Preparation of Papers for IEEE

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NOMENCLATURE

ℓ	number of lags
η	energy outflow curve
$\hat{Q}_{in}$	Forecasted Inflow per hour
Λ_t	Regularization Vector
$\mathcal{U}_t$	uncertainty set for $Q_{in,t}$ at time t
ω_j	j-th Pump speed
π	Day-ahead energy price
σ_t	Slack variable at time t
E	Energy Consuption
H	Upper MPC horizon
h	Lower MPC horizon
h	Tank's height
h_{ref}	Height Reference
p_j	Pipe-line Pressure
q_{in}	Estimate of the inflow per minute.
$q_{out,j}$	Outflow of the j-th pump
Q_{out}	Hourly Outflow of the Tank

I. INTRODUCTION

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POWER electronic converters (PECs) are ubiquitous, serving as critical interfaces in electrification by connecting loads, energy storage systems, sources, and the grid. For example, PECs are used to convert alternating current (AC) to direct current (DC) in electric vehicles (EVs), transform DC to AC in photovoltaic systems to align with grid frequency and voltage and facilitate operations in high-power applications and various industrial processes. With the ongoing transition to net-zero carbon grid, and the steady increase of installation electric motor drives (eg., pumps, compressor, and fans) it becomes clear how PECs could play a major role in orchestrating a large network of *prosumers*, i.e., flexible loads that could serve as consumers or producers based on the operational conditions of the grid.

Today, most industrial applications are still unidirectional, meaning they consume energy according to their strategy without taking grid conditions into account, primarily due to the fact that energy generation was traditionally dominated by large plants operating on a fixed schedule to meet specific demands during designated hours. However, in addition to the inverter-based grid, and stability challenges, with the energy landscape gradually shifting from centralized to decentralized and stochastic generation, it also pushes for significant technological advancements.

However, the aggregation of this flexibilities come with a price, especially in terms of data aggregation, computational resources, scalability and advances control techniques that are able to interact with cloud architecture, PLCs and APIs. (Read paper Musumeci)

Small summaries of paper analyzing could platform with gree transitions

[1] analyzes the challanges in communication, storages and computational capabilities in massive streams of data, while [2] presents how IoT benefit the accurate forecasting and predictive mantainance ensuring high security levels. Paper [3] extensively review the literature on the application of IoT in energy sectors ans smart grids, by distinguishes the the transmission and distribution levels, where IoT can be applied to energy efficiency, aggregation of distributed generations and electric vehicles aggregation (V2G), from the demand side where IoT can be used for battery energy storage management and control to smart building control.

Wi-Fi, Bluetooth, ZigBee [4] LTE-4G and 5G networks [5]

As an example in paper 1 the authors studies the return of investment of the design of distributed energy resources. Other studies focuses on how a distributed scenario could benefit the industry, or how policy maker could push for emerging markets for distribute resources. On the bottom level, the integration of grid-based inverters playing a pivotal role in designing a grid able to maintain a power quality and stability. In fact it is known that with the increasing amount of renewables, the grid is being more exposed to fluctation and stochasticty mainly driven by the weather forecast, requiring the energy storage and ancillary service includes managing voltage levels and frequency to prevent grid disturbances. Another part of the literature is focusing on scheduling and resource allocation under uncertainty. Methods like stochastic or robust optimization are now becoming more popular in order to minimize Value at Risk (VAr), under uncertain conditions.

II. System Description

The cloud is a service where all the application can be executed on a virtual environment owned either by private or company. In our application, we used the Internet of Things (IoT) Hub from Azure, which is a centralized platform that facilitates the connections and the management of fleets of IoT devices. The IoT Hub enables a streamlined bidirectional comunication from the Cloud to the physical devices, sensors. As reported above, nowadays most of the energy plant are equipped with SCADA (Supervisory Control and Data Acquisition) [6], which enables data real-time monitoring and control of industrial processes and infrastructure. It integrates hardware and software components to collect data from sensors, control equipment, and provide centralized oversight through Human-Machine Interfaces (HMIs). However, in comparison with SCADA, the IoT Hub has some more 7 support in terms of scalability, as it can support thousand of sensors and embedded devices, and also provide an extra layer of flexibility in terms of data collection for real-time and historical data. Moreover, it also provides different technologies for data driven modelling and artificial intelligence services.

IoT sensors can be controlled singularly from the Azure Hub, but this is not our case. In our application, all the sensors are aggregated using a Kunbus Revolution Pi, which is the industrial standard of Revolution Pi. The Revolution Pi enables a bi-directional communication and serves as bridge between the PLC and the Cloud. The communication between the Gateway and the PLC is Modbus TCP/IP, a tailored version of the protocol for network communication over internet. One of the key advantage of this chain strategy is that the majority of the sensors, VDFs are connected to the PLC directly, so there is not need to rebuild from scratch the communication between all the sensor and the RevPi. The PLC is the Siemens s7-1200, which support Profinet, a propetary version of Profibus protocol, developed by Siemens that enable fast and reliable communication in control. The PLC is the connected to the following devices: VDF1, VDF2, VDF3, Outflow sensor, level sensor, pressure sensor, Addionally, from each VDF can be retrieved the instantaneous speed and power consumption.

A crucial role in this application is played by the RevPi which not only combine the collected data from the PLC and the gateway and pushes the data to the cloud but also acts as real-time controller, overcoming the limitation of the PLC in terms of computational capabilities. In fact, the needs more comprehensive and optimization based control techniques , poses the needs of extra computational power, memory allocation and faster CPUs. This architecture, compared to purely

TABLE I
Sensors Overview

Sensor	Unit of Measurement	Protocol
Level	m	*Analog*
Speed	rpm	*Profinet*
Inflow	m^3/h	*Virtual*
Power	kW/h	*Profinet*
Pressure	psi	*Profinet*
Outflow	m^3/h	*Analog*

cloud-based controller, provides an extra layer of security, as the the on-site control device, can able to handle different situations, overcoming well-known limitations broader adoption, as delays or disruptions in communications.

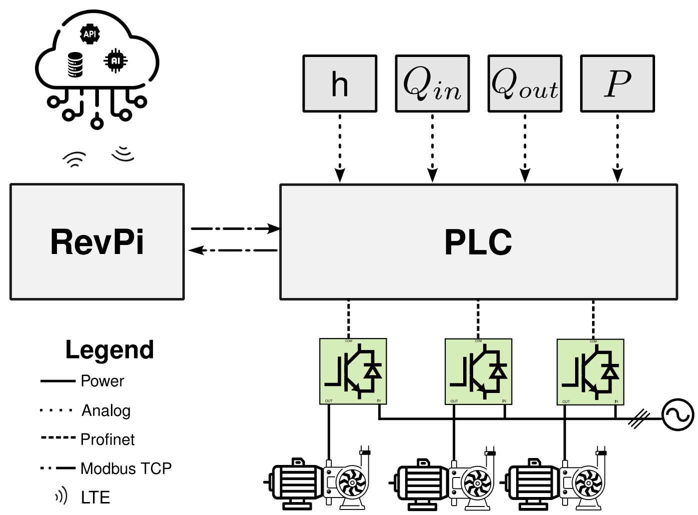

Fig. 1. Your caption text.

1) Data streaming and Features.: The resolution frequency of the data streaming is 1Hz, as every second one measurement is sampled, pushed and stored to a time series database located in the cloud. Each sensor has a time index and values and can be queried from external APIs. This architecture allows high modularity as different blocks perform different operation

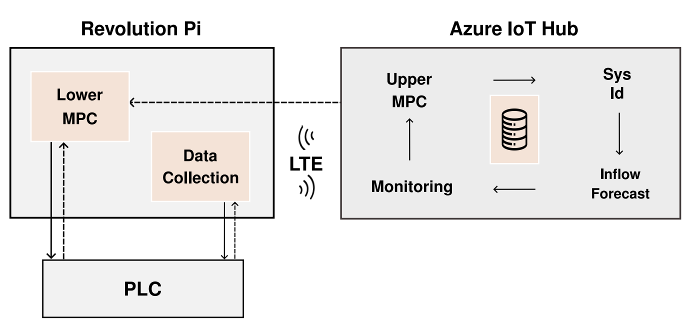

Fig. 2. Edge-Cloud Architecture

III. Proposed Methodology

A. ARX Model

We have chosen to represent the system in *discrete time*,

$$y_t + a_1 y_{t-1} + \cdots + a_n y_{t-p} = b_1 u_{t-1} + \cdots + b_q u_{t-q} \quad (1)$$

$$\theta = \left[a_1, \ldots, a_p, b_1, \ldots, b_q\right]^T \quad (2)$$

$$\varphi(t) = \left[-y_{t-1} \cdots - y_{t-p}, u_{t-1} \cdots u_{t-q}\right]^T \quad (3)$$

$$y_t = \varphi_t^T \theta_t \quad \forall t \in (1, N) \quad (4)$$

For a given system we can collect inputs and outputs over a time interval t

$$Z^N = \left\{u(t_0), y(t_0), \cdots, u(N), y(n)\right\} \quad (5)$$

$$\hat{\theta} = \arg\min_x V_N(\theta) + \lambda(\theta - \theta^*)R(\theta - \theta^*) \quad (6)$$

The ARX(p, q) model is given by:

$$y_t = \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{q} \beta_j x_{t-j} + \epsilon_t \quad (7)$$

B. Inflow Estimation

The considered wastewater pumping station, only the outflow and the height are measured, while the inflow is not measured or estimated. Therefore, in order to estimate the inflow of the tank, we implemented an observer by using the tank equation where the instantaneous rate of change of the height dh is proportional to the difference between the inflow and the outflow of the tank, scaled by the area of the tank, as pointed Eq.8.

$$h_t = h_0 + \frac{T_s}{A}(Q_{in,t} - Q_{out,t}) + v_t \quad (8)$$

where A, the cross-sectional area of the tank, T_s is the sampling time of the measurements, $Q_{in,t}$ and $Q_{out,t}$ are the measured inflow and outflow respectively, and v_t is the measurement noise.

By defining the the inflow $Q_{in,t}$ any time t, the hidden state the Eq.8, w_t the process noise, Q is the covariance of the process noise, and R is the measurement noise covariance.

$$Q_{in,t+1} = Q_{in,t} + w_t$$

The states can be estimated by means of the Kalman filter, at any given time t

Prediction Step:

$$\hat{Q}_{in,t+1|t} = \hat{Q}_{in,t|t}$$
$$P_{t+1|t} = P_{t|t} + Q$$

where Q is the covariance of the process noise.

Update Step: Compute the Kalman Gain and update the estimate with the measurement:

$$\Delta h_{t+1} = h_{t+1} - z_{h,t+1}$$
$$\Delta Q_{t+1} = \hat{Q}_{in,t+1|t} - z_{Q_{out},t+1}$$
$$\hat{Q}_{in,t+1|t+1} = \hat{Q}_{in,t+1|t} + K_{t+1}\left(\frac{A}{T_s}\Delta h_{t+1} - \Delta Q_{t+1}\right)$$

C. Inflow Forecast

The inflow estimation is the a first step to enhable the control of the system from a lower perspective. This means that the recursive estimation of the inflows allows, as it will be clarified in the next steps, to maintain the equilibrium between the inflow and the incoming outflow. This estimation can be performed at different time level, in order to accommodate the system. An example is that if the system is running at seconds resolution, then the estimation can support the balancing equation of the height. However, after visual inspection, it can be seen that the inflow is mainly driven by two large scale phenomena, i.e., the human behavior and the rain. In fact, in our application the inflow peaks in the morning, registering the most intensive water usage during the day. Additionally, the inflow patter follows a 24 hours seasonality with trend following the alternation of meteorological seasons. However, on the top of this components largely characterized by the large scale human behavior, the inflow is strongly affected by the rain. In fact, even in separate systems, the rain infiltration can strongly affect the inflow and thus the normal capacity operations of pumping or treatment stations, representing the main cause of overflow in most of the swage operations. Mitigation of overflow is among the challenges in modern pumping and treatment stations, but still represent one of the main driver of clean water pollution. Therefore, preventing this uncontrolled scenarios plays a pivotal economical, environmental and social issue. Nevertheless, building accurate inflow forecast is challenging for many reason, i.e., uncertainty in the rain forecast, mismatch between the rainfall forecasted and the actual precipitation and finally the availability of the historical rain forecasts. For this purpose, we build our own data collection, where the rainfall forecats are queried hourly from the Norwegian Meteorological Institute (Meteorologisk institutt), while the actual precipitation is retrieved from the Danish Meteorological Institute (Danmarks Meteorologiske Institut), which provides, on a per minute basis, measurements of the precipitation occurred in the past minute. Finally, the measured rainfall is resampled hourly, and use to train the model, while the forecast are used as future covariates to provide hourly forecast over an horizon of 1 day. Given the decomposable structure of the time series and the impulsive behavior caused by the rain, we found an online hybrid windowed model be the best fit for this application. The hybrid strategy can be devided into two different steps. The first one if time series modeling using Generalized Additing Models (GAM), where the time series is modeled as follows:

$$y_t = g_t + s_t + r_t + \epsilon_t \tag{9}$$

where:

- $\boldsymbol{g_t}$ represents the trend, modeled as piecewise linear trend with changes points:

$$g_t = (k + a_t^T \delta)t + (m + a_t^T \gamma) \tag{10}$$

with k defined as the growing rate, δ the rate adjustments, m an offset parameter, and γ a term to ensure the continuity of the function.

- $\boldsymbol{s_t}$ is the seasonality terms given by the N first Fourier terms, as reported in Eq.11

$$s_t = \sum_{n=1}^{N} \left(a_n cos\left(\frac{2\pi nt}{P}\right) + b_n sin\left(\frac{2\pi nt}{P}\right)\right) \tag{11}$$

- whereas, $\boldsymbol{r_t}$ is the external covariates representing the rain forecasted for the next 24 hours.

Once fitted the model, assuming the residuals are almost normally distributed and thta the time series is stationary, we model the residuals of the $\epsilon_{t,GAM}$ of a time series $Q_{in,t}$, using an ARIMA(p,d,q) model:

$$\Phi(B)(1-B)^d \epsilon_{,GAM} = \Theta(B)\nu_t \tag{12}$$

to fit these model we used the Pophet model developed by facebook using a recursive fitting widown and a simple arima for the remaning autocorrelation of the residuals.

D. Hierarchical Model Predictive Control

1) Higher-Level MPC:

$$\min_{\eta} \max_{Q_{in,t} \in \mathcal{U}_t} \quad \sum_{t=1}^{T} \left(\eta_t \mathcal{C}_t + \Lambda_t^T \sigma_t \right) \tag{13a}$$

$$\text{s.t.} \quad \sigma_t \geq 0, \ell \geq 0 \quad \forall t \in T \tag{13b}$$

$$\eta_t = \sum_{j=1}^{3} \eta_{j,t-1}, \quad \forall t \tag{13c}$$

$$h_{min} \leq h_{ref,t} \leq h_{max}, \quad \forall t \tag{13d}$$

$$E_{min} \leq E_t \leq E_{max}, \quad \forall t \tag{13e}$$

$$\hat{Q}_{in,t} = \hat{Q}_{in,t-n} \tag{13f}$$

2) Lower-Level MPC:

$$\min_{\omega, E, P, Q_{\text{out}}} \sum_{k=1}^{h} \mathcal{Q} \left\| h_k - h_{ref} \right\|^2 + \mathcal{R} \left\| \omega_k \right\|^2 + \Gamma \left\| E \right\|_k^2 + \Lambda_k^T \sigma_k \tag{14a}$$

$$\text{s.t.} \qquad \forall \sigma_k \geq 0,\ \ell \geq 0 \quad \forall k \in h \tag{14b}$$

$$Q_{\text{out},k} = \sum_{j=1}^{3} Q_{out_{j,k-1}} \tag{14c}$$

$$E_k = \sum_{j=1}^{3} E_{k-\ell} \tag{14d}$$

$$P_k = \sum_{j=1}^{3} P_{k-\ell} \tag{14e}$$

$$Q_{in,k} = \tilde{Q}_{in,k-1} \tag{14f}$$

$$h_k = \frac{1}{A}\left(\tilde{Q}_{in,k} - Q_{out,k}\right) \tag{14g}$$

$$P_{min} - \sigma_{P,t} \leq P_k \leq P_{max} + \sigma_{P,t} \tag{14h}$$

$$\omega_{min} - \sigma_{\omega,t} \leq \omega_k \leq \omega_{max} + \sigma_{\omega,t} \tag{14i}$$

$$h_{ref} - \sigma_{h,t} \leq h_k \leq h_{ref} + \sigma_{h,t} \tag{14j}$$

Algorithm 1: Hierarchical MPC of aggregation of power converters.

```
Set h ← lower-MPC horizon
Set H ← upper-MPC horizon
Set t ← 0
while control = True do
    t ← t + 1
    k ← k + 1
    q̂_{out,k} ← measure outflow state
    ĥ_k ← measure height state
    q̂_{in,k|k} ← estimate inflow state
    if k mod H = 0 then
        r_{t+H} ← update rain forecast from API
        π_{t+H} ← update price forecast from API
        Q̃_{in,t+H|k} ← forecast inflow state
        h_ref ← solve upper-OCP (scheduling)
    end
    {ω_k}_{j∈1,2,3} solve lower-OCP (drives control)
    apply {ω_k}_{j∈1,2,3} to the system
end
```

IV. Experimental Results

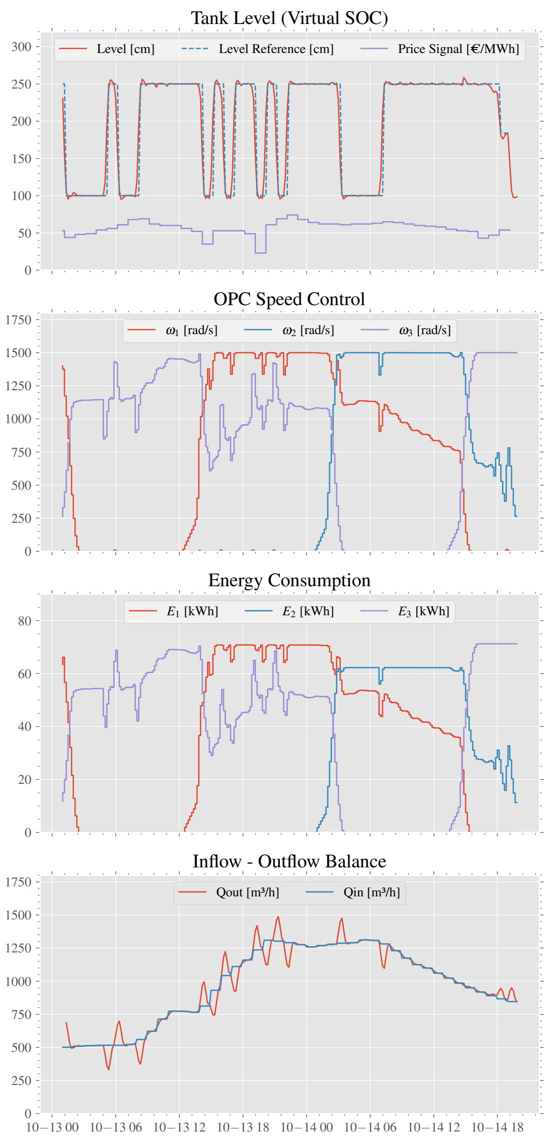

Fig. 3. Free simulation of the hierarchical control strategy over 42 hours.

V. Conclusion

References

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