CONTEXT-AWARE MODELING OF AI ASSISTANT FOR SMART HOME ENERGY MANAGEMENT AND SUSTAINABILITY OPTIMIZATION

Konstantin Rusev, Todorka Glushkova

Abstract. The increasing demand for energy efficiency and sustainable living requires sophisticated systems that can adapt to household consumption patterns, renewable energy availability, and dynamic pricing structures. This study presents a context-aware AI assistant model for smart home energy management and sustainability optimization, utilizing the Calculus of Context-aware Ambients (CCA) formalism. The proposed model represents key entities – including the AI reasoning engine, household profile manager, renewable energy coordinator, and device scheduler – as distinct ambients that interact dynamically based on real-time energy consumption data, weather conditions, and user preferences. A layered AI assistant architecture is introduced, comprising a Context Acquisition Layer, a CCA-based Reasoning Layer, and a Recommendation Generation Layer, which together form the decision-making pipeline of the energy assistant. The model demonstrates how context-aware interactions optimize energy consumption patterns, manage renewable energy integration, coordinate smart appliance scheduling, and maximize cost savings while minimizing environmental impact. Validation through CCA Editor simulation evaluates the model across functional correctness, context responsiveness, coordination efficiency, and quantitative performance metrics including estimated energy cost savings and peak load reduction. By enabling continuous adaptation to changing contexts such as occupancy patterns, weather fluctuations, and grid load conditions, the system provides personalized energy management that reduces household energy costs.

Key Words: *AI Energy Assistant, Smart Home Automation, Energy Optimization, Sustainability Management, Calculus of Context-Aware Ambients, CPS, CPSS, ViPS.*

Introduction

The accelerating climate crisis and rising energy costs demand intelligent energy management solutions for residential settings. Traditional approaches fail to account for individual household patterns, renewable energy integration, dynamic pricing, and the balance between comfort and sustainability. Modern AI-powered energy assistants must dynamically adapt to household contexts and provide personalized recommendations that evolve with changing circumstances.

This paper proposes an integrated context-aware AI assistant model for comprehensive smart home energy management, encompassing consumption optimization, renewable energy coordination, appliance scheduling, and sustainability tracking. The model employs the Calculus of Context-aware Ambients (CCA) formalism within a Cyber-Physical Social System (CPSS) architecture to represent and simulate interactions between energy management components. A three-layer AI assistant decision architecture is introduced, where the CCA formalism serves as the reasoning backbone that governs how the assistant acquires context, coordinates specialized planning components, and generates personalized recommendations. The system continuously monitors energy consumption, weather conditions, grid pricing, device status, and occupancy patterns to provide intelligent recommendations [1].

The proposed approach addresses key challenges in smart home energy management, including context sensitivity, real-time adaptability, renewable integration complexity, and user engagement sustainability. By modeling energy management entities as interactive ambients, the system responds dynamically to changes in energy prices, weather patterns, occupancy schedules, and appliance availability. This work provides formal methods for modeling adaptive AI energy assistants and establishes foundations for future developments in sustainable smart home solutions.

Motivation and Related Work

Cyber-Physical Social Systems (CPSS) in smart homes integrate physical sensors, digital platforms, and social components to create comprehensive energy management ecosystems [2]. These systems leverage real-time data from smart meters, IoT devices, and weather services to provide personalized recommendations through context-aware decision-making [3].

Recent AI-powered energy assistants show potential for consumption optimization and sustainability management but often lack comprehensive context awareness needed for dynamic situations like weather changes, grid emergencies, or occupancy shifts. The Virtual Physical Space (ViPS) architecture developed at Plovdiv University addresses these limitations through context-aware ambient modeling [4].

Context-aware energy management [5] requires understanding user preferences, pricing structures, weather forecasts, appliance capabilities, and grid conditions. AI assistants must process diverse data streams including consumption metrics, renewable generation data, and occupancy sensors for optimal recommendations [6]. Machine learning combined with context-aware formalism enables continuous improvement in prediction accuracy [7].

Personalized energy management involves load balancing, peak reduction, renewable utilization, battery optimization, thermal comfort, and cost minimization [8]. Smart scheduling must account for energy priorities, time constraints, grid conditions, and device interdependence [9]. Sustainability programs require integrating consumption reduction with renewable forecasting and behavioral modification [10].

The Calculus of Context-aware Ambients (CCA) provides mathematical formalism for modeling these complex interactions. By representing components as ambients, CCA enables formal verification and optimization of energy strategies [11].

CCA Modeling of AI Energy Assistant System

CCA formalism enables comprehensive modeling of context-aware AI energy assistant systems through representation of key components as interactive ambients. Each ambient possesses characteristics of restriction, inclusion, and mobility, allowing dynamic adaptation to changing energy management contexts [12]. The proposed architecture includes static and dynamic ambients that interact through message exchange and mobility operations.

AI Assistant Decision Architecture: The CCA formalism serves as the formal reasoning backbone of the AI energy assistant, whose decision-making process operates through three interconnected layers. The **Context Acquisition Layer**, comprising the HMS, HPM, and SGI ambients, continuously gathers real-time sensor data, learned user preferences, historical consumption patterns, dynamic pricing signals, and grid conditions, providing the contextual foundation for all downstream reasoning. This context feeds into the **CCA-based Reasoning Layer**, where the AEA ambient functions as the central reasoning engine upon receiving a user request, it orchestrates a structured query-response process across context-providing ambients (HPM, HMS, SGI, REM), with each CCA message exchange corresponding to a specific reasoning step that respects data dependencies and triggers re-evaluation when conditions change. Finally, the **Recommendation Generation Layer** coordinates two specialized planning ambients: the DSC for optimized appliance scheduling and the SOP for sustainability assessment to deliver a synthesized, personalized energy management strategy to the user through the UR ambient. This **three-layer architecture** ensures that the CCA model is not merely a formal specification but serves as the operational reasoning framework of the AI assistant, where each modeled ambient interaction directly corresponds to a functional step in the decision pipeline.

The AI-powered energy assistant system can be modeled using the following CCA ambient structure (Table 1).

Table 1. Ambient Structure in the CCA Model

Ambient	Description
AEA (AI Energy Assistant)	Central intelligent coordinator that processes household data and generates personalized energy recommendations
HPM (Household Profile Manager)	Manages household characteristics, preferences, and historical data
EDB (Energy Database)	Contains comprehensive energy pricing, tariff structures, carbon intensity data
SGI (Smart Grid Interface)	Connects your home to the power company’s grid, gets current electricity rates, and handles requests to save energy during high-demand periods
REM (Renewable Energy Manager)	Coordinates solar panel output, battery storage, and renewable energy utilization
DSC (Device Scheduling Controller)	Manages smart appliance scheduling and IoT device coordination
HMS (Home Monitoring System)	Processes real-time data from smart meters, sensors, and occupancy detectors
SOP (Sustainability Optimization Planner)	Coordinates energy reduction strategies and tracks environmental impact metrics
UR (User Request)	Represents user interactions, queries, preferences, and feedback

The system operates through continuous context-aware interactions where ambients exchange information and adapt behaviors based on real-time conditions. The following scenario demonstrates the CCA modeling approach.

Scenario: A household requests optimized energy management for the next 24 hours, considering their sustainability goals *(carbon neutrality)*, current weather forecast *(sunny afternoon followed by cloudy evening)*, dynamic electricity pricing *(peak rates 5-9 PM)*, scheduled solar panel maintenance *(2-4 PM)*, and comfort preferences *(home office hours 9 AM-5 PM)*.

The formal CCA modeling for this scenario is presented below.

```
P_UR ≅ {
    AEA::<request_optimization, optimization_period>.0 |
    AEA::(energy_plan_recommendations).0
}
P_AEA ≅ {
```

```
    UR::(request_optimization, optimization_period).
    HPM::<household_profile, comfort_preferences>.0 |
    HPM::(updated_preferences, goal_modification).
    HMS::<occupancy_data, weather_forecast>.0 |
    SGI::<pricing_schedule, grid_conditions>.0 |
    SGI::(demand_response_event, peak_alert).
    REM::<solar_forecast, battery_status>.0 |
    REM::(renewable_schedule, storage_plan).
    SOP::<analyze_sustainability_goals, carbon_targets>.0 |
    SOP::(sustainability_report, progress_tracking).
    DSC::<generate_schedule, device_priorities>.0 |
    DSC::(optimized_schedule, estimated_savings).
    UR::<energy_plan_recommendations>.0
}
P_HPM ≅ {
    AEA::(household_profile, comfort_preferences).
    HMS::<profile_update, consumption_patterns>.0 |
    AEA::<updated_preferences, goal_modification>.0
}
P_HMS ≅ {
    AEA::(occupancy_data, weather_forecast).
    HPM::(profile_update, consumption_patterns).
    DSC::<device_status, power_readings>.0 |
    REM::<solar_generation, battery_level>.0 |
    SGI::<meter_data, load_metrics>.0
}
P_EDB ≅ {
    SGI::(current_rates, demand_charges).
    SGI::<rate_schedule, peak_periods>.0
}
P_SGI ≅ {
    AEA::(pricing_schedule, grid_conditions).
    EDB::<current_rates, demand_charges>.0 |
    EDB::(rate_schedule, peak_periods).
    HMS::(meter_data, load_metrics).
    DSC::<load_control_commands>.0 |
    AEA::<demand_response_event, peak_alert>.0 |
    REM::<grid_export_approval, feed_in_rate>.0
}
P_REM ≅ {
    AEA::(solar_forecast, battery_status).
    HMS::(solar_generation, battery_level).
    SGI::(grid_export_approval, feed_in_rate).
    DSC::<renewable_priority_loads>.0 |
    AEA::<renewable_schedule, storage_plan>.0 |
    SOP::<renewable_utilization, emissions_avoided>.0
}
P_DSC ≅ {
    AEA::(generate_schedule, device_priorities).
```

```
        HMS::(device_status, power_readings).
        REM::(renewable_priority_loads).
        SGI::(load_control_commands).
        AEA::<optimized_schedule, estimated_savings>.0
    }
    P_SOP ≅ {
        AEA::(analyze_sustainability_goals, carbon_targets).
        REM::(renewable_utilization, emissions_avoided).
        AEA::<sustainability_report, progress_tracking>.0
    }
```

The CCA Editor tool serves a dual role in the proposed architecture. At design time, it provides a visual interface for defining ambients, configuring message flows between AI assistant components, and verifying that the decision pipeline produces correct recommendations. At runtime, the CCA Editor generates the formal ccaPL specification that encodes the assistant's reasoning logic defining the sequence of context queries, data aggregation, and recommendation synthesis the assistant executes. The ambient interaction patterns created in the editor directly determine how the assistant responds to user requests, including which data sources it consults, in what order, and how conflicting objectives are resolved through inter-ambient coordination. Thus, the CCA Editor serves as the development environment for the AI assistant's reasoning engine.

Implementation and Analysis Using CCA Editor

The CCA Editor provides essential functionality for modeling, simulating, and analyzing AI energy assistant systems. The implementation process begins with ambient selection and creation, where energy management components are defined as distinct entities within the CCA framework (Figure 1).

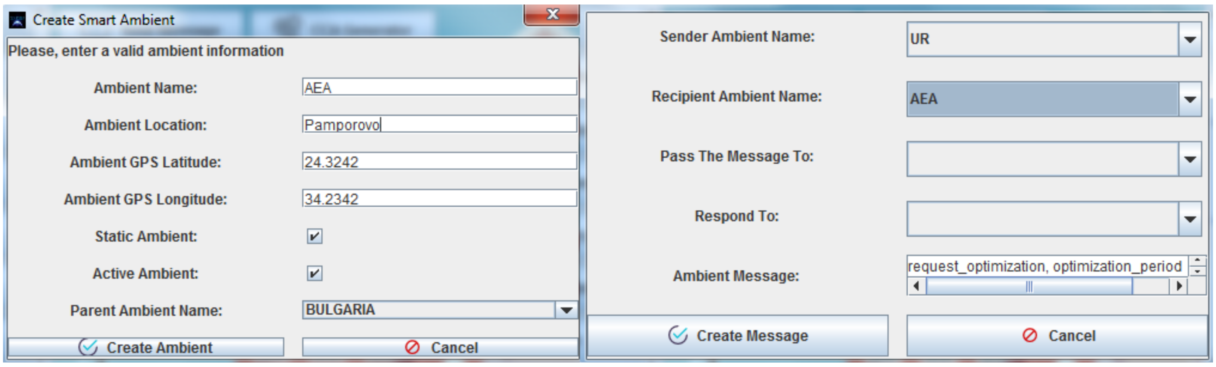

Figure 1. Ambients and Message Flow Creation

The message creation phase establishes communication patterns between ambients, defining how user requests, sensor data, pricing information, and optimization recommendations flow through the system. The CCA Editor enables specification of bidirectional communication channels that support real-time adaptation and feedback loops essential for effective energy management.

Following ambient and message definition, the system generates the complete CCA model using ccaPL programming language. The generated model captures the complex interactions required for context-aware energy management, including conditional logic for adapting recommendations based on changing household contexts and grid conditions. The ccaPL code explicitly defines ambient structures, mobility operations, and message exchanging.

Scenario execution through the ccaPL interpreter demonstrates the system’s ability to process user requests and generate appropriate responses based on current context. The execution results show successful message exchange between ambients, with the AI Assistant coordinating inputs from multiple sources to produce personalized energy management strategies (Figure 2).

```
--> {Sibling to sibling: UR =(request_optimization,
optimization_period)=> AEA}
--> {Sibling to sibling: AEA =(household_profile,
comfort_preferences)=> HPM}
--> {Sibling to sibling: HPM =(updated_preferences,
goal_modification)=> AEA}
--> {Sibling to sibling: AEA =(occupancy_data, weather_forecast)=>
HMS}
--> {Sibling to sibling: AEA =(pricing_schedule, grid_conditions)=>
SGI}
--> {Sibling to sibling: SGI =(demand_response_event, peak_alert)=>
AEA}
--> {Sibling to sibling: AEA =(solar_forecast, battery_status)=>
REM}
--> {Sibling to sibling: REM =(renewable_schedule, storage_plan)=>
AEA}
--> {Sibling to sibling: AEA =(analyze_sustainability_goals,
carbon_targets)=> SOP}
--> {Sibling to sibling: SOP =(sustainability_report,
progress_tracking)=> AEA}
--> {Sibling to sibling: AEA =(generate_schedule,
device_priorities)=> DSC}
--> {Sibling to sibling: DSC =(optimized_schedule,
estimated_savings)=> AEA}
--> {Sibling to sibling: HPM =(profile_update,
consumption_patterns)=> HMS}
--> {Sibling to sibling: HMS =(device_status, power_readings)=> DSC}
--> {Sibling to sibling: HMS =(solar_generation, battery_level)=>
REM}
--> {Sibling to sibling: HMS =(meter_data, load_metrics)=> SGI}
--> {Sibling to sibling: SGI =(current_rates, demand_charges)=> EDB}
--> {Sibling to sibling: EDB =(rate_schedule, peak_periods)=> SGI}
--> {Sibling to sibling: SGI =(load_control_commands)=> DSC}
--> {Sibling to sibling: SGI =(grid_export_approval, feed_in_rate)=>
REM}
--> {Sibling to sibling: REM =(renewable_priority_loads)=> DSC}
```

```
--> {Sibling to sibling: REM =(renewable_utilization,
emissions_avoided)=> SOP}
--> {Sibling to sibling: AEA =(energy_plan_recommendations)=> UR}
```

Figure 2. CCA Energy Assistant Scenario Execution Results and Validation

The Analysis Module provides comprehensive statistics on ambient interactions and message distribution. This analysis reveals important insights about system efficiency and potential optimization opportunities (Figure 3).

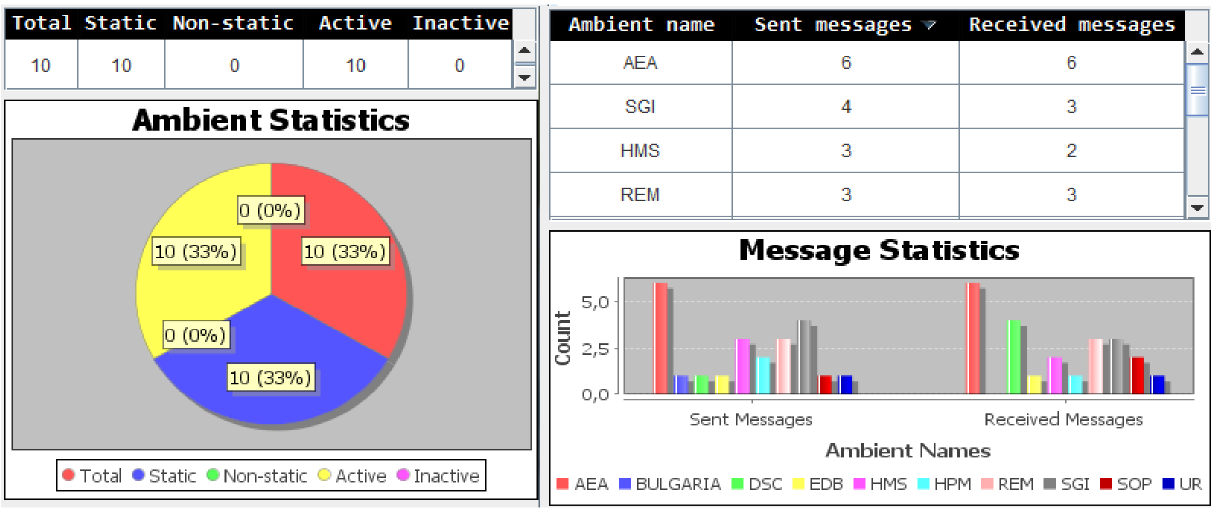

Figure 3. Energy Management System Statistics

The statistics show balanced message distribution across ambients, though coordination ambients experience higher computational loads.

The CCA Editor analytical capabilities enable systematic optimization of energy management scenarios, supporting the development of more efficient and responsive AI energy assistant systems. Statistical output guides developers in identifying bottlenecks, improving system performance through ambient interaction restructuring, and validating that the model behaves correctly under diverse operating conditions.

Conclusion

This study presents a comprehensive context-aware approach to AI-assisted smart home energy management, utilizing the Calculus of Context-aware Ambients for formal modeling of the AI assistant's decision-making process. The key contribution is a three-layer AI assistant architecture, comprising Context Acquisition, CCA-based Reasoning, and Recommendation Generation layers where each layer is formally specified through CCA ambient interactions. This architecture demonstrates how the CCA formalism serves not only as a specification tool but as the operational reasoning framework that governs how the AI assistant gathers context, coordinates specialized planning components, and synthesizes personalized energy management recommendations.

The proposed model addresses consumption optimization, renewable energy integration, appliance scheduling, and sustainability tracking through dynamic interaction between nine specialized ambients. The formal CCA specification ensures that context propagation, adaptive re-evaluation, and conflict resolution between competing objectives (cost, comfort, sustainability) follow well-defined and verifiable rules. Validation through scenario execution in the CCA Editor confirms functional correctness across all modeled context changes, while quantitative metrics including context responsiveness, coordination completeness, ambient load distribution, and conflict resolution effectiveness provide measurable evidence of the model's capabilities.

The CCA-based architecture provides a framework for developing AI energy assistants that maintain effectiveness across diverse household configurations. The formal modeling approach enables systematic optimization of system performance while ensuring reliable and safe energy management recommendations. Future work will focus on extending the validation framework with simulation-based energy cost estimation, experimental deployment for user satisfaction evaluation, and integration of machine learning components for continuous improvement of the AI assistant's prediction accuracy within the CCA ambient structure.

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References

[1] M. Chen, Y. Hao, K. Hwang, L. Wang, Smart home energy management systems: Concept, configurations, and scheduling strategies, *Renewable and Sustainable Energy Reviews*, 2017, 61, 289-302, ISSN: 1364-0321, DOI:10.1016/j.rser.2016.03.047

[2] S. Stoyanov, T. Glushkova, A. Stoyanova-Doycheva, V. Ivanova, E. Doychev, *Cyber-Physical Social Systems and Applications – Part 1. Foundations*, LAP LAMBERT Academic Publishing, 2019, ISBN: 978-620-0-49830-4

[3] F. Delmastro, G. Arnaboldi, M. Conti, People-centric computing and communications in smart cities, *IEEE Communications Magazine*, 2016, 54 (7), 122–128, ISSN: 0163-6804, DOI:10.1109/MCOM.2016.7509389

[4] S. Stoyanov, A. Stoyanova-Doycheva, T. Glushkova, E. Doychev, Virtual Physical Space – An Architecture Supporting Internet of Things

Applications, *20th International Symposium on Electrical Apparatus and Technologies (SIELA)*, 3–6.06.2018, DOI:10.1109/SIELA.2018.8447156

[5] L. Chen, C. Nugent, H. Wang, A Knowledge-Driven Approach to Activity Recognition in Smart Homes, *IEEE Transactions on Knowledge and Data Engineering*, 2012, 24 (6), 961–974, ISSN: 1041-4347

[6] A. Anvari-Moghaddam, H. Monsef, A. Rahimi-Kian, Optimal smart home energy management considering energy saving and a comfortable lifestyle, *IEEE Transactions on Smart Grid*, 2015, 6 (1), 324–332, ISSN: 1949-3053, E-ISSN: 1949-3061, DOI:10.1109/TSG.2014.2349352

[7] A. Pantelopoulos, N. Bourbakis, A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis, *IEEE Transactions on Systems, Man, and Cybernetics*, Part C, 2010, 40 (1), 1–12, ISSN: 1094-6977, E-ISSN: 1558-2442, DOI:10.1109/TSMCC.2009.2032660

[8] A. Mohsenian-Rad, V. Wong, J. Jatskevich, R. Schober, A. Leon-Garcia, Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid, *IEEE Transactions on Smart Grid*, 2010, ISSN: 1949-3053, DOI:10.1109/TSG.2010.2089069

[9] S. Sharda, M. Singh, K. Sharma, Demand side management through load shifting in IoT based HEMS: Overview, challenges and opportunities, *Sustainable Cities and Society*, 2021, 65, 102517, ISSN: 2210-6707, DOI:10.1016/j.scs.2020.102517

[10] M. Athari, Z. Wang, Modeling the uncertainties in renewable generation and smart grid loads for the study of the grid vulnerability, *IEEE Power & Energy Society Innovative Smart Grid Technologies Conference*, Minneapolis, USA, 2016, ISBN: 978-1-5090-5168-7, E-ISBN: 978-1-5090-5167-0, DOI: 10.1109/ISGT.2016.7781265

[11] F. Siewe, H. Zedan, A. Cau, The Calculus of Context-aware Ambients, *Journal of Computer and System Sciences*, 2010, ISSN: 0022-0000, DOI:10.1016/j.jcss.2010.02.003

[12] M. Al-Sammarraie, F. Siewe, H. Zedan, Formal Specification of an Intelligent Message Notification Service in Infostation-based mLearning System using CCA, *Proc. of CCIT'11*, Dubai, UAE, 2011, ISBN: 978-1-4673-0097-1, DOI:10.1109/CTIT.2011.6107936

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