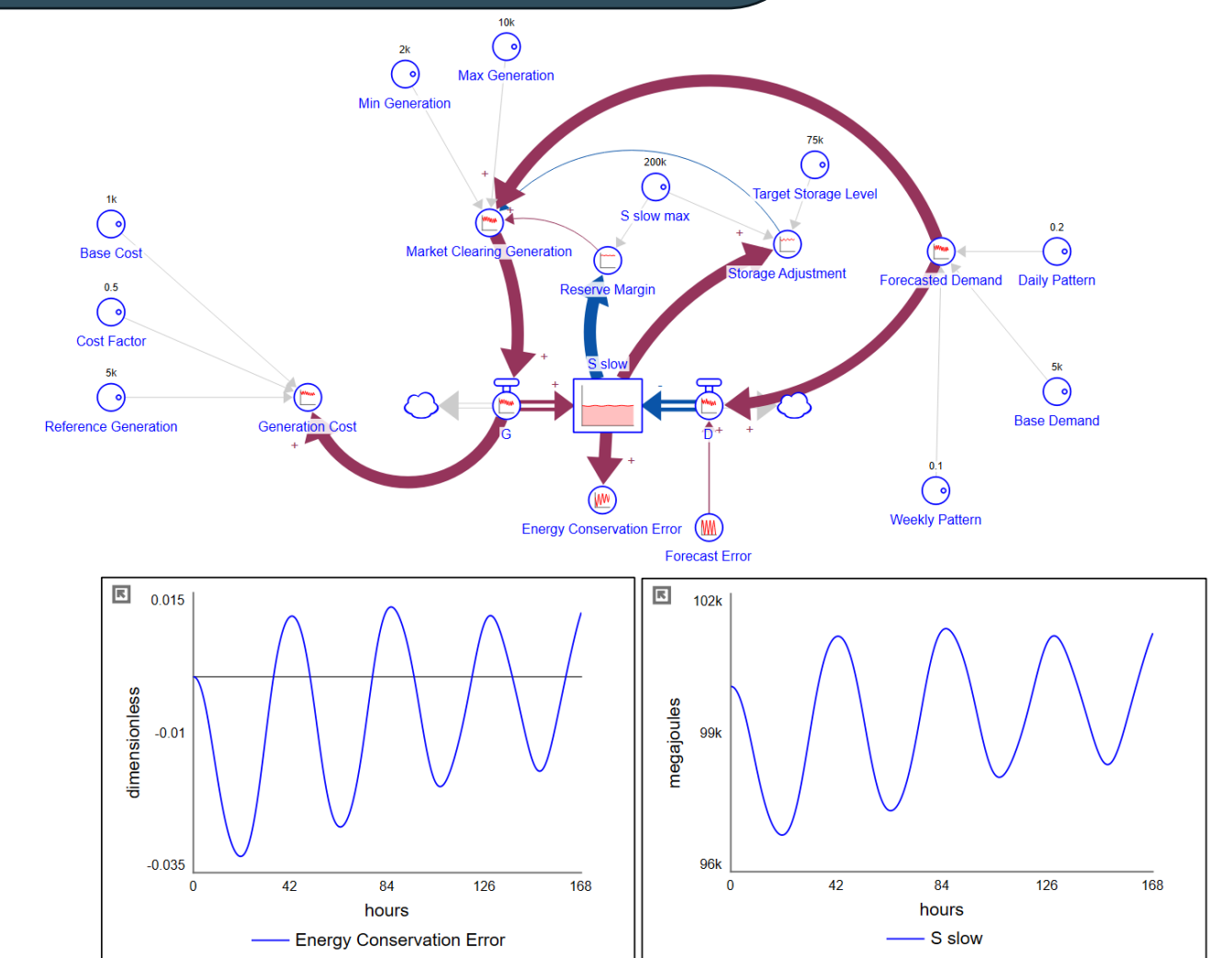
$$G = f_{\text{GFCO}} \quad (13)$$

$$D = D^{\text{forecast}} \cdot (1 + \eta) \quad (14)$$

$$f_{\text{GFCO}} = \text{min}(\text{max}(D^{\text{forecast}}, G^{\text{max}}), G^{\text{min}}) \cdot (1 + k_{\text{GFCO}} \cdot \sin(2\pi \cdot t)) \quad (15)$$

$$D^{\text{forecast}} = D^{\text{base}} \cdot (1 + k_{\text{D}} \cdot \sin(2\pi \cdot t)) \quad (16)$$

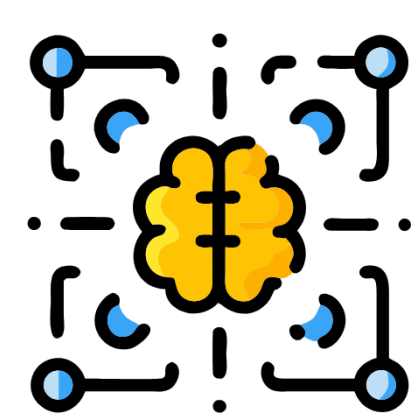
$$f_{\text{GFCO}} = \text{min}(\text{max}(D_{\text{GFCO}}, S_{\text{slow}} - S_{\text{slow}}^{\text{min}}), S_{\text{slow}}^{\text{max}}) \quad (17)$$



Operational Dynamics Stock and Flow Structure

Slow: 1h-days

Time domains (Fast to Slow)



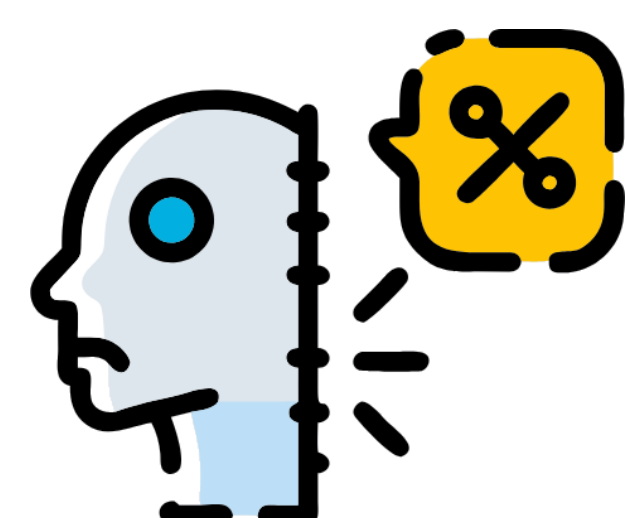
Discussions

Benefits of AI Enhanced SD

- Reduced Development time
- Improved Model Documentation
- Enhanced Error Detection
- Knowledge Integration

Limitations of AI Enhanced SD

- Domain Knowledge Dependencies
- Need for Human Verification
- Parameter Calibration
- Conceptual Boundaries



Technical Limitations of these basic models

Fast Timescale:

- Electromagnetic transients needed
- Power electronic switching dynamics
- Transmission line models with wave propagation effects



Medium Timescale:

- Detailed generator models
- Network representation of power flow
- Control loop modeling



Slow Timescale:

- Integration with established dispatch algorithms
- Transmission and marginal pricing constraints
- More sophisticated renewable uncertainty



Future Applications

Enhanced Technical Implementation

Cross-Scale Integration

AI Assisted Calibration

Expanded Model Libraries

Hybrid AC/DC System Extensions

Contributions:

AI-Enhanced Model Development Framework

Model Error Recognition

Cross Domain Knowledge Integration

Educational Scaffolding