Technical Specification Double-side Page

1. TECHNICAL SCOPE

PLATONIC (deeP LeArning neTwOrks for building's eNergy effICiency) will develop an occupancy & renewable energy sources (RES)-aware Heating, Ventilation and Air Conditioning (HVAC) recommendation system for commercial buildings. This project has been proposed under REACH's "Occupancy-driven monitoring & multi-factor recommendation systems for Energy Efficiency In Buildings" theme.

The challenge is to build a non-intrusive engine, capable of inferring building occupancy based on data collected from the HVAC systems (e.g., energy measurements), as well as indoor/outdoor data points (e.g., temperature, humidity, etc.) and to develop optimal, occupancy-informed, heating strategies for HVACs.

At Sensinov, we have a solid track record of helping our clients achieve better and long-lasting results on the energy efficiency front (30% less energy consumption on average). Our method is simple and yet, disruptive: propose an open, cost-efficient and evolutive hardware and software solution to efficiently monitor and control buildings.

Open, because we pride ourselves on originating from the need to revolutionize buildings through interoperability - across vendors, solutions and technologies. **Cost-efficient**, which translates our promise of achieving a quick return on investments (ROI) thanks to our modulable hardware solution, capable of serving any size building and easily adapting to multiple business use cases. **Evolutive**, since we keep our focus on continuously improving our solution to deliver the most performant and technologically advanced solution to facility managers. This last and final focus is what fuels PLATONIC.

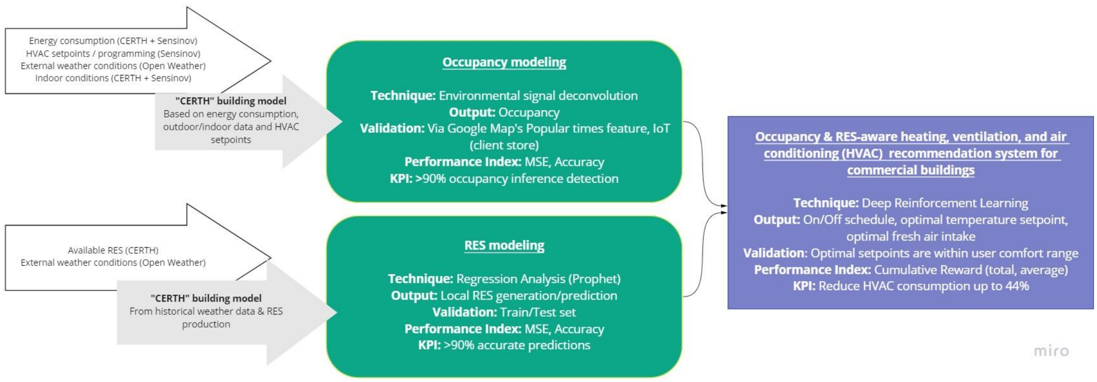

Figure 1. PLATONIC overview

PLATONIC's application architecture is composed of 3 asynchronous, modular, and reusable building-block components: the occupancy model, the RES model and the HVAC recommendation system model. These three modules use the data provided by the CERTH, our own platform, and Open Weather's API (in Figure 1, the most left-hand arrows represent the data inputs and their providers, while most right-hand blocks represent our three building block components, further described below).

2. ALGORITHMS, TOOLS AND CONCLUSIONS

The occupancy model is based on **environmental signals deconvolution**[1]. This method allows us to exploit readily available HVAC data in our system, such as temperature, CO2 levels, and HVAC ventilation setpoints. Thanks to this approach, occupancy can be estimated as the input that, when injected into our dynamic model, can best explain the measured CO2 levels. We will use Transfert Learning techniques to generalize the learning (features, weights) obtained from this model and apply it in a resource-efficient manner to CERTH's datasets.

Renewable Energy Sources (RES) modelling uses **Regression Analysis** (implemented using Facebook's popular **Prophet**, an Open Source forecasting model) to identify the relation between weather-related variables and local energy production. Based on this model, accurate predictions on future local RES availability can be made using localized weather predictions provided by OpenWeather's API.

Finally, our HVAC recommendation system model implements a **Deep Reinforcement Learning Algorithm (Q-learning)** to improve HVAC operations based on the data input/output of both previous modules[2]. In this step, we will define an environment for our RL agent. The latter will try to optimise its reward function (i.e., reduce energy consumption) while penalising any recommendation that is outside the user's pre-set comfort range. For this module, we privilege off-line learning given the sensitive nature of HVAC operations.

The knowledge created via these three components will be displayed to end-users via a new interface in our platform, titled

[1] This approached is based on the one developed in: Ebadat, A., Bottegal, G., Varagnolo, D., Wahlberg, B., & Johansson, K. H. (2013). Estimation of building occupancy levels through environmental signals deconvolution. In Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings. SenSys '13: The 11th ACM Conference on Embedded Network Sensor Systems. ACM. https://doi.org/10.1145/2528282.2528290

[2] A similar approach is developed in: Faddel, S., Tian, G., Zhou, Q., & Aburub, H. (2020). On the Performance of Data-Driven Reinforcement Learning for Commercial HVAC Control. In 2020 IEEE Industry Applications Society Annual Meeting. 2020 IEEE Industry Applications Society Annual Meeting. IEEE. https://doi.org/10.1109/ias44978.2020.9334865

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"Optimisation". The latter will contain week-ahead recommendation reports for our users, allowing them to easily implement the set of corresponding features thanks to a simple button click. The data produced can also be accessed via our REST API or via GraphQL.

The Big Data tools that will be used in this project are shown in Figure 2.

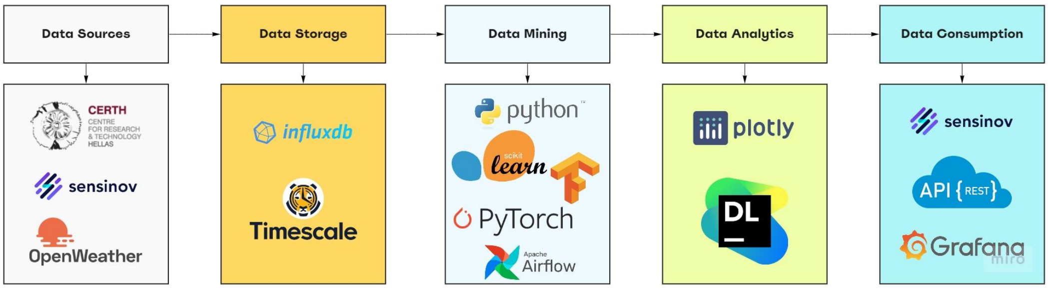

Figure 2. Big data tooling

3. SCALABILITY AND FLEXIBILITY OF THE SOLUTION

PLATONIC's planned data storage solutions are known for handling huge amounts of data (capacity can be measured in TeraBytes). Its data mining and data analytics solutions can efficiently scale horizontally, to cope with large or increasing data requirements. Moreover, the 3 components will run asynchronously, ensuring that if a component breaks down, our main component can continue to run, using the last recorded output from the broken component.

PLATONIC's component architecture also makes it very flexible: each component outputs autonomously a rich set of data that can be used in other fields or other applications (i.e., occupancy prediction).

4. DATA GOVERNANCE AND LEGAL COMPLIANCE

Our current solution uses a backend web framework (Django) implementing state-of-the-art security practices for protection against all major web security flaws (e.g., XSS, SQL Injections, CSRF, ...). Moreover, we have internal security authorizations for end-users that prevent unauthorized access to sensible data.

It is also important to note that, following the EU's GDPR, no personal, identifiable information will be shared (steps will be taken to ensure that such data is pre-anonymized and handled at a higher level of abstraction). Moreover, it is important to note that the occupancy model described above ensures the security and privacy of building occupants since only environmental data (e.g., temperature, CO2) is collected and treated to infer occupancy in the building.

5. QUALITY ASSURANCE AND RISK MANAGEMENT

Enabling smart autonomic buildings requires breaking down building systems into a network of building components, relying on appropriate software to collect & analyze significant amounts of data, enabling physical buildings to be managed, quickly understood & reconfigured as needed. As such, we can foresee the following technical risks:

- **Data-related risks:** The available amount of data is not adequate for computing with a high degree of accuracy optimal HVAC operations / available data does not support the level of detail required, thus attaining lower performance. The inclusion of our own database (incl. over 3 years of fine-grained data on energy consumption, HVAC operations, etc.) will allow us to curtail this risk.
- **Model-related risks:**
    - **Model overfitting**: Overfitting occurs when a model performs well on the training data, but does not generalize well. This is a risk given the complex nature o<f some of the models developed here, and by the possible noise in the data used for training. In this case, we will consider simplified approaches, backed by the scientific literature, and proceed to fix possible data errors (e.g., outliers). We will proceed to test and validate our models by presenting them with new cases and monitoring their overall performance.
    - **Black-box system (Model interpretability):** To avoid the "Black-Box" effect in our models, we will produce visualizations of our trained model results, containing information e.g., on variable importance, partial dependence plots, etc. This will help us better appreciate and summarize the different aspects of the resulting ML models and correct any evident bias.
- **Technology-related risks:**
    - **Design & Engineering:** Even if the technology is fully developed (e.g., home automation, IoT, big data), autonomous buildings will require significant design and engineering efforts. AI plays a pivotal role in this effort, facilitating the operation of the collected data to reinforce the creation of high added value data chains.
    - **High resource consumption:** Deep learning models create highly flexible models by using over-parameterization, which makes them often computationally costly models (compared to simpler models). To circumvent this issue, and whenever possible, we will focus on improving the model's efficiency (e.g., by using Transfer Learning techniques, which have been proven to greatly reduce training time), while providing a net positive balance between the energy consumed in training and the resulting improvement in building operations and consumption reductions.

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