A forecast-driven, comfort-aware load shifting optimization tool for optimizing solar self-consumption in island energy communities

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***Abstract*—Remote and non-interconnected island communities face persistent energy management challenges due to geographic isolation, constrained infrastructure, and dependence on imported fossil fuels. The integration of renewable energy sources (RES), particularly photovoltaics (PV), presents a promising pathway toward energy autonomy. However, the intermittent nature of solar energy complicates its efficient utilization. This study introduces a novel self-consumption optimization framework designed to facilitate intelligent load shifting at both the community and household levels, with a specific focus on the island of Chalki, Greece. The proposed system integrates PV generation and electricity consumption forecasting using Long Short-Term Memory (LSTM) models, coupled with non-intrusive load monitoring (NILM) techniques for disaggregating cooling-related demand. To ensure user comfort, thermal modeling is employed using customized Predicted Mean Vote–Predicted Percentage Dissatisfied (PMV–PPD) metrics. At the community scale, a heuristic algorithm identifies optimal time windows for load shifting based on projected PV surplus. Concurrently, household-level cooling demand is managed through a multi-objective optimization approach that balances thermal comfort with the availability of renewable generation. The framework is implemented as a user-centric web application, providing both a centralized energy management dashboard for the community and individualized control tools for end-users. The system aims to enhance renewable energy self-consumption and promote sustainable, resilient energy practices in insular communities.**

***Index Terms*—Photovoltaic systems, self-consumption optimization, energy management, load shifting, renewable energy, thermal comfort, machine learning, island microgrids**

I. Introduction & Related Work

Small and remote islands are often subject to unique challenges regarding their energy management due to their limited infrastructure, geographic isolation and dependency on imported fossil fuels [1]. In this context, integrating renewable energy sources (RES), such as wind and solar farms, offers a unique opportunity to mitigate these issues, since these locations often have high RES generation potential [2]. Despite their advantages, the inherent variability of RES creates difficulties in fully utilizing the generated power, resulting in either under-utilization of renewable energy or reliance on external, often fossil-based, sources to meet demand [3].

Fortunately, various methods to mitigate this challenge, such as demand response (DR), energy flexibility, peak shaving, and demand shifting, have been tested with successful results. DR programs enable buildings and prosumers to adjust their energy consumption patterns, often in response to external signals or incentives, and thereby contribute to grid efficiency and resilience [4], [5]. A key enabler of DR is the ability to quantify and forecast energy flexibility, which refers to the extent to which energy demand can be shifted without compromising user needs. This is often achieved through baseline consumption models and machine learning techniques, such as Long Short-Term Memory (LSTM), neural networks and Transformers, to predict deviations and flexibility margins in real-world scenarios [6]–[9]. Demand shifting, i.e. strategically adjusting energy consumption patterns to align with production peaks has been proven to be particularly successful for small island communities as displayed by the work of Sarmas et al [10]. Matching the aggregate consumption with RES production, can significantly reduce energy costs, increase energy independence, and lower the environmental footprint of the communities.

A particularly relevant case for this work is Chalki, a small island in Greece that is electrically isolated from the mainland grid and relies primarily on a local photovoltaic (PV) park for its energy needs. Chalki exemplifies the energy challenges faced by remote island communities, such as limited grid capacity, high reliance on renewables, and the need for intelligent energy management to balance supply and demand.

Most of the existing demand shifting strategies rely on accurate energy forecasting as it allows energy consumption to be aligned with expected renewable generation. Short-term PV predictions are critical for self-consumption optimization, especially in remote or island communities. Recent studies have demonstrated the effectiveness of advanced machine learning approaches in improving forecast accuracy across diverse PV installations [11], [12]. These improvements directly support the implementation of intelligent energy management systems that leverage forecast insights to guide load adjustments and enhance grid resilience. On the demand side, hierarchical architectures have been shown to enhance household-level load forecasting performance and reduce communication overhead [13].

In addition to energy forecasting, demand-side optimization increasingly incorporates thermal comfort modeling to enable more effective load shifting. Thermal comfort is typically quantified using the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) metrics, which reflect the subjective satisfaction of occupants based on environmental conditions [14]. Various studies have proposed methods to optimize heating, ventilation, and air conditioning (HVAC) operation while maintaining thermal comfort, using predictive control algorithms and machine learning. For instance, the authors of [15] use learning-based model predictive control to balance comfort and energy use in office environments. Ku et al. [16] demonstrate the efficacy of PMV-based control systems leveraging particle swarm optimization and neurofuzzy models. On a broader scale, unsupervised learning methods have been applied to cluster heating load profiles in residential buildings, offering insights into user behavior and improving the design of targeted demand response strategies [17].

Despite the advancements in energy management systems, existing tools predominantly focus either on aggregate community-level optimization or individual household optimization, leaving a gap in approaches that simultaneously address both scales.

In this paper, we present a novel self-consumption optimization tool that bridges this gap by providing integrated community-level and household-level optimization. Specifically, our contributions include:

- Development of a heuristic-based optimization method for community-level demand shifting utilizing PV production and consumption forecasts.
- Implementation of a user-level cooling load disaggregation methodology to accurately identify individual household cooling loads.
- Creation of a custom comfort index metric based on indoor temperature and humidity sensors following International Organization for Standardization (ISO) standards.
- Provision of personalized demand shifting suggestions at the household level that maintain comfort while maximizing the utilization of PV-generated energy.
- Deployment of the tool on an electrically isolated Greek island with high PV penetration, showcasing its applicability in a real-world, resource-constrained environment.

II. System Overview

A. Data Sources

The system integrates multiple data streams categorized at two levels:

- **Island-level**: PV production data and forecasts from a 1 Mega-Watt peak (MWp) PV park located on Halki island, along with consumption data from critical infrastructure and commercial sites including a medium voltage station, an osmosis plant, a café, a restaurant, a hotel, and select households. Data is retrieved via dedicated APIs and enhanced using forecasts generated by machine learning models (LSTMs)
- **Individual-level**: Smart sensors installed in selected households provide granular data on energy consumption and indoor environmental parameters. The data are retrieved via APIs. Energy data undergo load disaggregation through Non-Intrusive Load Monitoring (NILM), while environmental parameters are used to develop comfort models.

B. Overall Workflow

The workflow comprises four main stages:

1) **Ingestion**: Acquisition of real-time data from APIs and smart sensors.
2) **Forecasting**: Generation of predictive models for energy production and consumption using machine learning techniques.
3) **Optimization**: Deployment of heuristic algorithms to identify optimal strategies for load shifting at both community and household scales.
4) **Suggestions UI**: Delivery of user-friendly actionable recommendations aimed at balancing energy optimization and household comfort.

III. Methodology

This section outlines the methodologies used in the self-consumption optimization tool. The proposed solution addresses two distinct levels: the community-level optimization and the user-level cooling optimization.

A. Community-Level Optimization

The primary objective at the community level is to maximize self-consumption of locally generated PV energy. This is achieved through load shifting and it relies on integrating the forecasts of both PV production and the overall community load. More specifically, PV production forecasting is executed daily over a 3-day horizon, focusing primarily on next-day predictions. The forecasting methodology is primarily based on satellite and meteorological data [18]. For community-level energy load predictions, LSTM neural network models are employed, taking into account historical consumption patterns, and additional contextual parameters [19].

The core of the optimization at this level relies on a heuristic rule-based thresholding method. Specifically, the heuristic identifies intervals where forecasted PV production surpasses predicted consumption, and recommends load shifts for the flexible loads of the community during these periods. The provided daily load-shifting plan is aimed at aligning consumption more closely with production peaks and therefore enhancing local renewable energy utilization.

Applied load shifting methodology: At the current stage of development, our system does not incorporate data from specific flexible loads. Instead, we operate by analyzing the overall energy balance between forecasted PV production and aggregated community consumption. For each time interval t in our forecast horizon, the net surplus is computed as:

$$\Delta(t) = P(t) - C(t) \tag{1}$$

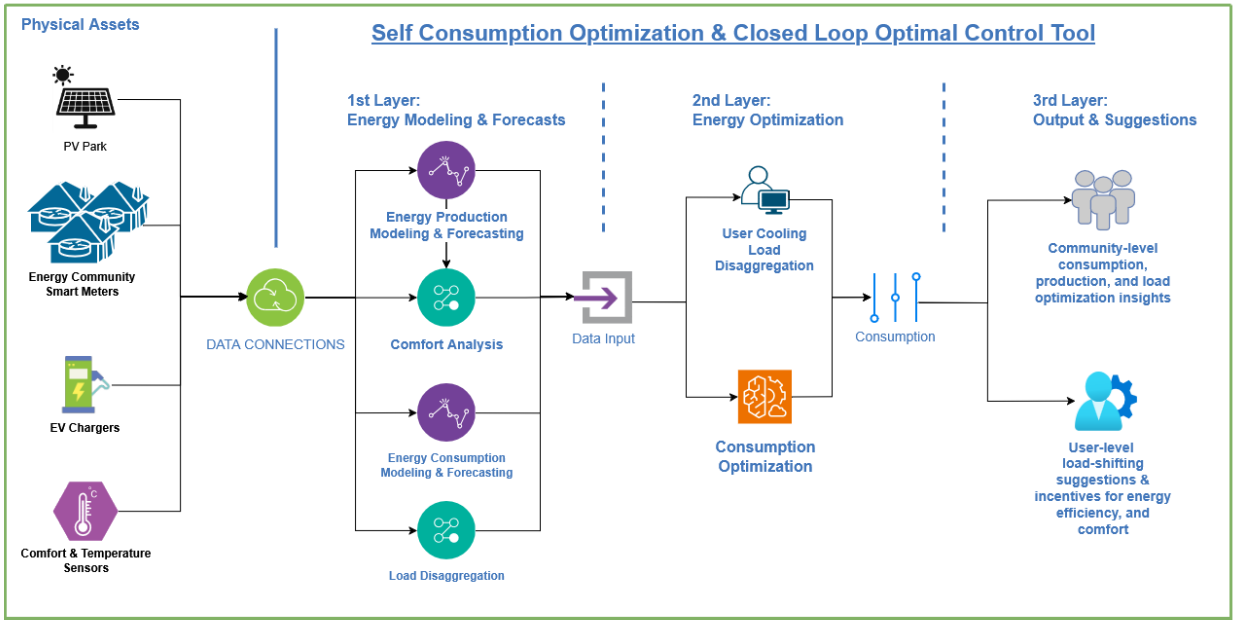

Fig. 1. Assets & Architectural Layers

where $P(t)$ represents forecasted PV production and $C(t)$ baseline consumption. When the surplus $\Delta(t)$ exceeds a predetermined threshold θ, that interval is recommended for load shifting. This approach provides actionable recommendations based on aggregate data, enhancing self-consumption and reducing the community's energy footprint.

Advanced Methodology for Incorporating Flexible Loads: In anticipation of receiving detailed data on flexible loads (e.g., EV chargers), we have developed a methodology based on a Model Predictive Control (MPC) framework [20]. In this future scenario, each flexible load i is assigned a decision variable $x_i(t)$, representing the load shifted to interval t. The optimization problem is formulated as:

$$\min_{x_i(t)} \sum_{t=1}^{T} \left[\left(C(t) + \sum_i x_i(t) \right) - P(t) \right]^2, \tag{2}$$

subject to:

$$\sum_{t=1}^{T} x_i(t) = L_i, \quad \forall i, \tag{3}$$

$$0 \leq x_i(t) \leq \Delta L_i(t), \quad \forall i, t, \tag{4}$$

where L_i denotes the total flexible load for device i, and $\Delta L_i(t)$ represents the maximum load shiftable to interval t, given user constraints. This formulation optimally allocates flexible loads during surplus energy periods, enhancing precise load management and self-consumption. Once flexible load data becomes available, this methodology will seamlessly integrate into the tool.

B. User-Level Cooling Optimization

At the user level, the optimization specifically targets household cooling loads, aiming to balance energy consumption and comfort constraints. Initially, household energy data from smart sensors undergo load disaggregation using statistical and machine-learning methods such as NILM [21] to isolate cooling-related consumption. This disaggregation isolates cooling-specific energy consumption, such as air conditioning, providing the target energy to optimize. Having specified the cooling load, we define the metric upon which the shifting will be based. Thermal comfort, defined as the subjective satisfaction with the thermal environment [22], relies on objective variables (indoor and outdoor temperature, relative humidity, air quality indicators) and subjective variables (individual physical and psychological characteristics). A custom comfort index was developed, that builds on the ISO-7730 [23] and the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) standard no 55 [22] standards, foundational to the widely applied Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) models [24]. We opted to utilize this variation due to the limitations of our sensor network, which provides only air temperature and relative humidity data and the fact that we required an easy-to-understand metric that we could embed in our web-app.

1) Thermal Comfort Estimation Methodology: The PMV model, as defined by Fanger [25], requires six inputs: air temperature, mean radiant temperature, relative humidity, air velocity, metabolic rate, and clothing insulation. Given our data constraints, we adopted standard default values for the missing parameters, as recommended by ASHRAE Standard 55 and related literature [26]–[28]:

- **Mean radiant temperature** (t_r): Assumed equal to air temperature (t_a).
- **Air velocity** (v): 0.1 m/s, representing still air conditions.
- **Metabolic rate** (M): 1.2 met, corresponding to sedentary

activities such as office work.

- **Clothing insulation** (I_{cl}): 0.6 clo, typical for indoor clothing ensembles.

Once the PMV is determined, the PPD is calculated using the following formula:

$$\text{PPD} = 100 - 95 \cdot e^{-0.03353 \cdot \text{PMV}^4 - 0.2179 \cdot \text{PMV}^2} \tag{5}$$

This equation predicts the percentage of occupants likely to feel thermally dissatisfied in a given environment.

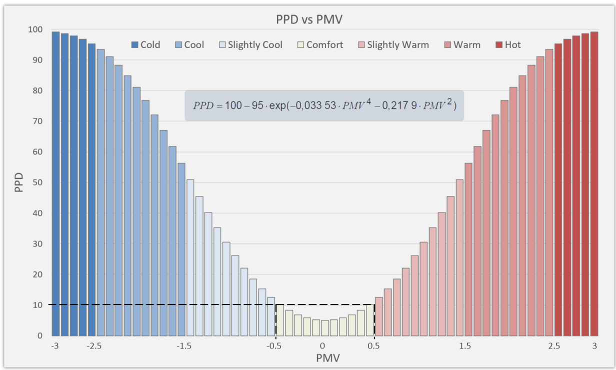

Fig. 2. Graphical representation of the relation between PMV-PPD as defined in [26]. Reprinted from https://tinyurl.com/pmv-vs-ppd with permission.Copyright © 2018 Sandip Jadhav.

Finally, we define a custom comfort index by inverting the PPD:

$$\text{Comfort Index} = 100\% - \text{PPD} \tag{6}$$

This index represents the percentage of occupants predicted to be thermally comfortable, offering a straightforward scale from 0% (no comfort) to 100% (maximum comfort). This approach allows for effective communication of thermal comfort levels to users, despite the limited sensor data available.

Based on this index and current community PV availability, the tool recommends cooling load adjustments, such as pre-cooling and smart scheduling. These recommendations ensure indoor comfort is maintained or enhanced while aligning cooling loads with periods of surplus PV generation.

Cooling Load Shifting methodology: we consider a discrete time horizon $\mathcal{T} = \{1, \dots, T\}$ (e.g., 30-minute slots) and N occupants with disaggregated baseline cooling demands $L_i(t)$, day-ahead PV forecasts $P_{\text{PV}}(t)$ and comfort index forecasts $\text{CI}_i^{\text{fcst}}(t)$. The goal is to compute shifted cooling profiles $L'_i(t)$ that preserve each occupant's total energy use:

$$\sum_{t \in \mathcal{T}} L'_i(t) = \sum_{t \in \mathcal{T}} L_i(t), \qquad L'_i(t) \geq 0.$$

We define total load $L'_{\text{tot}}(t) = \sum_i L'_i(t)$, grid import $G(t) = \max\{0,\, L'_{\text{tot}}(t) - P_{\text{PV}}(t)\}$, and comfort violations as

$$V_i(t) = [\text{CI}_i(t; L'_i(t)) - \text{CI}_{\max}]_+ ,$$

$$\text{where} \quad \text{CI}_i(t; L'_i(t)) \approx f\big(\text{temp}_i(t; L'_i(t)), \text{hum}_i(t)\big).$$

The optimal load schedule minimizes a weighted sum of energy cost and comfort violations:

$$\min_{\{L'_i(t)\}} \sum_{t \in \mathcal{T}} \left(\alpha\, G(t) + \beta \sum_{i=1}^{N} V_i(t) \right),$$

subject to the energy conservation and non-negativity constraints. Parameters $\alpha, \beta > 0$ control the trade-off between PV self-consumption and thermal comfort. The resulting $L'_i(t)$ prioritizes PV-aligned cooling while keeping comfort within acceptable limits.

IV. Use Case: Chalki Island

The current implementation of the self-consumption optimization tool is tailored for the Greek island of Chalki, which hosts a 1 MWp PV park designed to cover the region's energy needs according to the following priority:

1) The local energy community, consisting of 178 members
2) The remaining population and infrastructure of the island
3) Any excess energy is exported to the nearby island of Rhodes

Relevant infrastructure details, including the PV installation and consumption monitoring points, are presented in Section II-A.

The tool features two core modules:

1) Community-Level Self-Consumption Optimization Dashboard: This module offers an integrated interface for visualizing the community's key energy metrics, such as the real-time and forecasted PV production and community consumption time series. It includes interactive charts, weather-informed insights, and progress indicators for daily production, consumption, and self-consumption ratio. Finally, a dedicated section employs the self-consumption optimization algorithms from Section III-A. These generate load-shifting suggestions aimed at maximizing renewable energy utilization and reducing grid dependency.. The layout and functionality of this module are illustrated in Figure 3

2) User-Level Cooling Load Optimization Module: This module focuses on individualized cooling load management. It displays a time series chart of the total load and the disaggregated cooling load of the user, as well as real-time environmental metrics such as temperature, humidity, and the comfort index calculated in III-B1. The module then provides tailored shifting strategies that balance energy savings and thermal comfort through the process described in section III-B1. A multi-objective approach allows users to choose between strategies optimized for comfort, cost efficiency, or a compromise of both. Additionally, visual indicators compare the baseline and the suggested load profiles, along with the predicted comfort outcomes for each optimization strategy. A view of the corresponding user interface is provided in Figure 4.

While the two modules serve different scopes—community-wide versus individual optimization—they are designed to operate on a shared data infrastructure and complement each

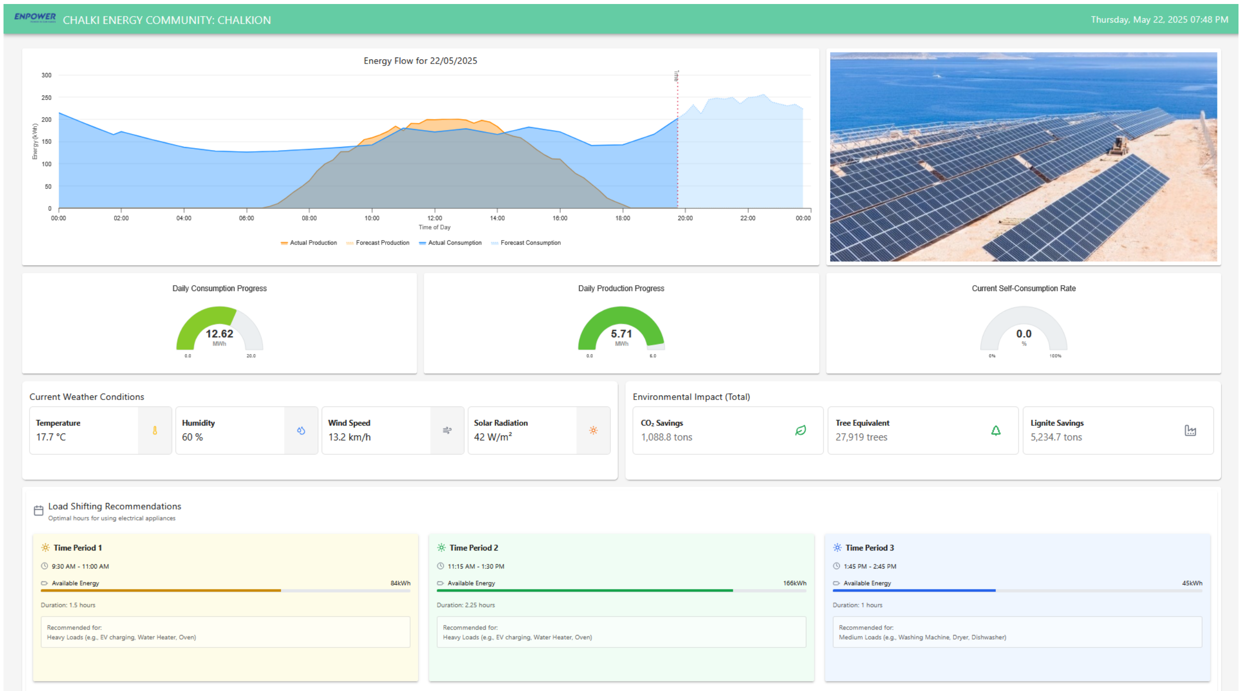

Fig. 3. Community-level energy optimization dashboard.

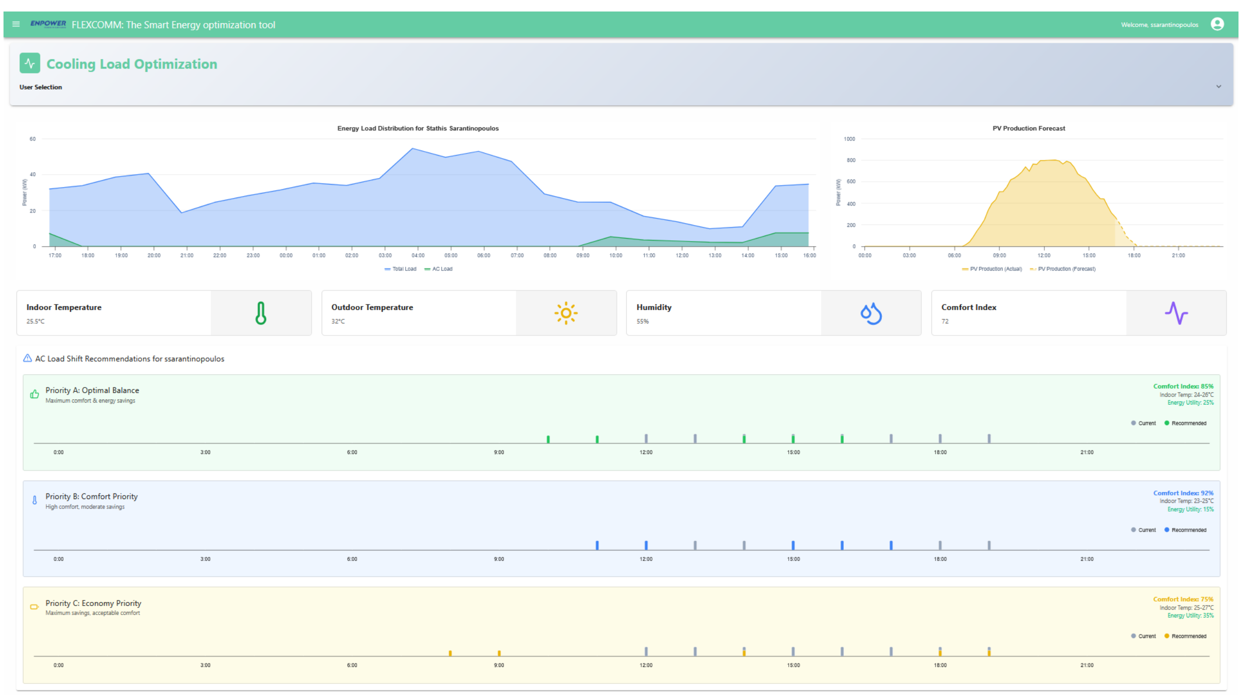

Fig. 4. User-level cooling load optimization interface.

other functionally. For example, forecasts and real-time measurements collected at the community level inform both the high-level load-shifting suggestions for the entire energy community and the personalized strategies delivered to individual users.

Upon its completion, the tool will serve multiple stakeholders:

- **Community Managers**: Administrative access for monitoring, analysis, and management of energy loads.
- **Community Members**: Individualized recommendations and visualizations tailored to personal energy consumption and comfort optimization.
- **Public Display**: General overview accessible to all residents via a central screen, providing real-time insights into island-wide energy performance.

V. Implementation Details

To deploy the proposed self-consumption optimization tool in a secure and modular environment, we developed a lightweight web-based application stack from scratch. The implementation includes several infrastructure and security components to ensure scalability, and data integrity.

A. Database and Backend

A `PostgreSQL` [29] database was initialized to serve as the primary data store with modular data tables to accommodate future expansion. Connection pooling and secure access configurations were implemented to ensure efficient operation. Finally we utilized `SQLAlchemy` [30] for the communication between the database and the backend Figure 5 presents the current database schema.

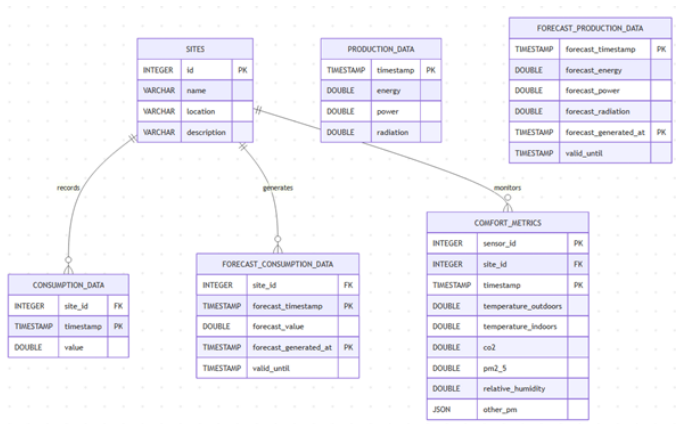

Fig. 5. Database schema.

The backend is implemented using `FastAPI` [31], chosen for its high performance and asynchronous capabilities. It handles all core logic, including data ingestion, preprocessing, optimization computations, and API endpoints for front-end communication. Additionally the forecasting models were built on TensorFlow, utilizing an LSTM model.

B. Hosting and Deployment

The application is hosted on a dedicated virtual machine running Ubuntu Server LTS. Docker and Docker Compose are used to manage the deployment stack, allowing modular service management and simplified updates.

An NGINX Proxy Manager container is used for routing and reverse proxying, providing dynamic host routing and HTTPS termination using Let's Encrypt certificates. In addition, we implemented automatic certificate renewal, and hardened HTTP headers (HSTS, CSP, X-Frame-Options).

C. Frontend and API Communication

The user interface is built with `React` [32], providing an interactive dashboard for visualizing forecasts, consumption profiles, and load-shifting suggestions. All data flows between the backend and frontend occur through RESTful APIs. Optimization outputs are computed server-side and transmitted to the frontend for visualization and user interaction.

D. Authentication and Access Control

`Keycloak` [33] was integrated for centralized identity and access management. The system was designed with role-based access control (RBAC) in mind, allowing seamless scaling to multiple roles and users.

VI. Conclusions & Future Work

The tool will be released and tested on the energy community of Chalki Island. Upon its adoption, it will offer users a platform to optimize their self-consumption based on real-time production and consumption data. Future work involves further enhancing the capabilities and robustness of the tool through comprehensive testing and performance evaluations. Planned activities include the collection and analysis of detailed self-consumption statistics to quantify its effectiveness.

Beyond its initial deployment, the tool is designed with scalability in mind, with potential applications in other island communities and remote areas facing similar energy management challenges. We also aim to continuously refine the user interface to enhance user experience—ensuring clarity, accessibility, and ease of use across a wide range of user groups. Future versions may incorporate predictive analytics for proactive load shifting, further integration with weather forecasting data, and support for demand response programs, expanding the tool's role in decentralized energy systems.

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