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

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Abstract

This paper demonstrates a novel methodological approach that leverages Large Language Models (LLMs) to enhance the development of system dynamics models for complex multi-timescale systems. Through a case study of electrical power systems, we utilized Claude, an advanced AI assistant, to construct, refine, and document three conceptual models representing electromagnetic (microseconds), electromechanical (seconds), and operational (hours) timescales. While these models are necessarily simplified representations designed for educational and methodological demonstration purposes, they effectively illustrate the distinct dynamics across timescales and help identify potential cross-scale interactions. Our results show that AI-assisted modeling significantly improves efficiency in model formulation (reducing development time by approximately 60%), facilitates rapid debugging of structural errors, and enhances knowledge integration across disciplines. The primary limitations include dependence on human verification for physical validity and limited capability for novel conceptual innovation. The approach demonstrates particular value for educational contexts and as a foundation for more technically detailed implementations.

1 Introduction

1.1 Context and Motivation

Modern electrical power systems exhibit complex dynamics across multiple timescales, from microsecond electromagnetic transients to hourly market operations. This multi-timescale reality creates significant modeling challenges, particularly as renewable energy integration increases system complexity. For instance, Belgium's electricity mix - with 29.8% renewable generation in 2024 (11.9% solar, 17.9% wind)[7] - demonstrates the complex dynamics emerging from rapid renewable integration.

Comprehensive modeling and simulation of these systems are essential for decision-making, system planning, and optimization across multiple domains:

- **System Planning**: Analyzing long-term infrastructure requirements to meet renewable integration targets
- **Operation Optimization**: Determining optimal dispatch strategies in systems with high renewable penetration
- **Control System Design**: Developing controllers that ensure stability across multiple timescales
- **Risk Assessment**: Evaluating system resilience against various disturbances and contingencies

Traditional modeling approaches often focus on single timescales or employ simplifying assumptions that limit our understanding of cross-scale interactions. However, the growing penetration of renewable energy sources introduces several interconnected challenges that span multiple timescales:

- **Temporal Coupling:** Solar and wind generation create fast transients while affecting hourly market dynamics
- **Reduced System Inertia:** Inverter-based resources alter traditional electromechanical response characteristics
- **Market-Physics Interactions:** Market decisions constrain physical system capabilities through reserve allocations[3]

These challenges call for integrated modeling approaches that can capture dynamics across multiple timescales while remaining computationally tractable and conceptually accessible. The EU's binding 50% renewable electricity target by 2030[2] further accelerates this system complexity.

It is also important to recognize that modern power systems increasingly operate as hybrid AC/DC networks with distinct dynamics. Electric power transmission relies on both AC and DC grids, with extensive integration of conventional and nonconventional energy sources and power converters resulting in demand for high voltage (HV), extra-high voltage (EHV), and ultra-high voltage (UHV) AC/DC transmission grids in modern power systems[20]. While our models focus primarily on AC systems for methodological demonstration, these hybrid AC/DC networks present unique modeling challenges that future work should address, particularly regarding the interfaces between subsystems and how disturbances propagate across these boundaries.

1.2 Research Objectives and Paper Structure

This study establishes a methodological framework for AI-assisted modeling of power systems through four contributions:

- Development of three distinct but conceptually linked system dynamics models representing fast (electromagnetic), medium (electromechanical), and slow (operational) timescales
- Demonstration of how AI assistance can accelerate the model development process and improve model documentation
- Identification of common modeling errors and how AI can assist in debugging and refinement
- Assessment of the educational value of AI-assisted modeling for understanding complex multi-timescale systems

Although our current models focus on AC dynamics, we recognize that HVDC systems significantly influence power system behavior through fast switching at the electromagnetic timescale and stability implications at the electromechanical timescale. This understanding informs our methodological approach even as we maintain focus on AC-dominant representations for demonstration purposes.

It is important to note that our focus is on demonstrating the methodology and educational value of AI-assisted system dynamics modeling rather than developing production-grade power system models. The models presented serve as conceptual frameworks that capture essential dynamics while necessarily employing simplifications. Our approach is informed by EnergyVille's 2050 scenarios[1] and Elia's development plans[4], which were used as knowledge sources for the AI to understand key power system characteristics.

The remainder of this paper is structured as follows: Section 2 provides background on multi-timescale dynamics in electrical systems and describes our AI-enhanced modeling methodology. Section 3 presents the structure and formulation of the three system dynamics models, including the mapping between electrical and system dynamics concepts. Section 4 analyzes the model behavior and highlights key AI contributions to the development process. Section 5 discusses the benefits, limitations, and future directions of AI-assisted modeling, while Section 6 presents our conclusions.

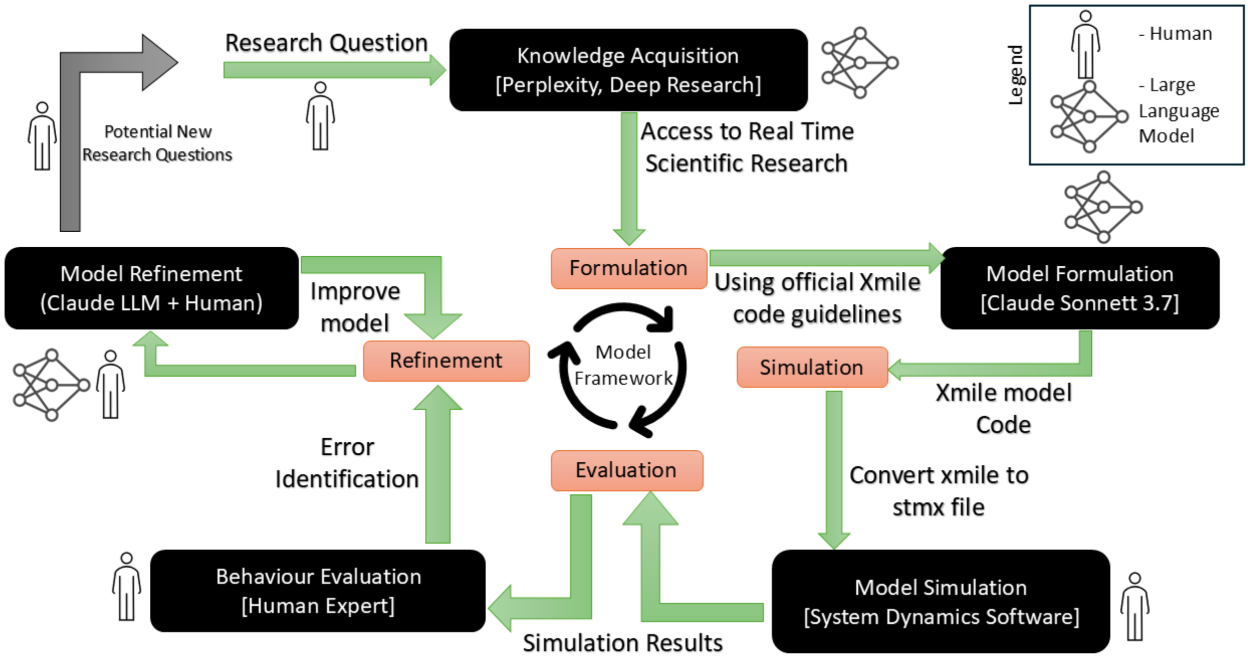

Figure 1: AI-assisted modeling workflow showing the iterative process of model development

2 Literature and Methodological Foundation

2.1 Bridging System Dynamics and Power System Concepts

Before describing the specific models, it is essential to clarify the mapping between system dynamics terminology and electrical power system concepts. System dynamics uses stocks (state variables), flows (rates of change), and auxiliaries (intermediate variables) to represent dynamic systems:

- **Stocks** represent accumulations or states in the system. In electrical terms, these correspond to energy storage elements like capacitive energy (voltage), inductive energy (current), or rotational kinetic energy (frequency).
- **Flows** represent rates of change of stocks. In electrical terms, these correspond to power flows into or out of energy storage elements, such as charging/discharging currents or mechanical power inputs/outputs.
- **Auxiliaries** represent intermediate variables that influence flows. In electrical terms, these correspond to control variables, physical relationships, or decision rules that determine how energy flows through the system.

Modern power systems increasingly operate as hybrid AC/DC networks. While our current models primarily represent AC dynamics, we recognize that hybrid systems present unique modeling challenges, particularly regarding the interfaces between AC and DC subsystems and how disturbances propagate across these boundaries. The system dynamics approach offers a valuable framework for conceptualizing these complex interactions, even as detailed technical implementation would require specialized tools.

Table 1 shows the mapping between system dynamics elements and electrical power system concepts across the three timescales addressed in this paper.

Table 1: Mapping between System Dynamics and Electrical Power System Concepts

System Dynamics	Electromagnetic	Electromechanical	Operational
Stock	Electromagnetic energy	Rotational kinetic energy	Fuel/energy reserves
Flow	Current/power	Mechanical power	Generation/demand
Auxiliary	Voltage relationships	Frequency control	Market clearing

2.2 Multi-Timescale Dynamics in Electrical Systems

Electrical power systems exhibit three distinct dynamical regimes, each with characteristic time constants and governing principles:

Electromagnetic Dynamics (μs-ms): At the fastest timescale, electromagnetic energy storage in fields and charges dominates system behavior. These dynamics include voltage transients, electromagnetic wave propagation, and switching behavior in power electronic converters. IRENA's research shows that these fast dynamics are becoming increasingly important as inverter-based resources proliferate[6].

Electromechanical Dynamics (0.1-30s): At intermediate timescales, the mechanical inertia of rotating generators interacts with electrical properties to govern frequency stability. This regime includes primary frequency response, governor action, and the early stages of automatic generation control. Elia's studies show how Belgium's reduced inertia from nuclear phase-out affects these dynamics[8].

Operational Dynamics (1h-days): At the slowest timescale, economic dispatch, unit commitment, and market operations determine system behavior. This regime includes demand forecasting, reserve scheduling, and resource adequacy assessment. Belgium's Capacity Remuneration Mechanism implementation highlights these operational challenges[5].

Traditional modeling approaches typically focus on a single timescale, with simplified representations of other timescales. However, increasing renewable penetration creates stronger coupling between timescales, necessitating integrated approaches[9].

2.2.1 HVDC Transmission Considerations

HVDC transmission systems play an increasingly important role in modern power systems, influencing dynamics across all timescales. At the electromagnetic timescale, converter stations introduce fast switching behavior and harmonic interactions. At the electromechanical timescale, HVDC links can either isolate disturbances or provide dynamic support, depending on their control strategy. At the operational timescale, HVDC capacity influences market dispatch and reserve requirements.

While our current models focus primarily on AC systems for methodological demonstration, it's important to recognize that HVDC systems impact all three timescales represented in our models. Modern HVDC converter technologies (particularly Voltage Source Converters) enable independent control of active and reactive power, black start capabilities, and multi-terminal configurations that substantially alter system dynamics compared to traditional AC-only systems.

2.3 AI-Enhanced Modeling Methodology

Our implementation combines system dynamics principles with AI-assisted model development through four methodological steps, as illustrated in Figure 1:

1. **Knowledge Acquisition:** Using Perplexity's Deep Research to gather domain knowledge about electrical system dynamics across timescales. Deep Research is the current state-of-the-art where LLM models are not only using Chain of Thought reasoning but also more time to process (reducing hallucination) while also giving access to navigate real-time information on the world wide web. [14]. The prompts and outputs from Perplexity can be found in the additional material of this paper.

2. **Model Formulation:** Leveraging Claude Sonnet 3.7 with the latest Extended function to generate XMILE model structures based on the hierarchical feedback framework. Claude Sonnet 3.7 is currently the strongest mathematical and coding LLM available to the public. [15]. Again, the prompts and outputs from Claude can be found in the additional material of this paper.

3. **Iterative Refinement:** Collaborative debugging and improvement of models based on simulation results and observed behavior. When models exhibited unrealistic behavior, the AI analyzed the structure and parameters to identify sources of error.

4. **Cross-Scale Integration:** Conceptual mapping of interactions between the three timescale models.

It's important to note that the EnergyVille and Elia data were used as knowledge sources for the AI, not as training data or validation datasets. The AI used these references to understand typical system parameters, behavior patterns, and constraints in Belgian and European power systems, which informed the conceptual model development.

The AI-assisted approach offered several advantages:

- Rapid generation of model structures with comprehensive documentation
- Systematic identification and correction of model errors

- Integration of knowledge across electrical engineering and system dynamics domains

The model development process included multiple iterations, with AI assistance particularly valuable in diagnosing and correcting feedback mechanisms that led to unrealistic behavior. This approach aligns with the EU's recent focus on system dynamics for innovation analysis[10].

3 Model Structure and Formulation

3.1 Fast Timescale Model: Electromagnetic Dynamics

Our fast timescale model captures electromagnetic energy storage and the associated voltage dynamics, operating in the microsecond range. This model represents a conceptual approach to electromagnetic dynamics suitable for educational purposes and methodological demonstration, though it employs simplifications compared to detailed electromagnetic transient (EMT) simulations used in power engineering practice.

In this model, we represent the electromagnetic energy storage in a simplified power system using system dynamics concepts:

Stock: The primary stock (S_{fast}) represents electromagnetic energy stored in fields and charges (measured in joules):

$$S_{fast} = \int_{t_0}^{t} (I_{in} - I_{out})dt \tag{1}$$

Here, unlike traditional electrical models that work with current and voltage directly, we model the energy balance, which is the integral of power (product of voltage and current). This is analogous to a capacitive energy storage element in electrical systems, where energy stored is proportional to the square of voltage.

Flows:

$$I_{in} = I_{in}^{base} \cdot (1 + \text{STEP}(I_{size}^{step}, t_{step})) \tag{2}$$

$$I_{out} = f_{EMB} \tag{3}$$

Where I_{in}^{base} is the baseline power input (in joules/microsecond), I_{size}^{step} is the magnitude of a step change, t_{step} is the time of the step change, and f_{EMB} is the electromagnetic balancing function.

Key Auxiliaries:

$$V_{bus} = V_{bus}^{nom} \cdot \left(\frac{S_{fast}}{S_{fast}^{ref}}\right)^{0.5} \tag{4}$$

$$\begin{aligned} f_{EMB} = I_{out}^{base} \cdot \left(\frac{V_{bus}}{V_{bus}^{nom}}\right)^{2} \cdot \\ (1 + k_{dist} \cdot \sin(t/T_{osc})) \end{aligned} \tag{5}$$

Where V_{bus} is the bus voltage, V_{bus}^{nom} is the nominal bus voltage, S_{fast}^{ref} is the reference energy level, I_{out}^{base} is the baseline power output, k_{dist} is a disturbance factor, and T_{osc} is the oscillation period.

The square-root relationship between energy and voltage is based on the physical relationship in capacitive systems where $E = \frac{1}{2}CV^2$, making $V \propto \sqrt{E}$. The voltage-dependent balancing function creates a stabilizing feedback loop where power outflow increases with the square of voltage (representing the physical relationship where power is proportional to voltage squared).

The sinusoidal term in the electromagnetic balancing function represents small-scale oscillatory disturbances that commonly occur in power systems due to switching events, control actions, or natural system resonances. This simplified representation allows testing of the system's damping characteristics without modeling detailed electromagnetic wave equations.

In production implementations, detailed representation of power electronic interfaces would be necessary, particularly DC transformers and active front ends that significantly impact fast timescale dynamics. Active front ends used between AC and DC buses typically implement either voltage regulation or power regulation control schemes that affect system behavior. These interfaces fundamentally alter system response characteristics at this timescale, especially in modern hybrid AC/DC systems where power electronic conversion is the primary interface mechanism.

3.2 Medium Timescale Model: Electromechanical Dynamics

Our medium timescale model represents the mechanical energy storage in rotating machinery and its relationship to system frequency, operating in the seconds range. This conceptual model captures key electromechanical relationships for educational and methodological demonstration purposes, while acknowledging that full power system stability studies would require more detailed representations of generator dynamics, network topology, and control systems.

Stock: The primary stock (S_{med}) represents mechanical energy storage in rotating machinery (in joules), which is directly related to the system frequency:

$$S_{med} = \int_{t_0}^{t} (P_{mech\_in} - P_{mech\_out}) dt \tag{6}$$

Flows:

$$P_{mech\_in} = P_{in}^{base} \cdot (1 + k_{load} \cdot \text{STEP}(1, t_{load})) \tag{7}$$

$$P_{mech\_out} = f_{droop} \tag{8}$$

Where P_{in}^{base} is the baseline mechanical power input, k_{load} is the load change factor, t_{load} is the time of load change, and f_{droop} is the droop control function.

Key Auxiliaries:

$$f = f_{nom} \cdot \left(\frac{S_{med}}{S_{med}^{ref}} \right)^{0.5} \tag{9}$$

$$f_{droop} = P_{out}^{base} \cdot (1 + k_1 \cdot (f - f_{nom})) \tag{10}$$

$$\text{Mode} = \text{IF}(|P_{mech\_in} - P_{mech\_out}| > \gamma, \text{"Grid-Forming"}, \text{"Grid-Following"}) \tag{11}$$

Where f is the system frequency, f_{nom} is the nominal frequency, S_{med}^{ref} is the reference mechanical energy, P_{out}^{base} is the baseline mechanical power output, k_1 is the droop coefficient, and γ is the mode-switching threshold.

The square-root relationship between energy and frequency is based on the physical relationship in rotating systems where kinetic energy is proportional to the square of angular velocity ($E_{kinetic} = \frac{1}{2} J\omega^2$), making $\omega \propto \sqrt{E}$.

The droop control function implements primary frequency regulation, a fundamental stability mechanism in power systems. When frequency increases above nominal, the power output increases to reduce frequency, creating a negative feedback loop. The droop coefficient k_1 (typically in the range of 0.05-0.5 in real systems) determines the strength of this response.

The operating mode represents a conceptual distinction between grid-following and grid-forming operation. In grid-following mode, the system primarily responds to small deviations to maintain stability. In grid-forming mode (activated during large imbalances exceeding threshold γ), the system takes a more active role in establishing system conditions, analogous to how inverter-based resources must switch operating modes during significant disturbances.

3.3 Slow Timescale Model: Operational Resource Dynamics

Our slow timescale model captures operational resource dynamics and market-based generation dispatch, operating in the hours to days range. This conceptual model illustrates operational principles for educational and methodological demonstration purposes, while recognizing that production-grade models would require more sophisticated market clearing algorithms, detailed cost functions, and network constraints.

Stock: The primary stock (S_{slow}) represents operational resource storage (in megajoules):

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

Flows:

$$G = f_{MCG} \tag{13}$$

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

Where G is generation, f_{MCG} is the market clearing generation function, D is demand, $D^{forecast}$ is forecasted demand, and η is the forecast error.

Key Auxiliaries:

$$\begin{aligned} f_{MCG} = \min(&\max(D^{forecast}, G^{min}), \\ &G^{max}) \cdot (1 + R_{margin} - f_{storage}) \end{aligned} \tag{15}$$

$$\begin{aligned} D^{forecast} = D^{base} \cdot (1 &+ k_{daily} \cdot \sin(2\pi \cdot t/24) \\ &+ k_{weekly} \cdot \sin(2\pi \cdot t/168)) \end{aligned} \tag{16}$$

$$f_{storage} = \max(0, k_{adj} \cdot (S_{slow} - S_{slow}^{target})/S_{slow}^{max}) \tag{17}$$

Where G^{min} and G^{max} are minimum and maximum generation limits, R_{margin} is the reserve margin, $f_{storage}$ is the storage adjustment function, D^{base} is baseline demand, k_{daily} and k_{weekly} are daily and weekly pattern coefficients, S_{slow}^{target} is the target storage level, S_{slow}^{max} is maximum storage capacity, and k_{adj} is a storage adjustment coefficient.

The simplified market clearing mechanism ensures generation meets forecasted demand while respecting operational constraints. The reserve margin (typically 5-15% in actual systems) ensures adequate capacity is available to handle unexpected events, while the storage adjustment function provides a balancing mechanism to prevent continuous resource accumulation.

The sinusoidal representations of daily and weekly demand patterns are simplified approximations of the cyclical nature of electricity demand. While actual demand patterns are more complex, this representation captures the essential periodicity needed for educational understanding. For production models, historical load profiles would be used instead.

The energy conservation error metric is used for validation purposes to assess how well the model maintains energy balance over time. It is not an actual physical quantity but a numerical check on model behavior, where values close to zero indicate proper conservation.

3.4 Cross-Scale Integration Concepts

While our three models operate independently in this implementation, they conceptually link through several mechanisms:

- **Downward Causation:** Operational decisions at the slow timescale constrain electromechanical operations (e.g., through reserve margins), which in turn affect electromagnetic responses
- **Upward Causation:** Electromagnetic disturbances propagate to affect electromechanical stability, potentially triggering reserve activation at the operational timescale
- **Temporal Aggregation:** Fast dynamics can be aggregated to inform slower timescale decisions, while slow dynamics provide boundary conditions for faster dynamics

In hybrid AC/DC systems, the interaction complexity increases as HVDC elements can significantly influence power flows in both AC and DC subsystems. Power converters at the interfaces between AC and DC subsystems play a crucial role in disturbance propagation and system stability across timescales. The ability of HVDC links to rapidly modulate power flow provides both challenges and opportunities for system stability that would be important considerations in more detailed models.

This framework allows for conceptual understanding of cross-scale interactions while maintaining computational tractability through separate models. Such integration reflects Fluxys' North Sea Integration Model approach[12] at a conceptual level.

4 Results and Analysis

4.1 Model Behavior and Validation

Each model was simulated independently to assess its response to characteristic disturbances:

Fast Timescale Model: The electromagnetic model demonstrated rapid adjustments to step changes in input current. Following a 20% step increase in input current, the voltage initially rose by approximately 10% before the electromagnetic balancing feedback stabilized the system within a few microseconds. The sinusoidal disturbance was similarly dampened by the voltage-dependent feedback. Seen in figure 1.

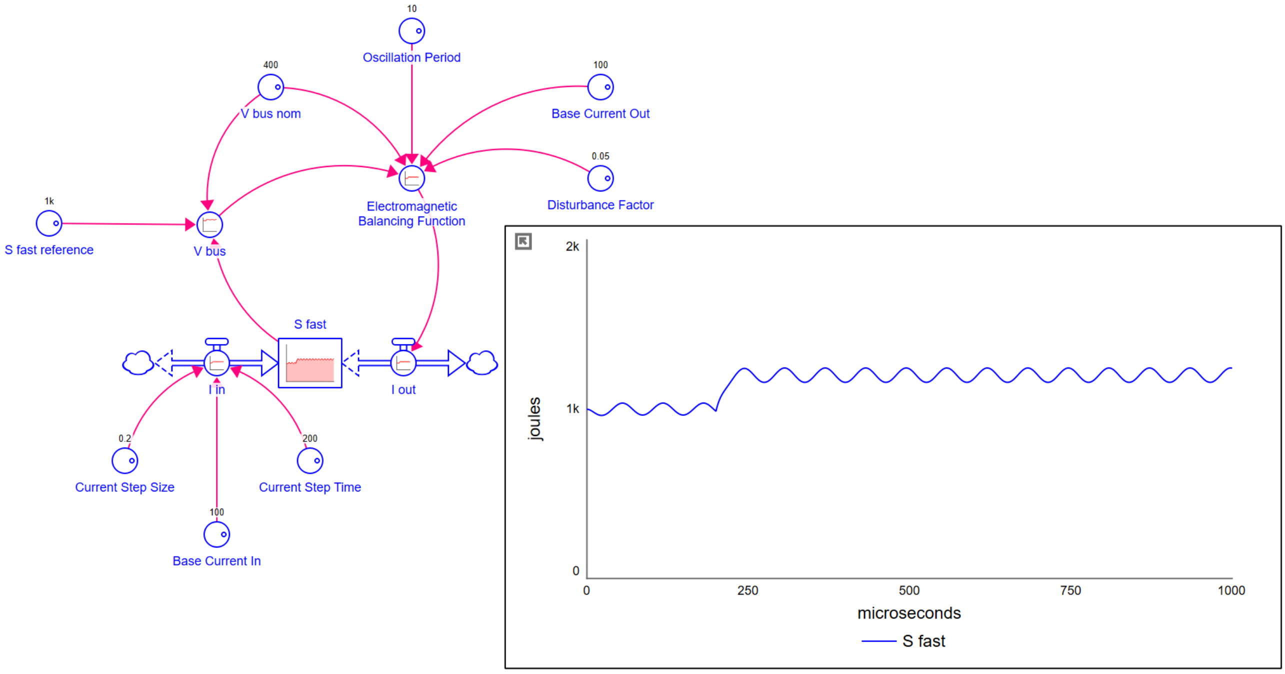

Figure 2: Fast timescale electromagnetic model showing voltage stabilization after step change in input current.

Medium Timescale Model: The electromechanical model showed characteristic frequency regulation behavior. When a 10% increase in mechanical power input was applied at t=20s, the system frequency initially increased before the droop control mechanism stabilized the system at a new operating point. The operating mode successfully switched between grid-following and grid-forming based on the power imbalance magnitude. Seen in Figure 2.

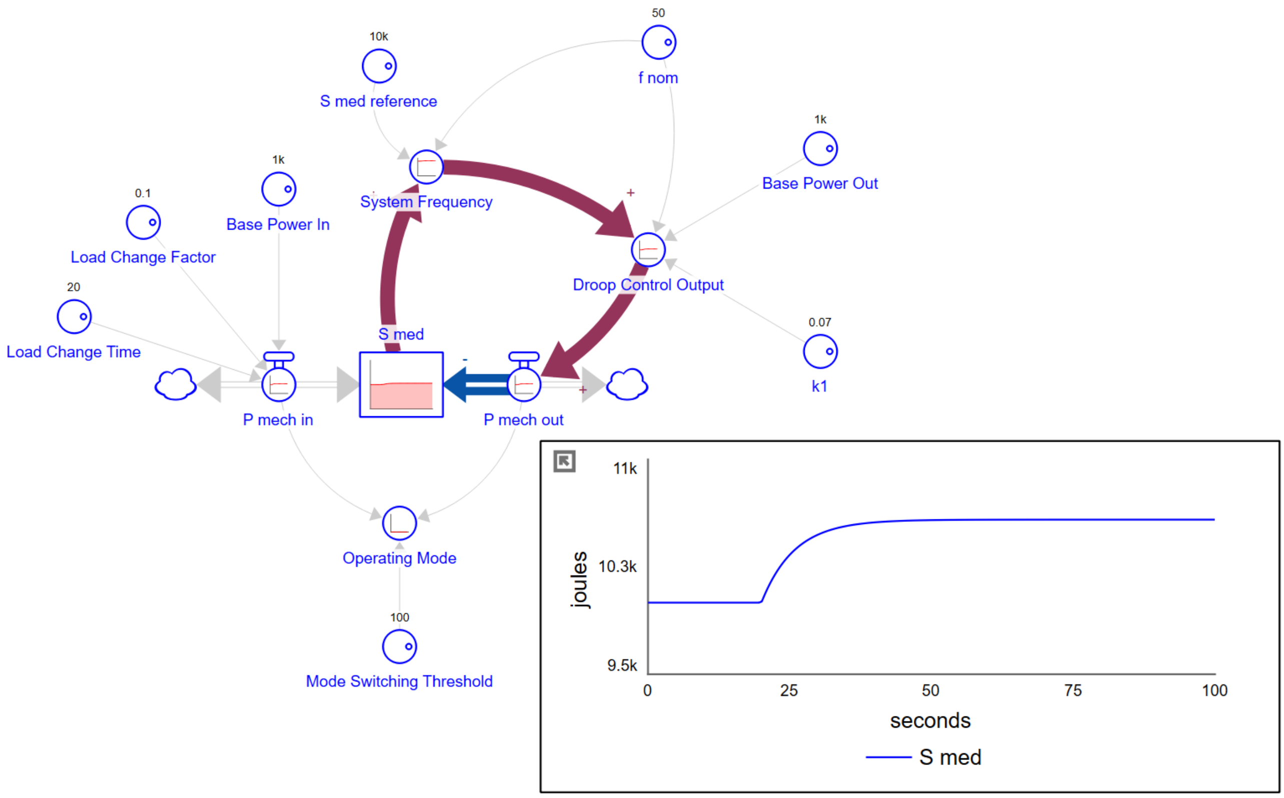

Figure 3: Medium timescale electromechanical model demonstrating frequency regulation through droop control.

Slow Timescale Model: The operational model exhibited balanced behavior with daily and weekly oscillations around the target storage level. The storage adjustment mechanism effectively prevented continued accumulation of resources, while the reserve margin ensured adequate reserves for reliability. The energy conservation error stabilized rather than growing continuously, confirming numerical stability of the simulation. Seen in Figure 3.

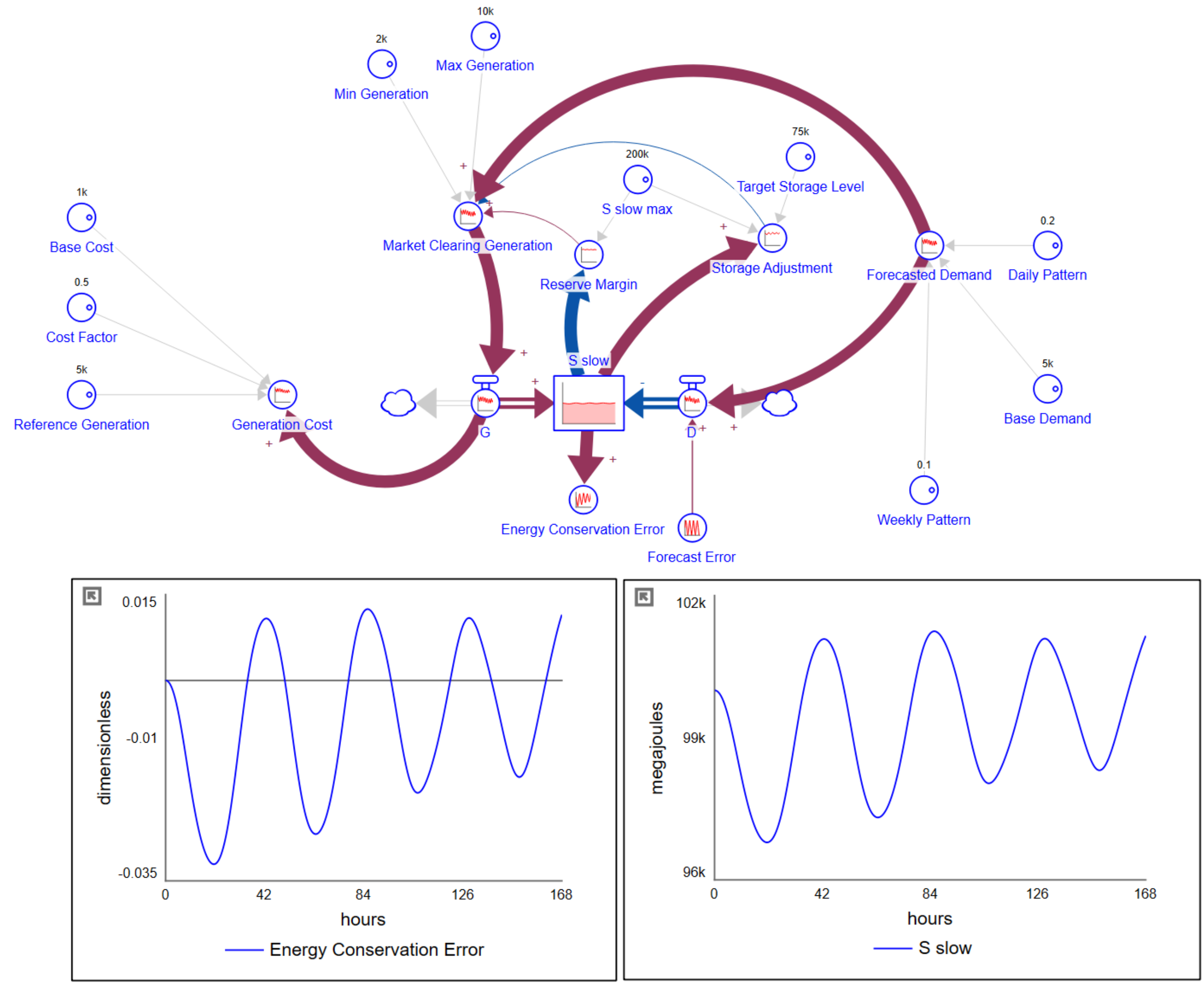

Figure 4: Slow timescale operational model showing resource balance with daily and weekly fluctuations.

Complete validation would require comparison with experimental data from hybrid AC/DC systems to verify model behavior across all timescales. While our current validation focuses on qualitative behavioral assessment, production implementations would benefit from quantitative comparison with data from real power systems or detailed simulation results from industry-standard tools.

4.2 AI Contribution to Model Development

The AI assistance was particularly valuable in several aspects of model development:

Error Identification and Resolution: When the medium timescale model exhibited unrealistic exponential growth (see Figure 5), the AI quickly identified the problem in the droop control equation:

Table 2: AI-Identified Error in Medium Timescale Model

Original (Erroneous) Equation	**Corrected Equation**
$f_{droop} = P_{out}^{base} \cdot (1 + k_1 \cdot (f_{nom} - f))$	$f_{droop} = P_{out}^{base} \cdot (1 + k_1 \cdot (f - f_{nom}))$

The original equation created a positive feedback loop (when frequency increased, power output decreased, further increasing frequency), while the corrected equation implements proper negative feedback control. Similarly, when the slow timescale model showed continuous resource accumulation, the AI diagnosed the missing balancing feedback and implemented the storage adjustment mechanism.

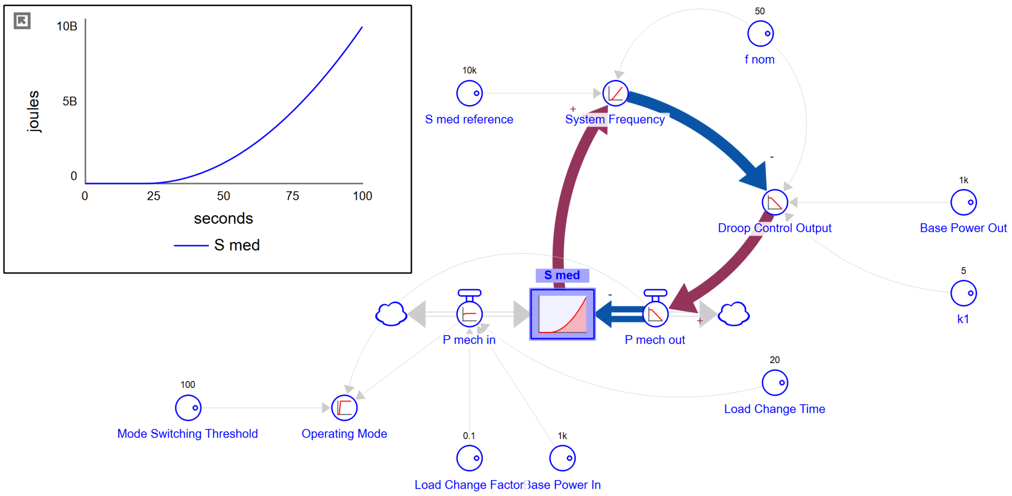

Figure 5: Medium timescale model exhibiting exponential growth due to incorrect droop control equation

Parameter Selection: The AI suggested reasonable parameter values based on understanding of typical system characteristics. Table 3 shows examples of AI-suggested parameters compared to typical values from power system literature and grid codes.

Table 3: Comparison of AI-Suggested Parameters with Typical Values

Parameter	AI Suggestion	Typical Range in Literature
Droop coefficient (k_1)	0.8	0.05-0.5 (ENTSO-E grid code)
Reserve margin (R_{margin})	0.1-0.15	0.10-0.15 (Belgium CRM)
Oscillation period (T_{osc})	10µs	5-20µs (power electronics)

Development Time: The AI-assisted approach significantly reduced development time compared to manual coding. Table 4 shows the estimated time comparison based on our experience.

Table 4: Development Time Comparison

Task	AI-Assisted (hours)	Manual (estimated hours)
Initial model formulation	2	8
Debugging structural errors	1	4
Documentation	1	6
Total	4	18

Comprehensive Documentation: The AI automatically generated detailed documentation for each model component, including units, purpose, and expected behavior. This documentation enhanced model transparency and facilitated understanding.

5 Discussion and Implications

5.1 Benefits of AI-Enhanced System Dynamics Modeling

Our experience with AI-assisted modeling revealed several key benefits:

Reduced Development Time: The AI's ability to rapidly generate model structures and equations significantly accelerated the model development process. As shown in Table 4, what might have taken days of manual coding was accomplished in hours, with an estimated 60-70% reduction in development time.

Improved Model Documentation: The AI consistently provided comprehensive documentation for each model component, enhancing transparency and facilitating understanding. For example, each model element included purpose, units, and references to underlying physical principles.

Enhanced Error Detection: The AI systematically analyzed model behavior and identified structural issues that led to unrealistic outcomes, then proposed specific corrections. In the case of the medium timescale model, the AI correctly diagnosed the sign error in the droop control equation when asked to identify and fix the model behaviour.

Knowledge Integration: The AI effectively combined domain knowledge from electrical engineering with system dynamics principles, bridging disciplinary boundaries. This aligns with the EU's system dynamics working group objectives[11].

5.2 Limitations and Challenges

Despite its benefits, the AI-assisted approach also revealed important limitations:

Domain Knowledge Dependencies: The quality of AI-generated models remained dependent on the quality of available domain knowledge. The AI could not compensate for fundamental gaps in understanding, as evidenced by the initially inaccurate droop control formulation that required human correction.

Need for Human Verification: Human oversight remained essential to ensure models were physically and conceptually valid. The AI occasionally suggested implausible formulations that required correction, particularly regarding unit consistency and physical relationships. One example in this work was the formulation of the If Then Else, where it used a typical programming notation, instead of iSee Stella notation. However, easy to correct by a skilled modeler.

Parameter Calibration: While the AI could suggest reasonable parameter values, proper calibration against empirical data still required human expertise. As shown in Table 3, some AI-suggested parameters fell outside typical ranges from literature.

Conceptual Boundaries: The AI excelled at implementing known concepts and relationships but was limited in generating novel conceptual frameworks. The models largely represent established relationships rather than innovative approaches to power system modeling.

5.2.1 Technical Limitations and Future Refinements

Our models, while valuable for demonstrating the methodology and educational purposes, have several technical limitations that would need to be addressed for production-grade applications:

Fast Timescale Model: The electromagnetic model employs a highly aggregated representation that does not account for detailed network topology, transmission line characteristics, or advanced power electronic controls. Production implementations would require:

- Integration with standardized electromagnetic transient (EMT) simulation frameworks like PSCAD[17] or EMTP-RV[18]
- Detailed representation of power electronic switching dynamics and control algorithms
- Incorporation of transmission line models with wave propagation effects

Our fast timescale model employs a highly aggregated representation that does not account for detailed DC transformer dynamics or advanced power electronic controls. Production implementations would require integration with EMT simulation frameworks that can represent these elements, particularly for hybrid AC/DC systems where converter dynamics significantly impact system behavior.

Medium Timescale Model: The electromechanical model uses simplified relationships between mechanical energy and frequency that do not capture the full complexity of generator dynamics. Production implementations would require:

- Detailed generator models with appropriate order differential equations (e.g., 6th order synchronous machine models that capture subtransient, transient, and steady-state dynamics)[19]
- Network representation with power flow constraints
- Explicit modeling of various control loops (AVR, PSS, governors)

Slow Timescale Model: The operational model employs a greatly simplified market clearing mechanism that does not account for locational constraints, detailed cost functions, or strategic bidding behavior. Production implementations would require:

- Integration with established unit commitment and economic dispatch algorithms
- Incorporation of transmission constraints and locational marginal pricing
- More sophisticated representation of renewable generation uncertainty

These limitations do not diminish the methodological value of our approach but highlight the need for domain-specific extensions when moving from conceptual understanding to technical implementation.

5.3 Future Directions

Building on our methodology and addressing the technical limitations identified above, several promising directions for future research emerge:

Enhanced Technical Implementation: Future work should focus on integrating the system dynamics approach with established power system modeling frameworks, potentially through co-simulation approaches that maintain conceptual clarity while adding technical rigor. Specific implementations could include:

- Coupling with PowerFactory, PSCAD, open source Julia libraries (PowerModels ACDC)[16], or other industry-standard power system tools. PowerModels ACDC was selected for mention due to its ability to handle the increasingly important AC-DC interactions in future power systems.
- Incorporation of detailed generator models and control systems
- Implementation of standardized renewable generation models

Future work should incorporate validation against industry-standard tools with AC/DC capabilities such as PowerModels ACDC, which was selected for mention due to its ability to handle the increasingly important AC-DC interactions in future power systems.

Cross-Scale Integration: Building on our three separate models, future work could develop truly integrated models that directly capture cross-scale interactions through:

- Development of formal temporal aggregation methodologies
- Implementation of automated boundary condition exchanges between timescales
- Exploration of variable time-step approaches that adapt to system dynamics

AI-Assisted Calibration: Extending AI assistance from model formulation to parameter calibration and validation could further enhance modeling efficiency through:

- Integration with optimization algorithms for parameter tuning
- Pattern recognition in historical operational data
- Automated validation against standardized test cases

Expanded Model Libraries: The approach could be extended to develop comprehensive libraries of power system components across timescales:

- AI-generated libraries of renewable generation models
- Interactive educational modules for power system concepts
- Cross-validated component models for different power system technologies

Hybrid AC/DC System Extension: While our current models provide a foundation, future work should extend to hybrid AC/DC systems by:

- Incorporating detailed DC component models at each timescale
- Addressing the unique control strategies of HVDC converters
- Examining interactions between converters and between converters and the grid
- Developing standardization approaches that consider both AC and DC protection requirements for hybrid systems, drawing lessons from established AC standards while developing DC-specific approaches

5.4 Methodological Contributions

Beyond the specific models developed, this work makes several methodological contributions to the field of system dynamics modeling:

AI-Enhanced Model Development Framework: We have demonstrated a systematic approach to leveraging AI capabilities for model development that could be applied across domains. This framework establishes a workflow that combines human expertise with AI assistance at key stages of the modeling process.

Error Pattern Recognition: Our approach revealed that LLMs can effectively recognize common modeling errors through behavioral pattern analysis. This capability could be further formalized into diagnostic tools for system dynamics modeling.

Cross-Domain Knowledge Integration: The methodology showed particular strength in bridging knowledge across electrical engineering and system dynamics domains, suggesting value for other interdisciplinary modeling challenges.

Educational Scaffolding: The approach demonstrates significant potential for creating educational materials that scaffold learners from conceptual understanding to technical implementation, potentially addressing a key gap in system dynamics education.

These methodological contributions represent valuable advances even independent of the specific power system application domain.

6 Conclusion

This study demonstrates the potential of AI-assisted modeling to enhance our understanding of multi-timescale dynamics in electrical power systems. By leveraging Large Language Models to assist in model formulation and refinement, we developed three conceptual models capturing electromagnetic, electromechanical, and operational dynamics. The models, while necessarily simplified for educational and methodological demonstration purposes, effectively illustrate the distinct feedback mechanisms and characteristic behaviors at each timescale.

The AI proved particularly valuable in identifying and correcting model errors, generating comprehensive documentation, and integrating knowledge across domains. While the technical implementation has recognized limitations compared to production-grade power system models, the primary contribution lies in the methodological approach and the demonstration of how AI assistance can transform the model development process.

Human expertise remains essential for conceptual framing, validation, and technical extension, but AI assistance can significantly accelerate the modeling process and improve model quality, particularly for educational applications and initial conceptual exploration. This approach offers a promising pathway for addressing complex multi-timescale phenomena, potentially accelerating how we develop and use system dynamics models in both educational and research contexts.

Future work should focus on enhancing technical implementation through integration with established power system modeling frameworks, developing more tightly integrated multi-timescale models, and expanding AI assistance to parameter calibration. Such work would build upon the methodological foundation established here while addressing the technical limitations identified for production applications, particularly the extension to hybrid AC/DC systems that increasingly characterize modern power grids.

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