

AN ITERATIVE CO-SIMULATION PIPELINE FOR COUPLED MODELS

Amy Liffey¹, Khoa Nguyen², Sandro Luh³, René Schumann¹

¹HES-SO Valais-Wallis University of Applied Sciences and Arts Western Switzerland, Switzerland

²Center For Primary Care and Public Health (Unisanté), Switzerland

³Paul Scherrer Institute, Laboratory for Energy Systems Analysis, Switzerland, Current: Accenture AG
email: amy.liffey@hevs.ch

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ABSTRACT

The study of complex energy systems requires models that capture both system-level dynamics and individual behavior. Energy system optimization models identify least-cost technology pathways but represent human behavior through aggregate projections, abstracting individual decisions. Agent-based behavioral models capture this heterogeneity, but do not see the energy system. Coupling the two model types is non-trivial as they operate at different time resolutions and conceptual paradigms. This paper presents an iterative co-simulation pipeline that couples a national energy system optimization model with a behavior-driven agent-based model of household mode choice and electric vehicle adoption. A shared version-controlled repository serves as the data exchange hub, with automated execution triggered by commits. The proposed pipeline enables reproducible, automated bidirectional coupling while preserving the independence of both models.

INTRODUCTION

Energy systems are complex socio-technical systems where technological infrastructure and human behavior interact continuously. The low-carbon energy transition amplifies this complexity and demands realistic modeling across scales. Large techno-economic energy system models (ESMs) such as STEM (Panos et al. 2023), MARKAL/TIMES (Loulou et al. 2016) and OSeMOSYS (Howells et al. 2011) capture this complexity at the system level. These models usually use a set of policy targets and external constraints to identify the least-cost technology pathway for the energy system. However, because they are computationally intensive, they typically represent behavior at an aggregate level rather than capturing individual heterogeneity. Behavioral aspects are especially important in the mobility domain (Luh et al. 2022), where individual decisions often depend on more than cost alone. Mode choice tends to be influenced by individual habits, while the adoption of an electric vehicle (EV) can be influenced by different aspects such as bounded rationality (Nguyen et al. 2023). Agent-

based models (ABMs) can capture this heterogeneity by simulating a population of individual agents. For example, Bed-DeM simulates Swiss households as a population of individual agents, each making mobility decisions based on their personal attributes, habits, and social influences, grounded in an established psychological theory (Nguyen et al. 2023).

Coupling specialized models, rather than increasing their complexity, can provide a bridge between different modeling approaches and scales, creating more realistic representations (Filatova et al. 2025). The ESM and behavioral ABM coupling should be bidirectional, as fuel prices influence individual choices, while aggregated demand affects the design and cost of the energy system. This coupling can be realized through a co-simulation pipeline, which is the coordinated execution of different models (Gomes et al. 2018). This process is often challenging, as it involves dealing with interdisciplinary design and different conceptual and time scales (Adelt et al. 2023, Filatova et al. 2025). For example, STEM operates over decades with low resolution time steps (Panos et al. 2023), making close synchronization unsuitable and favoring asynchronous approaches such as file exchange (Luh et al. 2022). However, existing model coupling solutions often rely on manual file-based exchange between modeling teams (Luh et al. 2022, Blanco et al. 2019, Torralba-Díaz et al. 2024) demanding effort and domain expertise, which limits automation, reproducibility and traceability of such pipelines (Keppo et al. 2026). Although automated iterative coupling (Torralba-Díaz et al. 2024) and ontology-driven frameworks (Torlini et al. 2026) exist and can provide reproducibility, our approach aims to add lightweight and model-agnostic artifact exchange with minimal manual intervention, providing automated and re-constructable coupling.

This paper presents an automated, iterative co-simulation pipeline for the ESM-ABM coupling, developed within the PROBOUND project (Schumann et al. 2021). The pipeline provides a reproducible Git-based workflow for traceable co-simulation. We demonstrate the approach for a Swiss transport policy scenario, where we show the iterations of both models.

RELATED WORK

Efforts to incorporate consumer behavior into energy system optimization models range from travel time constraints (Daly et al. 2014), substitution elasticities (Salvucci et al. 2018),

and heterogeneous consumer segments (Tattini et al. 2018), to external model coupling (Luh et al. 2022). Coupling approaches include soft-linking transport behavior models with JRC-EU-TIMES (Blanco et al. 2019), linking ABMs with computable general equilibrium models (Niamir et al. 2020), and iterative coupling between electricity market models and ABMs (Torralba-Díaz et al. 2024). To the best of our knowledge, no published work couples an ESM with a psychologically grounded ABM, simulating both mode choice and EV adoption in a single iterative loop. Co-simulation frameworks such as Mosaik (Ofenloch et al. 2022) and HELICS (Hardy et al. 2024), and standards such as FMI (Junghanns et al. 2021), are designed for runtime synchronization between models operating at the same temporal resolution. STEM and BedDeM operate at decadal and annual resolutions, making this solution unfeasible. Our approach instead uses sequential file exchange via a shared Git repository, with a webhook-triggered pipeline automating each iteration.

Another widely recognized challenge in energy system modeling is reproducibility (Pfenninger et al. 2017, Morrison 2018). Workflow tools such as Snakemake (Mölder et al. 2021) address this for single-model pipelines. Our approach applies similar principles to a two-model iterative coupling, providing scenario-level traceability through a shared repository structure and covering the interactions of the models during their joint execution. To the best of our knowledge, reproducible, iterative, and bidirectional coupling has not yet been addressed with a model-agnostic version-controlled architecture.

CO-SIMULATION PIPELINE DESIGN

The pipeline couples two models with different purposes, time resolutions and modeling approaches: the STEM energy system optimization model (Panos et al. 2023) and the agent-based mobility model BedDeM (Nguyen et al. 2023). STEM operates at a decadal resolution to estimate system-level outcomes, while BedDeM simulates annual household decisions influenced by behavioral factors such as costs, travel time, and social interactions. Within BedDeM, mobility behavior is represented through two coupled interacting ABM models: an annual mode choice model and a vehicle purchase model. BedDeM simulates around 3000 agents representing the Swiss household population. Agents’ decision-making is based on Triandis’ Theory of Interpersonal Behavior. Each agent evaluates available transport options based on cost, travel time, and other attributes, while vehicle replacement and adoption decisions are triggered by vehicle lifetime or changing attractiveness of alternative options (Nguyen et al. 2023). These decisions update the fleet composition and feed back into future mode choices. Aggregated outputs such as trip counts, charging demand, and total mobility demand are produced annually and form the input to STEM for re-optimization of the overall energy system under these constraints.

The interaction between the two models is shown in Figure 1. STEM provides fuel prices and initial fleet compo-

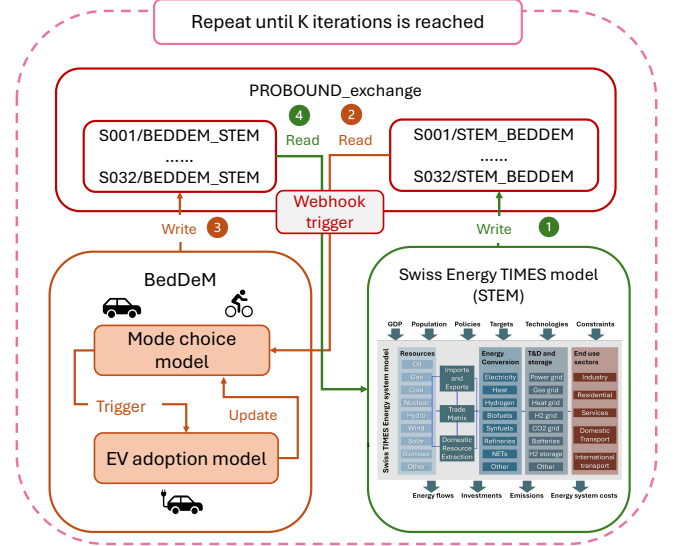


Figure 1: Co-simulation architecture: STEM (Panos et al. 2023) and BedDeM (Nguyen et al. 2023) exchange data via the shared repository. ① STEM commits fleet clusters and fuel prices to STEM_BEDDEM/; ② git webhook triggers BedDeM to pull and run; ③ BedDeM commits trip counts and charging demand to BEDDEM_STEM/; ④ git webhook triggers STEM to pull and re-run.

sitions, which are used as input to BedDeM, while BedDeM returns aggregated mobility demand and fleet changes to STEM. Data exchange is implemented via a shared Git repository **PROBOUND.exchange**, which cannot be released publicly because it contains data derived from sources under a non-disclosure agreement. The repository is organized by the scenarios to be investigated by the coupled models (S001–S032). Each scenario contains two interface directories:

- STEM_BEDDEM/: decadal STEM outputs (fuel prices and fleet clusters) used as input to BedDeM
- BEDDEM_STEM/: annual BedDeM outputs (trip counts, charging demand, and aggregated mobility demand including fleet changes) used as input to STEM

All data artifacts are versioned within the repository, allowing the exchange process to be tracked across scenarios and model runs. Repository events trigger subsequent model executions, enabling automated co-simulation.

Model Input and Output Mapping

Coupling requires alignment of time resolution and model semantics. STEM provides outputs at decadal checkpoint years (2020–2050), while BedDeM requires annual inputs over the simulation horizon. This mismatch is resolved on the BedDeM side by linearly interpolating STEM outputs into annual time series. Fuel prices provided by STEM at decadal checkpoint years are linearly interpolated to produce annual

Algorithm 1: STEM–BedDeM Coupling

Input: Scenarios $\mathcal{S}$, shared Git repository $\mathcal{R}$ **Output:** Fleet composition, fuel prices, mobility demand and CO_2 emissions

```
// Initial setup
Run STEM for fleet composition and fuel prices
Map STEM fleet clusters to BedDeM agents
Each side (STEM, BedDeM) registers a webhook on  $\mathcal{R}$ 
// On each webhook trigger
foreach  $s \in \mathcal{S}$  with new commits from the other model do
    Pull updated results for  $s$  from  $\mathcal{R}$ 
    Update local inputs (fuel prices for BedDeM;
    fleet/demand for STEM)
    Run own model for  $s$ 
    Commit and push results to  $\mathcal{R}$ 
    if  $K$  iterations reached or other criteria then
        Stop coupling for scenario  $s$ 
```

values written to the BedDeM database according to Equation (1):

$$p(y) = p(y_{\text{start}}) + \frac{p(y_{\text{end}}) - p(y_{\text{start}})}{y_{\text{end}} - y_{\text{start}}} \cdot (y - y_{\text{start}}) \quad (1)$$

where $p(y_{\text{start}})$ and $p(y_{\text{end}})$ are the STEM provided prices at the first and last checkpoint year, respectively, and $y \in \{y_{\text{start}} + 1, \dots, y_{\text{end}}\}$. Differences in model representation also require harmonization. Vehicle fleets are represented as technology clusters in STEM, but as individual household choices in BedDeM, requiring a translation between aggregate shares and agent-level attributes. Fuel prices differ conceptually, with system-level values in STEM and household cluster level prices in BedDeM that may include taxes and behavioral perceptions. In addition, BedDeM produces agent-level mobility and charging data that are aggregated into sector-level inputs for STEM. These transformation choices may influence the behavior of the iterative loop. All mapping assumptions and file structures are documented and versioned in the shared repository, allowing changes to be tracked across iterations.

Pipeline Automation

On the BedDeM side, the process is automated via a Git webhook that triggers a BedDeM’s CI pipeline when new files are pushed to STEM_BEDDEM/. The pipeline retrieves the updated data, interpolates the decadal inputs to annual values, executes the BedDeM model, and commits the yearly outputs (Trips, MobilityDemand, E-Charging) to BEDDEM_STEM/, which are then pushed back. This incoming update to the STEM model inputs triggers another webhook, which then promptly re-executes the model for the given scenario. Together, these mechanisms create a fully automated iterative loop, requiring no manual intervention between STEM and BedDeM executions. All exchanged artifacts are versioned under a consistent scenario identifier, allowing previous states to be reconstructed from the repository history.

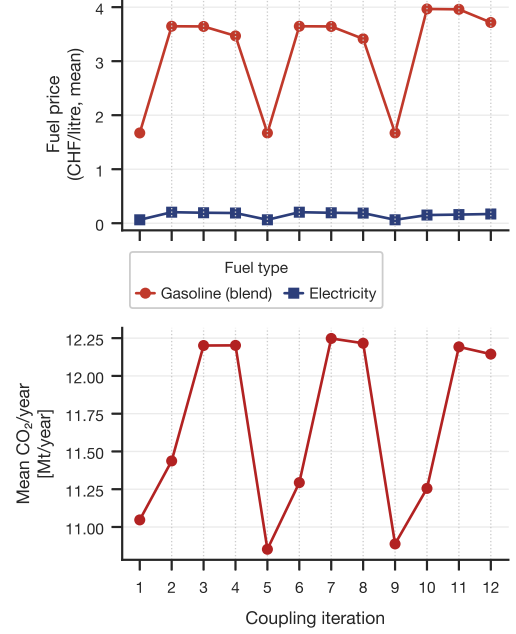


Figure 2: STEM-BedDeM coupling iterations

ITERATION DEMONSTRATION

In the following, we demonstrate the application of our approach in policy scenario S009, detailed in Schumann et al. (2021). This scenario investigates the effect of increased fuel taxes on household mobility behavior, reflected through changes in the total cost of ownership including purchase costs, fuel costs, and ownership-related expenses as produced by STEM and consumed by BedDeM.

STEM commits updated fuel prices and fleet clusters to the repository. The webhook triggers BedDeM, which returns an updated mobility demand. Figure 2 shows the resulting trajectories across coupling iterations. The top graph gives the mean price of gasoline and electricity per iteration, and the bottom graph the corresponding mean annual CO_2 emissions. Gasoline prices and CO_2 emissions oscillate between iterations, alternating between lower and higher taxes as STEM and BedDeM exchange updated inputs. This comes from the different modeling approaches of both models. STEM reacts to adjusted behavior, and people react to adjusted prices. This pattern illustrates the iterative nature of the coupling. Each model responds to the other’s previous output; the loop runs until K iterations is reached.

The computational cost of running the optimization model can be high, especially when multiple iterations are required. The automated pipeline executes the full iteration sequence without manual intervention, reducing user interaction in long-running simulations. In Table 1, we present the total run times of each model and the number of iterations. Out of 313 recorded model run iterations, 64 were removed as statistical outliers, excluding test runs and development commits that do not reflect production run times. Without the automated pipeline, each coupling iteration would have required

Table 1: Coupling iteration run times

Model	Model runs	Median	Mean	Total
STEM	249	2h 23m	2h 56m	731h 17m
BedDeM	249	18 min	18 min	75h 06m
Total	498	2h 41m	3h 14m	806h 23m

a manual trigger on both sides, resulting in 498 manual interventions across the 249 clean iterations. Each introduces an additional delay on top of the model runtime, which the git webhook removes entirely.

CONCLUSION

This paper presents a co-simulation pipeline, coupling an energy system optimization model and an agent-based mobility model in an iterative and bidirectional way. Behavioral responses, such as mode choice and vehicle adoption, influence system-level outcomes, which can affect future decisions. This interaction can offer additional insights, although convergence remains dependent on modeling assumptions, aggregation choices, and interpolation over time.

The exchange is implemented through an automated Git workflow in which model outputs are treated as versioned artifacts, reducing the need for manual intervention during co-simulation (e.g., eliminating 498 manual interventions in our demonstration). This supports structured scenario exploration and traceability while introducing challenges, such as large data volumes in file exchange, which can be handled with Git Large File Storage (LFS) or Data Version Control (DVC).

The approach involves simplifying assumptions in time interpolation and semantic mapping between models. Future work may include recalibration of both models to more recent conditions (e.g. a new baseline), integration with extended versions of BedDeM incorporating more detailed representations of perception (Liffey and Schumann 2025) and potential coupling with additional Energy system models, as well as quantifying the coupling effect on the system-level outcomes.

Overall, the pipeline provides a basis for exploring interactions between system-level optimization and individual decision-making, and may offer a transdisciplinary, model-agnostic approach to coupling different model types without having to adjust the models.

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