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HABITAS: Home agent-based individualized time and activity simulator for household energy dynamics in smart homes

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ABSTRACT

The rise of IoT devices and smart technologies has transformed homes into complex interconnected environments, creating new challenges for energy management. Understanding how people actually use energy is now a key requirement for designing smarter, more efficient systems, and simulation provides a controlled way to test decisions before deploying them in real homes. However, traditional simulation tools rely on static occupancy profiles and deterministic models that overlook the variability of real household behavior. This paper introduces Home Agent-Based Individualized Time and Activity Simulator (HABITAS), a flexible agent-based framework capable of emulating diverse household scenarios and testing energy optimization strategies. HABITAS represents occupants as autonomous agents with unique routines, preferences, and needs, enabling realistic modeling of energy and resource use. The simulator integrates solar generation, battery storage, appliance use, water consumption, and environmental monitoring through a modular architecture that supports both real-time and fast-forward simulation. Through detailed simulations, HABITAS generated plausible residential load shapes and variability patterns consistent with behavioral expectations, illustrating its practical applicability. Its detailed, individualized outputs support research in demand response, energy policy, smart home design, and decentralized energy systems.

1. Introduction

Over the last decade, the increasing integration of sensor networks, Internet of Things (IoT) devices, digital twins and advanced communication infrastructures has transformed the modern dwelling into a highly instrumented, data-rich system [1–4]. This connectivity enables fine-grained monitoring and control of occupant activity, appliance operation and local generation, opening the door to user-centered energy management strategies that were previously impractical [5–8]. Yet implementing such strategies at scale involves operational risks and uncertainties that can be explored more safely and cheaply in simulation. At the same time, new decentralized distribution models, peer-to-peer exchanges and community energy schemes, increase the need for simulation tools that can represent both physical systems and heterogeneous human behaviors with fidelity [9,10].

Early smart-home simulators successfully modeled devices, spatial layouts and simple schedules, but they often relied on static or deterministic profiles that smooth over the variability inherent to real households [11–13]. More recent work has shifted attention to occupant-driven models, showing that capturing user heterogeneity, stochastic behavior and context-dependent decisions is essential for realistic predictions of load shapes, peak timing and the effectiveness of demand-side measures [14–18]. Agent-based modeling is particularly well suited to this task because it represents individuals (occupants, devices, controllers) as autonomous entities that interact within a configurable environment, producing emergent system-level behavior from simple local rules [19,20]. ABM has been successfully applied to problems ranging from demand response and renewable adoption to market participation of distributed resources [21–23].

Despite this progress, a persistent trade-off remains: simulators that prioritise high physical fidelity frequently become rigid and hard to configure, while highly configurable frameworks sometimes sacrifice the behavioral realism required to evaluate control strategies or community-level interactions. Moreover, validation practices vary widely: many studies report long-term aggregated statistics (e.g. weekly or monthly averages) that are appropriate for baseline accounting but insufficient when the target is temporal fidelity, i.e., correct prediction of peaks, their timing and short-term dynamics,

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which are crucial for grid services, storage management and real-time control.

In this work we take a complementary approach. We present HABITAS: Home Agent-Base Individualised Time and Activity Simulator, a modular, highly configurable ABM designed to prioritise temporal fidelity and reproducibility while remaining easy to parametrise for diverse household archetypes. HABITAS bridges the gap between physical energy fidelity and abstract behavioral modeling by natively integrating stochastic, needs-driven occupant behavior with 5-minute physical energy modeling (including PV, battery storage, and device constraints). Through its customizable JSON-driven architecture, this enables researchers to evaluate real-time demand response strategies under realistic behavioral conditions that deterministic schedules fail to capture.

All behaviors and physical parameters are explicitly exposed via a JSON-style configuration, ensuring that experiments are straightforward to parameterize and reproducible. The simulator records high-resolution traces at each timestep, producing individualized outputs suitable for control algorithm development, policy evaluation, and community-energy studies.

The flexibility and parameterization of HABITAS allows it to model a wide spectrum of configurations, from compact apartments to complex prosumer households equipped with PV generation and storage. Its modular and scalable design supports diverse applications, enabling researchers, educators, and policy makers to explore demand-side management strategies, evaluate tariff changes, and prototype smart-home solutions.

It is important to explicitly distinguish HABITAS from a standard Home Energy Management System (HEMS). While a HEMS is a physical technology deployed in real-world dwellings to monitor, control, and optimize actual energy production and consumption, HABITAS serves as a comprehensive simulation and data generation environment. Rather than replacing a HEMS, HABITAS provides a virtual testbed capable of emulating both the physical HEMS infrastructure and the stochastic human behavior that continuously interacts with it. This allows researchers to safely prototype, validate, and optimize HEMS control strategies and demand response policies using synthetic data before their physical implementation, thereby avoiding real-world operational risks.

The main contributions of this work are summarized as follows:

- Development of a hybrid framework integrating stochastic occupant behavior with high-resolution physical energy modeling.
- Implementation of a reproducible, JSON-driven architecture to configure diverse smart-home archetypes and energy systems without code modifications.
- Validation of the simulator as a synthetic data engine through seasonal plausibility assessments against Spanish benchmarks [24] and a machine-learning forecasting case study.

The remainder of this paper is organized as follows. Section II reviews the state-of-the-art in energy simulation tools and agent-based frameworks, situating HABITAS within the current research landscape. Section III provides a high-level overview of the HABITAS design, while Section IV details its technical implementation, including the system architecture and the agent-based behavioral models. Section V describes the comprehensive parametrization of the simulator. Section VI presents the plausibility assessment, analyzing the generated consumption profiles. Section VII details a case study optimizing energy allocation. Section VIII discusses the applications of the model, its limitations, and future development directions. Finally, Section IX concludes the paper.

2. Related work

In the context of smart homes and decentralized energy systems, two major families of simulation tools can be identified: *(i)* traditional platforms focused on modeling energy flows and building performance, and *(ii)* agent-based modeling frameworks designed to simulate occupant behavior and decision-making. This section reviews representative tools from both categories and situates HABITAS within this landscape.

2.1. Energy simulation tools

Traditional simulation tools have served as the foundation for evaluating building performance and energy system efficiency. These platforms typically rely on deterministic physical models and detailed thermodynamic or electrical equations, often treating occupants as passive elements with static profiles. Table 1 provides a comparative overview of widely used traditional energy simulators, highlighting their primary focus, temporal resolution, and limitations regarding occupant modeling.

2.2. Smart home and agent-base frameworks

Agent-based frameworks enable the representation of autonomous entities, such as occupants or devices, with memory, internal states, and decision rules, allowing for the emergence of complex behaviors in dynamic environments. Table 2 details prominent agent-based simulation frameworks frequently used in smart home modeling, comparing their physical modeling capabilities, behavioral resolution, and general extensibility.

While traditional simulators offer high fidelity in modeling the building's physics, their primary limitation is the reliance on simplistic, static occupancy schedules. These schedules fail to capture the dynamic and stochastic nature of actual user behavior, leading to a significant *performance gap* between simulated predictions and real-world energy consumption. ABM platforms address this specific limitation by representing individual occupant routines and decisions. HABITAS aims to bridge this gap by combining high-resolution energy modeling with agent-based behavior emulation, offering a hybrid solution that captures both system dynamics and occupant heterogeneity in smart homes.

3. HABITAS design overview

HABITAS is a software framework [25] designed to model energy and resource consumption in smart home environments, covering solar generation, battery management, appliance usage, water consumption, and environmental monitoring. It supports both fast-forward and real-time simulation modes, as summarized in Table 3.

A key feature is its occupant-driven approach: agents are modeled with individualized physiological needs (hunger, hygiene, energy, fun) and personal schedules (work, school, leisure), triggering realistic actions such as cooking or showering that directly drive electricity and water consumption. The simulator also accounts for out-of-home periods, and its modular architecture supports integration with external data sources such as live solar irradiance APIs.

4. Implementation and methodology

HABITAS implements an agent-based modeling simulation engine within a hierarchical system architecture. The resulting design merges agent-centric behavioral modeling with modular subsystems for energy, water, and environment management. The unified architecture enables both long-term fast-forward experiments and real-time operational monitoring while preserving traceable, timestamped outputs for analytics and validation.

4.1. Architecture and multimodal operation

The system architecture follows a hierarchical design pattern, as shown in Fig. 1, where a central orchestrator coordinates interactions between specialized modules for energy management and occupant behavior simulation. The architecture supports a flexible dual-mode operational paradigm:

Table 1
Comparative overview of traditional energy simulation tools.

Feature	EnergyPlus	TRNSYS	PVsyst	BESOS	Modelica	BOBTEST	HABITAS
Main Focus	Building energy, HVAC, lighting	Transient systems, thermal/solar	PV generation	Optimization of simulations	Control systems, thermal/HVAC, DR	Building control benchmarking	Behavior + energy
Occupant Modeling	Static schedules	Predefined behavior via components	None	Low (via EnergyPlus)	None	Static schedules	Agent-based simulation
Temporal Resolution	Sub-hour (configurable)	Sub-hour (fixed)	Hourly	Hourly	Sub-second to hourly	Sub-hour	5-minute
DR Support	Limited	Limited	No	Limited	Yes (control models)	Yes (native)	Yes (agent behavior)
ML Support	No	No	No	Yes (surrogates)	Limited (via FMI)	Yes (via RL)	Planned
Customizability	Medium (IDF)	High (modular)	Low	High (Python API)	High (eq.-based)	High (API)	High (agents)
License	BSD (DOE)	Commercial	Commercial	Open source	Open source	Open source	Open source

Table 2
Comparative overview of agent-based simulation frameworks for smart home modeling.

Feature	NetLogo	Mesa	Repast	AnyLogic	GAMA	GridLAB-D	HABITAS
Agent Architecture	Basic state–behavior (NetLogo)	State/rules (Python)	Social & spatial (Java)	Hybrid ABM/DES/SD (Java)	Spatial, layered (GAML)	Node-level loads (C++)	Multi-layer needs/memory (Python)
Smart Home Support	No (generic)	No	No	Partial (manual)	No	Yes (grid-aware)	Yes (home layout, appliances)
Physical Modeling	None	None (extendable)	None (can couple)	Medium (modular)	Basic (scripting)	High (electrical, tariff)	High (solar, battery, water)
Behavioral Resolution	Low	Medium	Medium–High	High	Medium	Medium (load profiles)	High (5-min, contextual)
Extensibility	High (GUI)	High (Python)	High (Java)	High (Java/UI)	Medium	Medium (C++)	High (JSON + Python)
Learning Curve	Very Low	Low	Medium	High	Medium	High	Medium
Visualization	Yes (GUI)	Yes (Jupyter)	No (external)	Yes (dashboard)	Yes (map layers)	No (CSV)	No (JSON output)
License	GPL	BSD	BSD	Commercial	GPL3	BSD/DOE	GPL-3.0

Table 3
HABITas operational modes and capabilities.

Feature	Fast-Forward	Real-Time	Common
Time Resolution	5-min intervals	5-min updates	Configurable
Data Source	Historical/forecasted	Live data feeds	User-defined
Use Case	Long-term analysis	Live monitoring	Consumption modeling
Duration	Days to weeks	Continuous	Flexible
Output	JSON timestamped	JSON timestamped	Comprehensive metrics

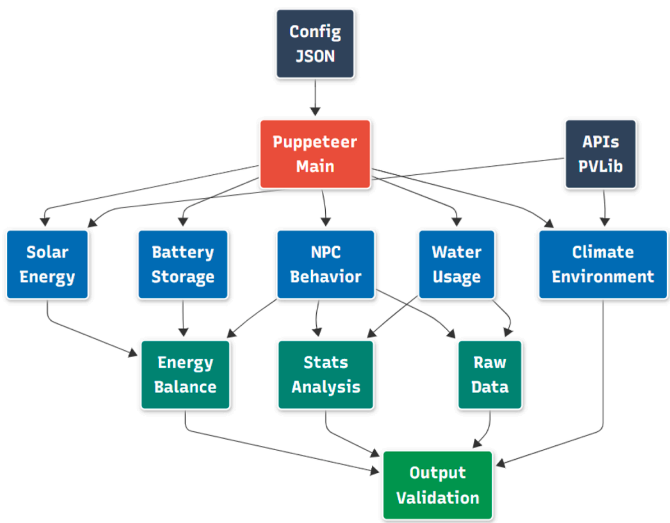

Fig. 1. General architecture of the HABITAS framework. The flow of information begins with initialization parameters (Config JSON) and external weather data (APIs) feeding into the central orchestrator (Puppeteer Main). The orchestrator synchronizes 5-minute ticks across all simulation subsystems (teal). Device usage and generation data flow downward into the analytics layer (blue) to compute the energy balance and statistical metrics, ultimately merging into timestamped JSON validation outputs (green). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

- **Fast-forward simulation**: Accelerated time-based simulation over extended periods (weeks to months) with configurable high-resolution timesteps, enabling long-term behavioral and resource-use studies.
- **Real-time simulation**: Immediate operational modeling synchronised to wall-clock time for monitoring and control applications.

Time management and synchronization is central to system correctness: the orchestrator algorithm enforces timestamp synchronization across all modules and uses ISO-format timestamps with timezone awareness for international compatibility. The central orchestration is managed through the `puppeteer.py` script, which serves as the primary integration hub for multiple external and internal data sources. This orchestration layer seamlessly incorporates solar irradiance data (e.g., via *pvlib*), implements battery state-of-charge and efficiency models for energy storage simulation, and provides real-time analytics capabilities for resource consumption monitoring and anomaly detection.

4.2. Core module structure and agent integration

The system is organized into modular subsystems that interact with the ABM engine.

4.2.1. Central orchestration layer

The main orchestration module serves as the system's backbone, implementing the primary simulation control logic and data integration pipeline. The current functions are:

- Defines the operational modes.
- Controls simulation clock advancement with configurable timestep resolution.
- Coordinates module lifecycle events (initialisation, time steps, shutdown).
- Implements data pipelines for timestamped inputs/outputs and persistent state snapshots.
- Provides APIs for both internal modules (energy, water, environment, agents) and external data sources (weather/irradiance APIs).

Timestamp synchronization, timezone-aware ISO timestamps, and standardized JSON-based state dumps are core responsibilities. The default granularity was chosen because it balances behavioral fidelity with computational tractability, enabling multi-week/month runs without prohibitive overhead. The implementation supports both single-process runs for smaller experiments and distributed/parallelised execution for large synthetic populations (extension hooks provided in the orchestrator).

4.2.2. Energy management subsystem

The energy management implementation consists of three interconnected components whose state and actions are driven by both device-level usage generated by agents and external data:

Solar Energy Production: The PV module calculates generation using clear-sky Global Horizontal Irradiance (GHI, in W/m^2) derived from the *pvlib* library. Assuming standard atmospheric conditions without cloud cover masking, the power output P_{pv} (in kW) is calculated as:

$$P_{pv}(t) = \frac{GHI(t) \cdot A_{panel} \cdot N_{panels} \cdot \eta_{pv}}{1000}$$

where A_{panel} is the surface area of a single panel (in m^2), N_{panels} is the total number of panels, and η_{pv} represents the module's conversion efficiency. The energy generated $E_{pv}(t)$ (in kWh) over the interval Δt (in hours) is bounded by $E_{pv}(t) = P_{pv}(t) \cdot \Delta t$.

Battery Management System: The battery capacity is first normalized from Ampere-hours (C_{Ah}, in Ah) to kilowatt-hours (C_{kWh}, in kWh) using the nominal voltage (V_{nom}, in V):

$$C_{kWh} = \frac{C_{Ah} \cdot V_{nom}}{1000}$$

The net available energy $E_{net}(t) = E_{pv}(t) - E_{load}(t)$ (in kWh) dictates the charge or discharge state. The change in the State of Charge, $\Delta SOC(t)$ (expressed as a dimensionless fraction), considers charging efficiency (η_c), discharging efficiency (η_d), and conversion losses (l_{conv}):

$$\Delta SOC(t) = \begin{cases} \frac{E_{net}(t) \cdot \eta_c \cdot (1 - l_{conv})}{C_{kWh}}, & \text{if } E_{net}(t) > 0 \\ \frac{E_{net}(t)}{C_{kWh} \cdot \eta_d \cdot (1 - l_{conv})}, & \text{if } E_{net}(t) \leq 0 \end{cases}$$

The battery SOC is then updated and strictly bounded between 0 and 1:

$$SOC(t) = \max\left(0, \min\left(1, SOC(t-1) + \Delta SOC(t)\right)\right)$$

The system concurrently tracks cumulative cycles (ΔSOC) and time-based degradation to update the battery's state of health history.

Grid Integration Logic: The net grid power requirement $P_{grid}(t)$ (in kW) is computed by aligning the timestamped electrical load $P_{load}(t)$ (in kW) against the available PV generation $P_{pv}(t)$ (in kW):

$$P_{grid}(t) = P_{load}(t) - P_{pv}(t)$$

In this formulation, a positive $P_{grid}(t)$ indicates net grid import (consumption), while a negative value signifies grid export (feed-in).

4.3. Agent architecture and behavioral modeling

Agents implement a decision model in which physiological variables (hunger, energy, hygiene and recreation) evolve over time and trigger probabilistic action selection based on urgency and context [26–28]. Each autonomous agent encapsulates a unique demographic profile

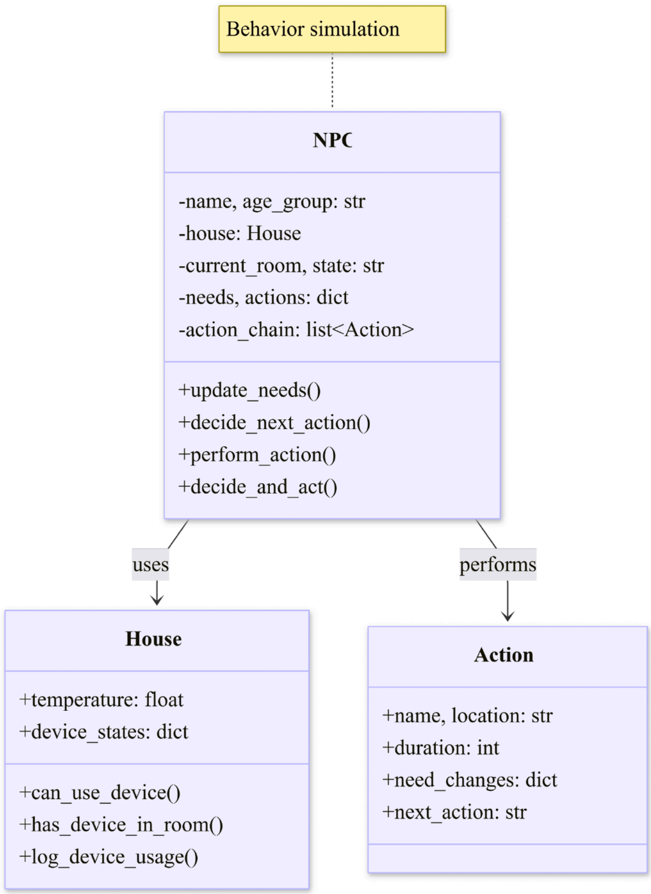

Fig. 2. UML-style diagram of the agent class.

and personal routine, yet competes with the rest of the household for shared appliances and spaces. Every agent is initialised with four components that work together to create realistic household behavior. This is reflected in the Agent class. In Fig. 2, it can be observed that personal attributes form the foundation of each agent's identity, including the agent's name, life-stage cohort (child, teenager, adult, or elderly), a configured daily sleep schedule, and pre-scheduled periods of time spent outside the home that reflect real-world work and social commitments.

The internal state continuously tracks hunger, energy, hygiene and fun, each normalized from 0 to 100, alongside spatial information such as the current room location and temporal flags indicating the ongoing action, its remaining duration, and the agent's sleep status. Behavioral rules provide the decision-making framework that governs what actions each agent may perform based on their age and current circumstances, while also defining critical threshold values that determine when physiological needs should trigger specific behaviors. The memory module maintains a comprehensive log of recent action sequences, timestamps of significant events and a detailed record of device usage throughout the day.

4.3.1. *Agent decision-making and behavioral model*

To overcome the limitations of static operational schedules, HABITAS implements a dynamic, autonomous decision-making engine for each simulated occupant. The algorithm utilizes a hybrid mathematical framework combining homeostatic drive-reduction theory with Random Utility Theory (RUT) [29]. In this paradigm, actions proactively compute their utility based on the agent's real-time physiological state and contextual environment, allowing complex daily routines to emerge stochastically rather than deterministically. The overall decision flow is illustrated in Fig. 3.

Agent State Space and Homeostatic Decay. At any discrete time step t, the internal physiological state of an agent i is defined by a vector of normalized needs:

$$\mathbf{n}_i(t) = \begin{pmatrix} n_{\text{hunger}} \\ n_{\text{energy}} \\ n_{\text{hygiene}} \\ n_{\text{fun}} \end{pmatrix} \in [0, 100]^4 \tag{1}$$

The evolution of these needs is governed by non-linear decay functions that accelerate as the agent's condition worsens, simulating biological urgency [26,28]. The discrete-time update for a given need k is formulated as:

$$n_k(t+1) = \max\left(0,\ n_k(t) - \beta_k \cdot \gamma_k(h) \cdot \phi_k(n_k)\right) \tag{2}$$

Where β_k represents the baseline decay rate specific to each physiological drive, $\gamma_k(h)$ is a circadian multiplier dependent on the current hour of the day [30] $h \in [0, 24)$, and $\phi_k(n_k)$ introduces a non-linear scaling factor based on the current saturation of the need. Furthermore, biological imperatives such as bladder urgency are modeled as forced-interrupt mechanisms. If the time elapsed since the last restroom use (τ_{toilet}) exceeds a critical threshold, it overrides the standard utility evaluation to enforce immediate action.

Utility Evaluation (Advertising Score). Agents do not follow rigid schedules; instead, at each Δt, the environment presents a finite set of available actions $\mathcal{A}$. Each action $a_j \in \mathcal{A}$ projects a state-change vector δ_j, representing its expected impact on the agent's needs. The base utility of an action $U_{\text{base}}(a_j)$ is dynamically computed based on how effectively it addresses the agent's most critical deficits:

$$U_{\text{base}}(a_j) = \sum_{k \in \mathcal{N}} f_k(\delta_{j,k},\ n_k) \tag{3}$$

The function f_k ensures that an action restoring a severely depleted need yields an exponentially higher utility than one addressing a satisfied need. To capture real-world human behavior, this base utility is subjected to contextual heuristics: appliance interaction bonuses (B_{device}), temporal and circadian peak modifiers ($C(a_j, h)$), and emergency overrides for extreme state thresholds ($C_{\text{emergency}}$). The final comprehensive utility score $U(a_j)$ is formulated as a multiplicative composition:

$$\begin{aligned} U(a_j) = \max\Big(0, &\big(U_{\text{base}}(a_j) + B_{\text{device}}(a_j)\big) \\ &\cdot \mu_{\text{urgency}} \cdot C(a_j, h) \\ &\cdot C_{\text{emergency}}(a_j) \cdot \alpha_{\text{age}}(a_j)\Big) \end{aligned} \tag{4}$$

Where α_{age} acts as a demographic filter.

Stochastic Selection and Action Chaining. To prevent deterministic loops and mirror human unpredictability, HABITAS avoids greedy selection. Instead, it employs weighted random sampling among the top-K scoring actions. The probability of selecting an action a_j from this subset is:

$$P(a_j \mid \text{top-}K) = \frac{U(a_j)}{\sum_{a_l \in \text{top-}K} U(a_l)} \tag{5}$$

Once an action is probabilistically selected, the simulator translates the behavioral choice into physical energy demand. The electrical consumption E_d over the active duration Δt_{active} is registered by the energy module:

$$E_d = \frac{P_d \cdot \Delta t_{\text{active}}}{3{,}600{,}000} \quad [\text{kWh}] \tag{6}$$

Where P_d is the rated power of the utilized device (in Watts) and Δt_{active} is the duration of the action in seconds.

To optimize computational overhead, the model implements action chaining, where high-level activities automatically enqueue coherent logical successions (e.g., cook → eat → use_dishwasher), bypassing the utility evaluation loop until the chain concludes.

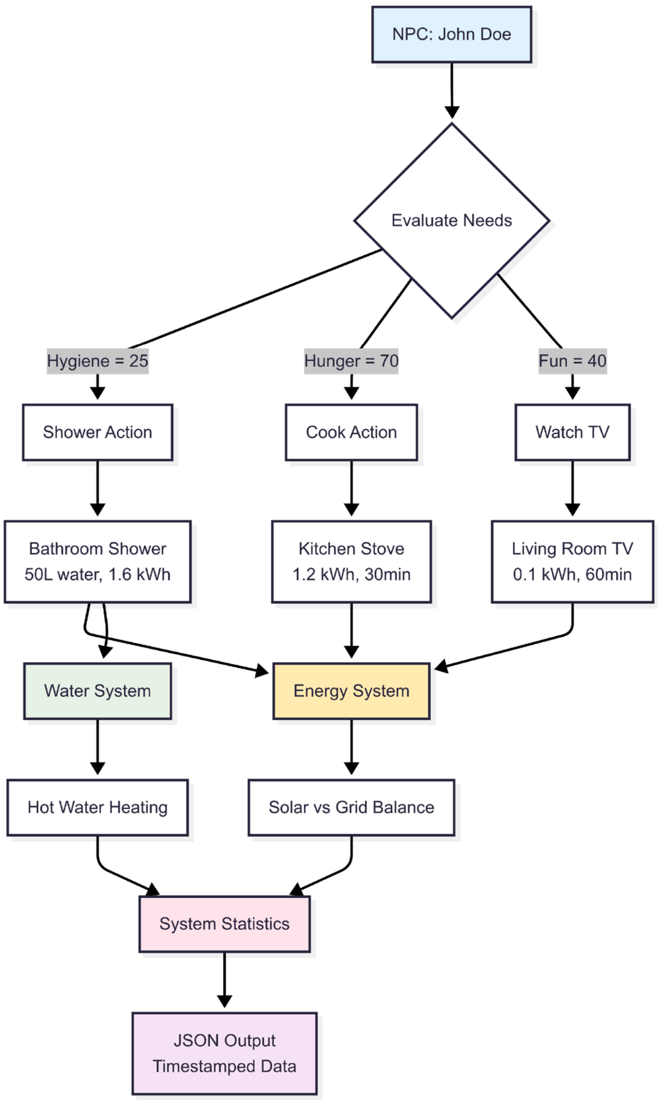

Fig. 3. Example agent decision-making flowchart showing the evaluation of needs, action selection, and system resource tracking for smart home simulation.

4.4. Action system

HABITAS implements sixteen actions distributed across six functional categories. These categories encompass physiological needs such as eating, sleeping, and toilet usage; hygiene activities like showering and brushing teeth; domestic chores including cooking and cleaning; entertainment options such as watching TV or reading; external activities like jogging and shopping; and social or educational tasks, namely studying and phone calls.

Each action is strictly parameterized with typical duration ranges, device and location requirements, and specific age-group permissions. The system also defines the physiological effects on internal state variables alongside precise electricity and water consumption values.

To prevent conflicts, device contention is enforced through locks restricted to a single user per device, meaning actions trigger device reservations managed by the orchestrator.

4.5. Smart home structure

The `House` class represents the built environment (rooms, appliances, on-site energy/water infrastructure). Room definitions (bathrooms, kitchen, living room) and a catalogue of appliances (showers, sinks, toilets, stoves, TVs, computers) are configurable via the local configuration. Real-time state tracking prevents device conflicts, enforces usage limits and accumulates consumption metrics for each subsystem.

4.5.1. Resource management and constraints

To preserve physical realism, the simulator enforces several operational constraints.

The primary constraint is device contention, which strictly allows only one agent per device at a time, supplemented by daily usage limits and caps required for maintenance. Additionally, the system applies precise resource models, calculating energy consumption derived from device-rated wattage and actual runtime, while water modeling is based on either per-minute flow rates or per-use volumes.

Ultimately, these constraints feed the scheduler within the orchestrator, which validates resource reservations, queues requests, and resolves contention using priority rules derived directly from the agents' utility scores.

4.6. Configuration management system

A comprehensive configuration system using JSON parameterizes the entire simulation, allowing extensive adjustments without any code modification. The major configuration blocks define the physical environment, including house physical parameters such as room counts, volumes, and layout definitions. Within this environment, occupant profiles establish the demographic cohort, daily schedules, individual preferences, and behavioral parameters. The system also requires detailed device specifications that cover power consumption, water flow rates, usage constraints, and efficiency parameters.

Finally, the broader infrastructure is defined through the energy system configuration, which details solar panel specifications, battery characteristics, and grid connection parameters, all complemented by an emission factor database containing carbon footprint coefficients for environmental impact assessment.

Configuration files are loaded at system startup and may be reloaded in real time operation mode for experimentation.

4.7. Model applications in energy management

The high temporal resolution and behavioral modeling of HABITAS enable diverse applications in demand response, energy optimization, and policy analysis. By modeling heterogeneous occupant responses to price signals and physical constraints, the framework provides realistic estimates of demand flexibility. Furthermore, integrating distributed energy resources (solar, batteries) with agent-driven consumption allows for the evaluation of self-consumption rates and peak-shaving algorithms. Ultimately, its modular architecture supports macro-level scenario modeling to assess regulatory frameworks, tariff structures, and energy efficiency programs without risking real-world deployments.

5. Simulation parameters

Simulator parameters define the temporal structure, agent characteristics, internal state evolution, action-device mapping, and energy models.

The calibration of the behavioral model parameters, including need-decay rates, utility thresholds, and stochastic selection weights, was conducted through a heuristic, literature-driven approach. Initial baseline values for physiological decay and circadian multipliers were extracted from behavioral studies [30,31] and time-use surveys [32,33]. These parameters were then iteratively fine-tuned to ensure that emergent actions align with established domestic routines. Similarly, the stochastic decision rules, specifically the top-K probability weights, were adjusted through iterative testing to prevent deterministic action loops while preserving natural behavioral heterogeneity. To ensure full reproducibility,

Table 4
Comprehensive overview of HABITAS simulation parameters [24,30,32–34].

Parameter	Default	Range	Description
Global Simulation Settings			
Simulation type	`fast_forward`	`{real_time, fast_forward}`	Execution mode
Temporal boundaries	N/A	ISO format	Start/end dates for fast-forward
Sampling rate	300 s / 5 min	60–3600 s / 1–60 min	Update and data collection frequency
Actions in minutes	true	{true, false}	Duration specification unit
Agent Profiles & Need Decay Rates			
Age group	`adult`	`{child, teen, adult, elderly}`	Behavioral category
Initial state needs	`random`	0–100%	Initial levels: hunger, energy, hygiene and fun
Hunger decay	1.0–3.0%/h	Morning: 2.0×, Eve: 2.5×	Higher decay at meal times
Energy decay	0.8–2.5%/h	Morning: 0.5×, Eve: 2.0×	Lower after sleep; higher when tired
Hygiene decay	0.5–1.5%/h	Morning: 1.5×, Eve: 1.2×	Small increase before sleep
Fun decay	0.3–1.0%/h	Evening: 1.8×, Wknd: 1.3×	Higher evenings and weekends
Electrical Devices & Actions			
Stove	2000 W	20–60 min (Max 3/day)	Dinner: 0.9, Morning: 0.4
Microwave	1000 W	2–8 min (Max 3/day)	Midday: 0.7, Morning: 0.5
Kettle	1500 W	1–3 min (Max 4/day)	Morning: 0.9, Midday: 0.5
Computer	120 W	90–300 min (Max 4/day)	Evening: 1.0, Midday: 0.8
TV	80 W	120–360 min (Max 3/day)	Evening: 0.95, Night: 0.7
Washing machine	500 W	45–90 min (Max 0.25/day)	Evening: 0.4, Midday: 0.3
Energy Resources (Solar PV & Battery)			
Solar PV panels	4 units, 20% eff.	1–50 units, 15–25%	1.5 m^2 per panel
Battery Information	50 Ah, 48 V	10–500 Ah, 12–48 V	Main storage parameters
Initial SoC & Degradation	80%, 2%/yr	0–100%, 1–5%/yr	Starting charge and annual capacity loss
System efficiencies	95%	80–98%	Charge/discharge efficiencies
Conversion loss	2%	1–10%	AC/DC conversion loss

the calibrated parameter profiles are openly available in the project's repository [25].

A comprehensive overview of all configuration defaults, operational ranges, and usage patterns is consolidated in Table 4. These parameters are categorized as follows:

- **Global simulation parameters:** The global setup defines the temporal resolution, duration, number of households, and the number of random seeds for stochastic replication. These parameters allow the user to scale experiments from a single household to larger populations while preserving comparability.
- **Agent parameters:** Each household is populated by agents representing individuals (children, teenagers, adults, elderly). Agents are characterized by physiological thresholds (hunger, hygiene, fun), daily schedules (sleep, work/school), and decay rates that determine how needs evolve over time. These parameters govern when and why agents trigger actions, resulting in emergent load profiles [30,31].
- **Need decay rates:** The evolution of each agent's state is modeled through exponential or linear decay functions that reduce hunger, hygiene, and fun levels over time. Different cohorts may use distinct ranges, allowing the model to capture heterogeneity in habits. The decay rate defaults and time multipliers are aligned with behavioral studies [32].
- **Devices and actions:** Actions available to agents are tied to household devices, each with specific power demands, typical durations, and restrictions (e.g., maximum daily frequency, eligibility by cohort). This mapping ensures that agent behavior translates directly into energy and water consumption patterns. Device and action parameters are derived from high-resolution demand models [24,33].
- **Energy resources:** Finally, HABITAS integrates physical models of photovoltaic (PV) generation, battery storage, and grid interaction. These components provide the necessary infrastructure to evaluate self-consumption, flexibility, and peak-shaving strategies under diverse conditions.

6. Plausibility assessment

HABITAS has been evaluated by analyzing its ability to generate daily consumption patterns that are both consistent across stochastic seeds and coherent with expected household behavior. The goal is to demonstrate plausibility and robustness through statistical and visual analysis.

6.1. Single day consumption profile analysis

Fig. 4 presents the simulated weekday electricity consumption. The analysis reveals distinct daily behavioral patterns. Overnight power consumption remains near baseline levels of 0.3 kW, corresponding to standby loads such as refrigeration and idle electronics. A primary demand peak occurs in the early morning, roughly between 06:30 and 08:00, driven by cooking and dish-washing activities before occupants leave for work and school, reaching approximately 2.5 kW. After that, daytime consumption drops back to baseline levels, confirming the absence of residents. In the evening, a second pronounced cooking peak appears around 18:00 to 19:00, again exceeding 2.5 kW. This is followed by moderate consumption during leisure activities in the late evening before gradually returning to the baseline at night. These defined peaks reflect the strong behavioral regularity characteristic of working-family weekday routines.

6.2. Variability across simulations

Fig. 5 illustrates the variability bands of electrical consumption for the *simpson_smart_home*, computed from multiple simulated weekdays. The solid red line denotes the median consumption, while the dashed orange line represents the mean profile. The shaded regions correspond to the interquartile range, spanning from the 25th to the 75th percentile, as well as the wider 10 to 90 percent probability band.

The profile shows two distinct peaks that coincide with household activity periods. The first peak occurs around 06:30-08:00, associated with

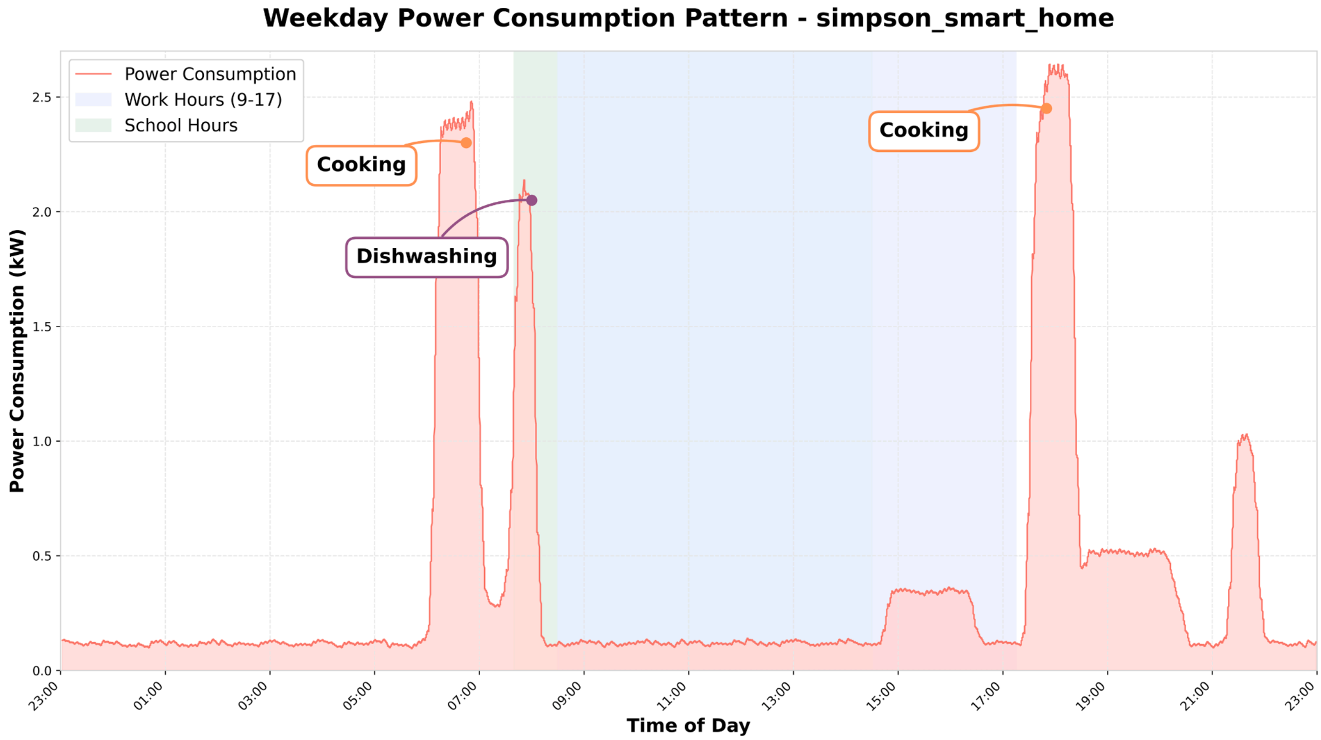

Fig. 4. Electricity consumption analysis showing daily consumption profile for a three-person household with occupancy patterns indicated by shaded regions.

morning routines such as cooking and dishwashing before occupants leave for work and school. The second, broader peak between 18:00 and 21:00 corresponds to evening activities, primarily meal preparation and leisure usage of appliances.

During daytime hours (09:00-17:00), the profile remains close to baseline consumption levels of approximately 0.03-0.04 kWh per simulation interval, reflecting standby loads from refrigeration and other always-on devices. The larger evening IQR indicates higher variability across simulations, suggesting greater behavioral heterogeneity in post-work routines. Overall, the variability pattern aligns with typical weekday occupancy-driven consumption behavior.

6.3. Annual seasonality analysis

A full-year simulation was conducted to demonstrate the framework's long-term execution capabilities. Fig. 6 illustrates the daily total electricity consumption overlaid with a 30-day moving average to highlight seasonal trends.

The data exhibits a clear seasonal curve, peaking in winter and dipping in summer [35]. This seasonality organically emerges from behavioral and environmental factors: shorter winter daylight increases lighting demand, colder temperatures require more energy for hot water [36], and occupants spend more time on indoor leisure activities compared to summer [35]. This confirms that the simulator can produce plausible long-term macro-trends.

6.4. Distributional properties

Fig. 7 summarizes the distributions of total daily consumption, peak magnitudes, hourly variability, and probability of exceeding demand thresholds.

To assess the plausibility of the generated profiles, the simulated daily consumption was compared against real-world estimates for equivalent households. According to official data from the Institute for the Diversification and Saving of Energy (IDAE) [37], three-member households in Spain present an average non-thermal electricity consumption of 2,765 kWh annually. When incorporating seasonal thermal loads, the estimated total average consumption for a 3-person family falls within the range of 8 to 11 kWh per day, as reported by energy sector estimates. HABITAS generated a median daily consumption of 13.43 kWh. This value sits slightly above the upper bound of this statistical average, which is expected for a fully equipped smart home [34]. Therefore, these results show that the simulator produces robust and plausible consumption load shapes, accurately reflecting the expected peaks and variability of residential behavior.

Peak magnitudes fall between 0.16 and 0.24 kWh per timestep (equivalent to 2–3 kW), which is typical of cooking or simultaneous appliance usage. Boxplots of hourly demand highlight low dispersion during nighttime and significantly higher variability during morning and evening activity periods.

Finally, the probability curve shows that all simulations exceed 0.14 kWh per timestep at least once, about 50% surpass 0.17, and only 20% reach 0.22–0.24, which matches the expected stochastic nature of residential demand peaks.

Overall, the simulator produces daily load profiles with stable baselines, realistic peak magnitudes, and variability consistent with residential behavior.

7. Case study: optimizing energy allocation

To demonstrate the practical applicability of HABITAS as a data-generation engine, we conducted a case study focused on dynamic energy allocation within a Citizen Energy Community (CEC). The objective was to validate whether the synthetic profiles generated by the simulator contained sufficient behavioral complexity to train and differentiate between competing forecasting algorithms.

7.1. Experimental scenario and methodology

We configured a heterogeneous community consisting of six distinct households to generate a diverse dataset. The simulator was parameterized to reflect different demographics, ranging from a high-

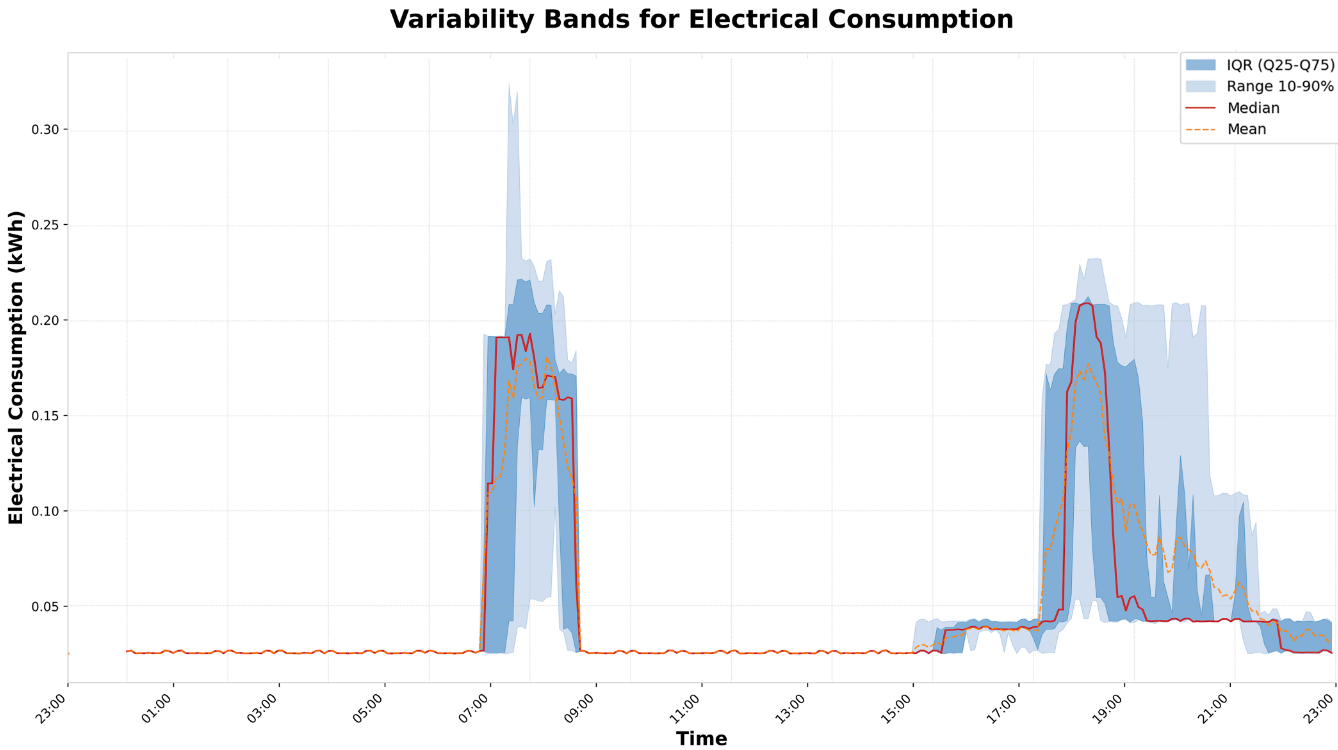

Fig. 5. Variability band of the simulated electrical consumption across 20 seeds. The median (solid red) and mean (dashed orange) curves are shown together with the interquartile range (blue) and the 10–90% band (light blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

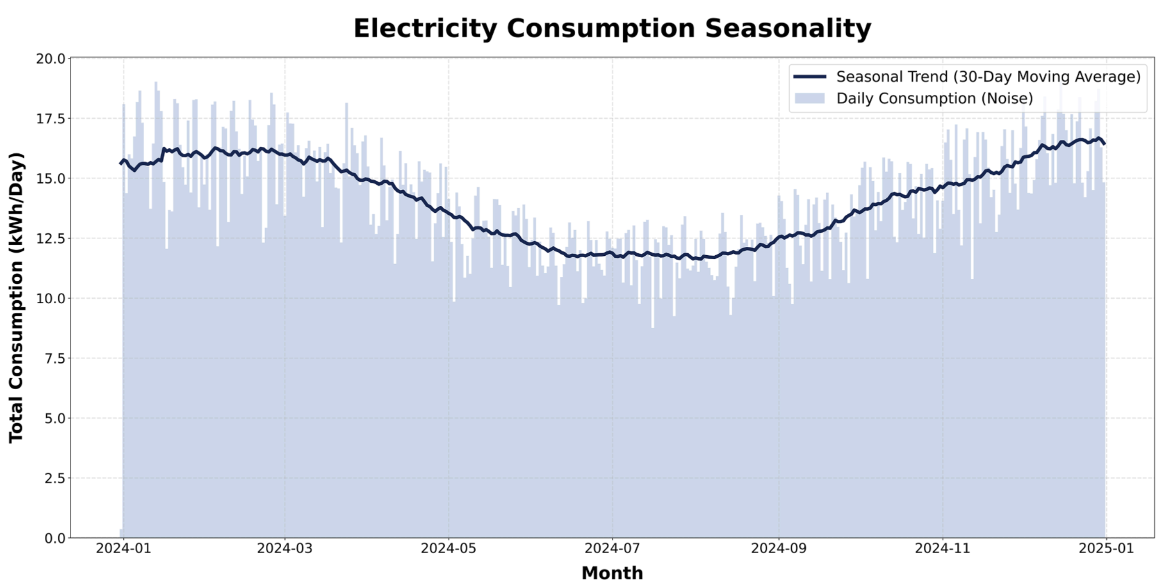

Fig. 6. Total daily electricity consumption over a simulated one-year period, demonstrating emergent seasonal trends via a 30-day moving average.

consumption household (House 1: 5 occupants, elderly presence, approx. 17 MWh/year projected) to smaller, energy-efficient units (House 3: 2 occupants, approx. 3.7 MWh/year projected) [38]. The simulation executed from January 1st to March 7th, 2023, producing high-resolution data aggregated into hourly intervals.

To evaluate the utility of this data for algorithmic training, We implemented two contrasting forecasting methodologies. The specific implementation details are as follows:

- **Holt-Winters Seasonal Approach:** This method was implemented using the `statsmodels` Python library. We selected an *additive* model structure to capture constant seasonal variations. Based on an Autocorrelation Function (ACF) analysis of the HABITAS-generated data, which revealed a dominant weekly cycle, the seasonal period was explicitly set to 168 hours. The smoothing parameters (α, β, γ) were automatically optimized using the library's estimation routine.
- **XGBoostLSS:** We utilized the XGBoostLSS extension to perform probabilistic forecasting. The model was configured to output a *Dirichlet distribution*, ensuring that the predicted allocation coefficients naturally sum to one. The input data consisted of 54 engineered features, including cyclical temporal encoding, lagged con-

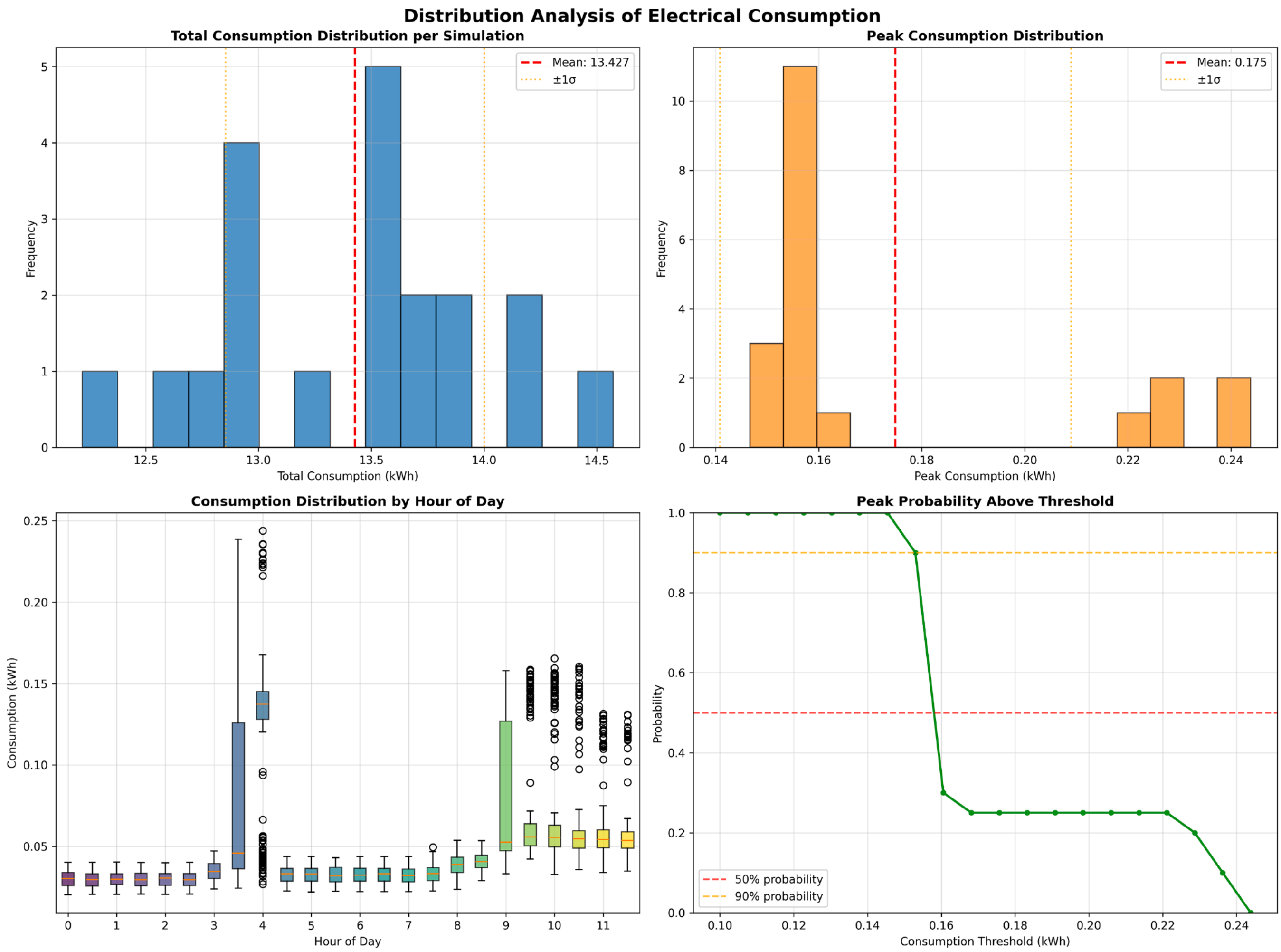

Fig. 7. Distributional analysis: (top-left) total daily energy, (top-right) peak magnitudes, (bottom-left) hourly distributions, (bottom-right) probability of exceeding demand thresholds.

sumption values (1-6 hours), and rolling window statistics (24h and 48h means). Hyperparameter tuning (e.g., learning rate, max depth) was conducted via Bayesian optimization using the `Optuna` framework over 200 trials [38].

7.2. Comparison with DR forecasting literature

HABITAS forecasting results align with residential demand response (DR) literature, confirming that gradient boosting systematically outperforms seasonal baselines [39]. While [39] reports a 9.68% MAPE on real smart meter data, the higher error observed is expected due to metric differences (SMAPE vs. MAPE).

Furthermore, capturing occupant dynamics is essential for realistic DR simulations, as standard deterministic or purely stochastic schedules fail to reproduce real low-voltage variability [40]. HABITAS addresses the challenge of limited intra-daily prediction accuracy at low aggregation levels through its needs-driven, probabilistic agent architecture and configurable demographic profiles.

7.3. Results and validation

The experiment demonstrated that the data produced by HABITAS exhibits non-linear dynamics and complex behavioral patterns that challenge simple statistical models. As shown in Table 5, the Machine Learning approach (XGBoostLSS) significantly outperformed the traditional method across all metrics.

Table 5
Forecasting performance on simulated data.

Metric	Holt-Winters	XGBoostLSS
MAE	0.023	**0.016**
RMSE	0.031	**0.022**
SMAPE	19.50%	**13.89%**
MASE	0.240	**0.167**

Lower values indicate better performance.

The simulator successfully replicated the stochastic nature of human behavior, such as irregular cooking times or distinct work schedules, allowing the XGBoostLSS model to leverage its 54 input features (e.g., lagged consumption, rolling statistics) to capture patterns that Holt-Winters missed. This case study confirms that HABITAS is not merely a visualizer, but a robust source of synthetic data valid for training and validating complex energy management algorithms. Gallinad et al. [38]

8. Discussion

8.1. Model applications in energy management

The temporal resolution and behavioral modeling implemented in HABITAS enable applications in demand response and energy optimization contexts. The configured timestep captures household activity dynamics, providing data on load peak magnitudes and timing patterns that inform grid stability and storage management analyses.

For demand response applications, HABITAS can model occupant responses to price signals or load control mechanisms through its agent decision-making framework. The heterogeneous agent profiles allow analysis of demographic variations in response patterns, enabling assessment of program targeting strategies. The simulator's modeling accounts for physical constraints on simultaneous load modifications, providing estimates of achievable demand flexibility under realistic operational conditions.

For energy optimization studies, HABITAS integrates distributed energy resources with agent-driven consumption patterns. The solar generation and battery storage models combined with occupant behavior profiles enable analysis of self-consumption rates, peak reduction potential, and grid interaction patterns. The framework supports evaluation of energy management algorithms that must balance technical optimization objectives with occupant behavioral constraints.

The modular architecture supports policy analysis through scenario modeling under different regulatory frameworks, tariff structures, or technology deployment rates. The simulator can model aggregate effects of individual household decisions, providing data for evaluating energy efficiency programs or renewable energy policies.

However, the practical application of these capabilities depends on addressing the model's current limitations, which constrain its applicability to certain research questions and operational contexts.

8.2. Model limitations

HABITAS does not incorporate socioeconomic variables that affect energy consumption patterns. Factors such as household income, education levels, environmental awareness, or technology adoption rates are not represented in the agent decision-making processes, limiting its ability to represent the full range of behavioral patterns across different demographic segments.

The simulator is specifically optimized for non-thermal household electricity and water consumption driven by occupant behavior. While room-level occupancy is tracked, it does not model thermal dynamics, spatial temperature distributions, or HVAC systems. Assessments involving whole-building heating or cooling energy loads therefore fall outside the simulator's baseline capabilities and would require future thermal modeling extensions.

These limitations point toward specific areas where model extensions could expand the framework's applicability and improve its representation of household energy dynamics.

8.3. Future development directions

Several extensions could address current limitations and expand HABITAS capabilities. Priority enhancements include electric vehicle modeling, covering charging behavior, travel patterns, and vehicle-to-home energy flows, and the integration of building thermal dynamics to address HVAC and occupant comfort. Long-term dataset development would enable studies of seasonal patterns, holiday effects, and behavioral evolution over time. Machine learning integration could allow agents to adapt their decision-making based on historical patterns and changing conditions, while community-scale extensions would support peer-to-peer energy trading, shared storage, and neighborhood-level coordination strategies.

While HABITAS currently tracks basic environmental parameters, it lacks specific occupant comfort metrics. Future iterations will integrate a simplified Predicted Mean Vote (PMV) index by mapping agent activities to metabolic rates. This will enable basic comfort-cost trade-off analyses without requiring complex spatial thermal modeling.

To foster continuous development and community contribution, the HABITAS source code and documentation are publicly hosted on GitHub [25]. Bug tracking, feature requests, and future extensions are actively managed through the repository's issue-tracking system.

Furthermore, integrating prescriptive techniques and advanced artificial intelligence represents a highly promising avenue for future holistic smart home simulations. Recent advancements demonstrate the value of this approach, such as the use of digital twins for prescriptive appliance management [41], the application of Large Language Models combined with behavioral modeling to guide energy-efficient usage [42], and the simulation of power consumption anomalies like appliance malfunctions [43]. While HABITAS currently focuses on baseline behavioral emulation, coupling its high-resolution physical modeling with these emerging prescriptive and anomaly-detection frameworks could significantly enhance its predictive and advisory capabilities in future iterations.

The implementation of these extensions would require systematic validation approaches to ensure that increased model complexity maintains or improves predictive accuracy. The development trajectory would benefit from integration with empirical studies to validate behavioral assumptions and parameter values across different household types and geographic regions.

9. Conclusion

This paper presents HABITAS, an agent-based simulation framework for modeling energy consumption in smart home environments. By representing occupants as autonomous agents with individualized needs and schedules, and integrating physical models of PV generation, battery storage, and grid interaction, HABITAS produces high-resolution consumption profiles that maintain plausibility over daily and extended periods, with characteristic morning and evening peaks consistent with established residential benchmarks.

The modular, JSON-driven architecture provides a flexible platform for demand-response evaluation, battery storage optimization, energy policy analysis, and smart home algorithm development. The case study on Citizen Energy Community allocation further demonstrates its utility as a synthetic data generation engine capable of producing behaviorally complex profiles for training and validating forecasting algorithms. Future work will focus on adaptive learning mechanisms, EV integration, thermal modeling, and community-scale extensions.

CRediT authorship contribution statement

Ramon Gallinad: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization; **Sebastian Madrigal:** Writing – original draft, Visualization, Validation, Supervision, Investigation, Formal analysis, Conceptualization; **Jose L. Vicario:** Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization; **Antoni Morell:** Validation, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization; **Montserrat Meneses:** Funding acquisition; **Ramon Vilanova:** Visualization, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The source code of the HABITAS framework used to perform the simulations and generate the datasets in this study is openly available in GitHub [25].

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