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Edge Intelligence in Distributed Energy Grid

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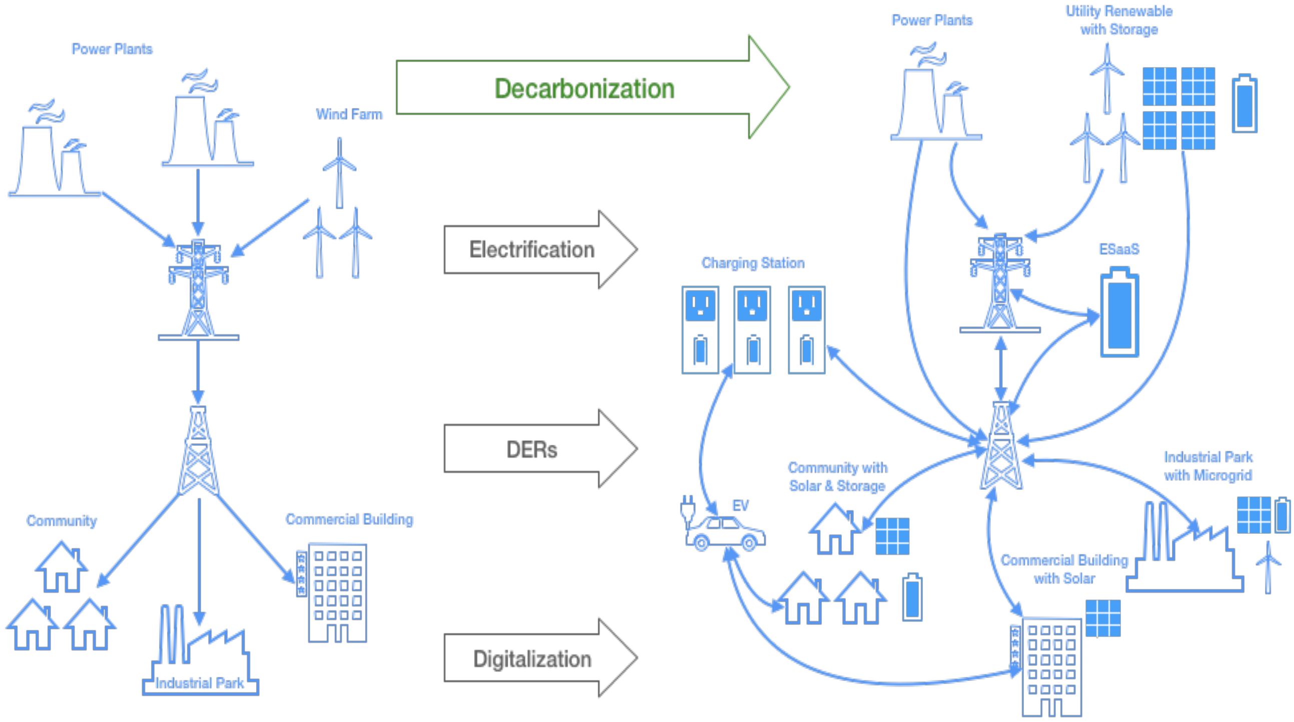

Fig. 1. (left) The Current Power Grid: "Top-down" with control from a central node is difficult to scale; (right) The Future Smart Grid: More complex grid with addition of DERs and storage.

Abstract— The grid is getting complex with the addition of DERs and storage at the edge. The edge management needs to be easy and intuitive. At EQuota, we develop an analytics-driven and smart-edge-device-enabled digital solution. Compared with current technologies or practices, our solution is able to sense better, think smarter and act with ease to allow high level of scalability by Plug & Play IoT devices and analytics-enabled operation flexibility, operation optimization accommodating constraints, and market dynamics.

Keywords—DER, Smart Grid, Plug & Play IoT, Edge Management

I. Introduction

Power grid is a huge physical network connecting tens of thousands of power generators to billions of end-consumers It links public and private enterprises operating within a web of government institutions: federal, regional, state, and municipal. The grid will face a number of serious challenges over the next couple of decades, while new technologies also create valuable opportunities for meeting these challenges. A failure to recognize these opportunities or meet these challenges could result in deterioration in reliability, significantly increased costs, and a failure to achieve several public policy goals [1]. Fig. 1 shows the illustration of our current and future power grid.

From the blackout of super cities like Tokyo, New York and London in the past 15 years, these energy systems are much fragile than we imagine, especially when more renewable energy sources are admitted to the system. The system needs a central node to coordinate for system operation and edge nodes then act at their own interests to central signals. The success relies heavily on the participation of edge owned by end-customers. The edge management hence needs to be easy and intuitive while leaving the complexity behind the scene.

II. Electricity Reform in China

A. Problems

The Chinese energy industry is now facing critical transformation. China's 13th Five Year Plan plans to reduce energy intensity by 15% and reduce carbon intensity by 18%. The 3% gap appeared in government's policy indicates that non-fossil energy sources will become more important to the Chinese economy. Carbon reduction target can be achieved by improving energy efficiency and shifting economy from its traditional dependence on heavy industry to less energy-intensive sectors. Currently, the energy efficiency in China is lower than designed specification due to the following problems:

- Throughout the energy value chain, energy data is of poor quality and consistency and scattered rather than integrated into one digital platform. If you ask a steel mill for their energy-related data, you may end up with several incomplete and inconsistent data sets manually generated from different sources. There is a lot information, but no possible insight.
- Interaction within the Chinese energy industry chain between different segments is inadequate, from the most micro level of individual consumers to operational level of power plants and transmission grid, up to the most macro level of centralized power supply planning and power quota. The need for interactivity between power plants, grid, and end-users reflects the needs for China's reform of its existing energy structure.

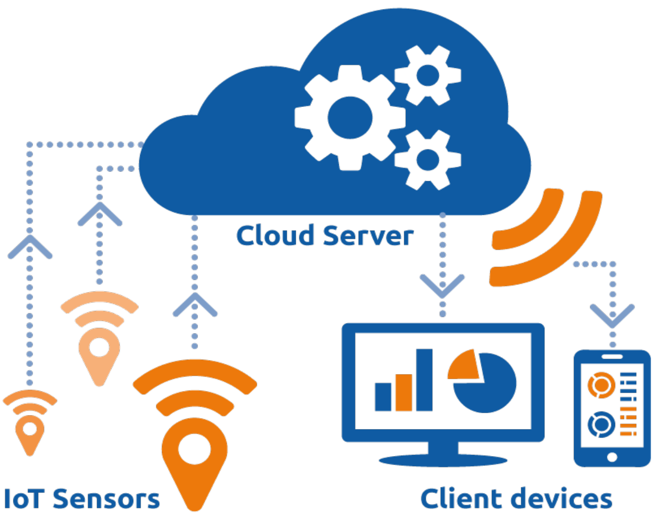

Fig. 2. Solution Architecture.

- Lack of advanced operation and maintenance technology, causing energy inefficiency. Most industrial estates are still making their annual energy demand and devices maintenance plan base on traditional experience. There are obvious unnecessary energy consumptions and wastes. The energy efficiency requires further increase.
- China's current policies are promoting distributed power systems. Such electricity reform will change the power landscape, opening the centralized grid network to other power resources to sell directly to the users. Opening the power market to new services depends on cutting-edge data analytics technology.

B. Solutions

At EQuota, we develop an analytics-driven digital solution on edge devices for generation, storage and consumption to provide analytics enabled services for the ease in management to secure customer participation. Fig. 2 shows the solution architecture. In particular, we develop inexpensive digitalization solution and easy to scale in hardware and operation. The solution enables the customers to sense better, think smarter and act with ease.

- Sense better monitors the performance in a more granular scale by advanced analytics such as non-intrusive load monitoring.
- Think smarter enables edge to plan to the best of its interest in term of efficiency, energy cost, availability, convenience by responding to central signals knowing its current status and future demand forecasting.
- The hardware device serves not only as the core for above two features but also provides compatibility to a variety of protocols for sensing and actuating flexibility.

Fig. 3 summarizes the challenges and desired solution features.

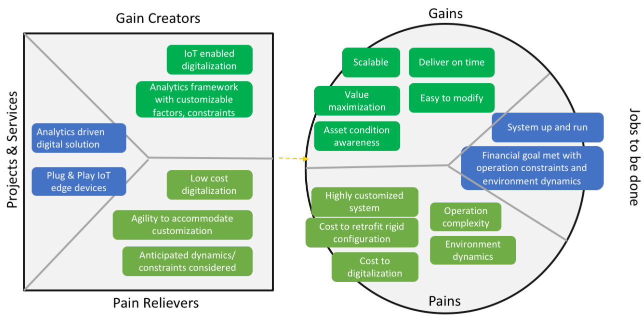

Fig. 3. Challenges and Solution Features.

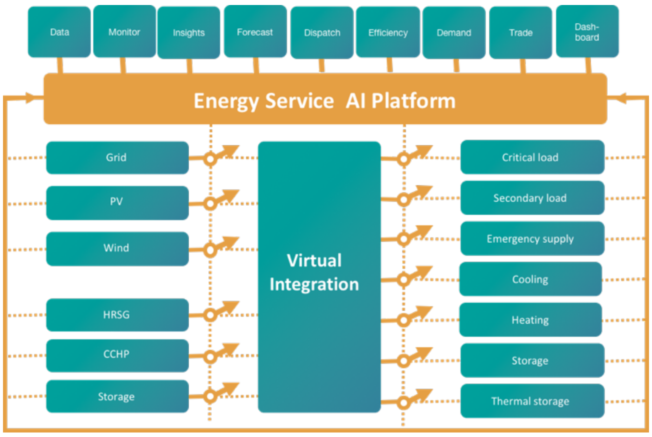

Fig. 4. A proposed platform orchestrating DERs plus optimizing consumption.

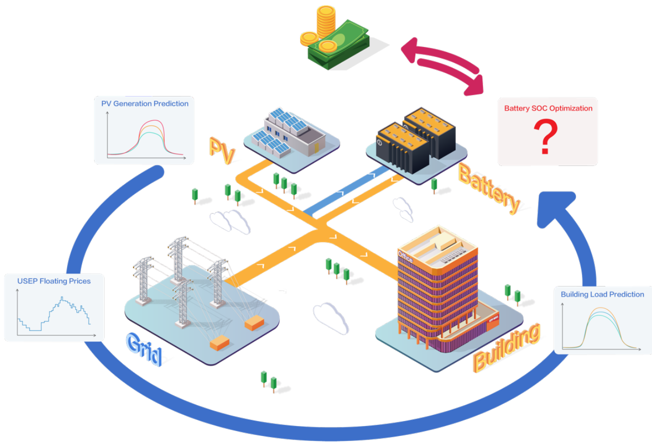

Fig. 5. Illustration of a commercial building with energy storage system and renewable energy.

III. Energy Service Platform

Fig. 4 shows our proposed Megacity Energy Service AI Platform in Shanghai. A few features on selected sub-systems of the Megacity are described below:

Phase 1

- Two 5.2 MW Combined Cooling, Heating and Power (CCHP) units consisting of gas engine generators and lithium bromide absorption chillers with rated power generation of 1.4 MW
- Connecting but not transmitting power to grid
- Serve 1,700,000 m^2 building area
- Provide at maximum 13.3 MW 60 ^oC chilled water or 13.6 MW 95 ^oC hot water

Phase 2

- Heating source from thermal power plant to serve 740,000 m^2 area with district heating and cooling
- Energy storage for peak shaving

Phase 3

- The system consists of 2 gas turbines, 4 boilers, 2 absorption chillers, 8 chillers, 31 heat pumps, 2 screw chillers, 12 cooling towers, 4 diesel generators for 4 MW power, 36.9 MW heat and 47.0 MW cooling at rated conditions

The goal is to develop an intelligent, resilient and scalable energy management system to serve as an energy reserve to keep municipal critical assets (such as hospitals, transportation hubs, shelters etc.) running during extreme events. The system builds upon enabling technologies in IoT, Cloud and Edge Computing, high fidelity physical system simulation, with main features include asset health condition monitoring, load and demand balancing, predictive analytics that facilitates energy trade, proprietary data modeling, optimization & control strategies. The platform is delivered via integrating distributed energy resources of electricity, gas, heating and cooling, coordinating with energy consumers, and collaborating with power distribution, communication, and equipment manufactures

IV. Case Study

Based on our proposed energy service platform, a scaled-down version of our energy management system was applied to a commercial building with battery and solar panels installed as shown in Fig. 5. In this framework, the electricity consumed by the building comes from the grid, PV system and battery system (discharge), while electricity can also flow in the battery (charge). Our energy management system provides the optimal battery operation.

A. Define Variables

To be more precise, let us define the energy flows as follows: energy from grid to load (E_{G2L}), energy from PV to load (E_{P2L}), energy from grid to battery (E_{G2B}), energy from battery to load (E_{B2L}); energy costs as follows: electricity price (P_G), battery charge/discharge cost ($P_B \approx 0$), PV generation cost (P_{PV}).

B. Contraints

Operating constraints of the system are mostly related to the battery. Let us define a battery model

$$E_{btty}(t) = E_{btty}(t - \Delta t) + \Delta E \tag{1}$$

The corresponding constraints can be described as below:

Battery Capacity:

$$E_{btty,MIN} \leqslant E_{btty} \leqslant E_{btty,MAX} \tag{2}$$

Charge/Discharge Efficiency (one of the followings):

$$\Delta E = E_{G2B} * e_{charge} \tag{3}$$

$$\Delta E = E_{B2L} * e_{discharge} \tag{4}$$

$$\Delta E = E_{loss} \tag{5}$$

Charge/Discharge Speed (one of the followings):

$$0 \leqslant \Delta E / \Delta t \leqslant CR_{charge} \quad (6)$$

$$CR_{discharge} \leqslant \Delta E / \Delta t \leqslant 0 \quad (7)$$

where e_{charge} is the charge efficiency, $e_{discharge}$ is the discharge efficiency, E_{loss} is the overall electricity loss in battery, $E_{btty,MIN}$ is the battery the minimum capacity, $E_{btty,MIN}$ is the battery the maximum capacity, CR_{charge}, charge speed, $CR_{discharge}$ discharge speed.

C. Problem Formulation

To determine the optimal battery operation for the case study, let us consider the following Cost Function:

$$Cost = (E_{G2L}+E_{G2B})*P_G + (E_{G2B}+E_{B2L})*P_B + E_{P2L}*P_{PV} \quad (8)$$

where both PV generation and building load forecast uncertainties can be described as follows:

$$E_{P2L} = (E_{PV\_prd} + \varepsilon_{PV}) * \ \varepsilon_{PV} \sim N(0, \sigma_{PV}(t)) \quad (9)$$

$$E_{Load} = (E_{bd\_prd} + \varepsilon_{bd}) * \ \varepsilon_{bd} \sim N(0, \sigma_{bd}(t)) \quad (10)$$

E_{PV_prd} is the predicted PV generation, E_{bd_prd} is the predicted load, ε_{PV} and ε_{bd} are normal distributions with σ_{PV} and σ_{bd} respectively. Fig. 6 depicts

The constrained stochastic programming problem [2] can be formulated as follows:

$$\min \Sigma Cost, \text{ for } t = 0 \text{ to } N$$

subject to Contract Capacity (CC) constraints as follows:

$$E_{G2L} + E_{G2B} \leqslant CC \quad (11)$$

$$E_{Load} - E_{P2L} + E_{G2B} \leqslant CC \quad (12)$$

$$\alpha \leqslant P\{ E_{G2L} + E_{G2B} \leqslant CC \} \quad (13)$$

where P is the probability, α is the confidence level and N is the total number of time steps being considered. Fig. 6 illustrates the effect of uncertainty in the battery operation curve.

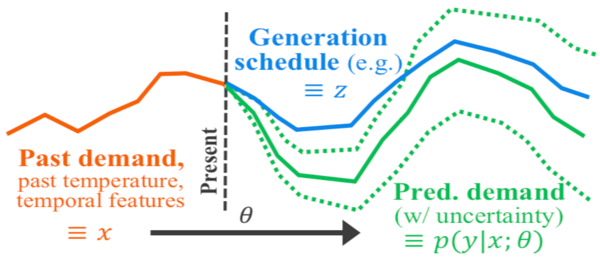

Fig. 6. Illustration of Stochastic Optimization.

D. Results – Client #1

Let us consider the following example from our customer in South-East Asia [3]:

Battery Capacity: 2500 Ah

Charge/Discharge Speed: 1C

Efficiency: 90%

Electricity Price: Extracted from reference [4]

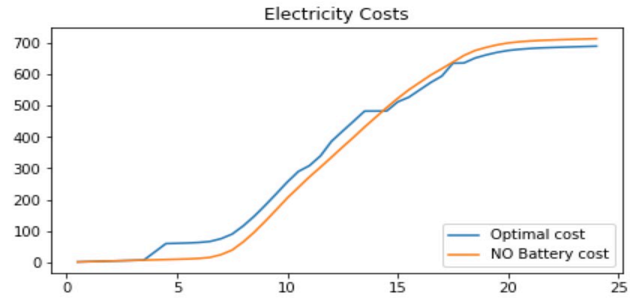

Fig. 7. Comparison of electricity bill between 2 different battery operating sequences during a typical day.

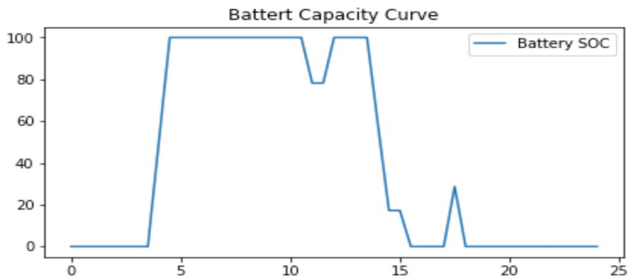

Fig. 8. Battery capacity sequence of the corresponding battery operation in Fig. 7.

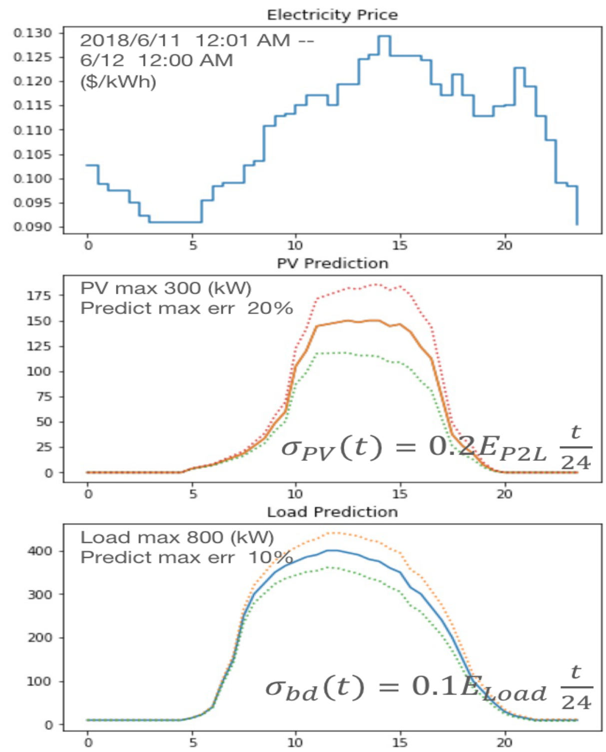

Fig. 9. (a) Top: Electricity Price; (b) Middle: PV Generation; (c) Bottom: Load Prediction. Simpe uncertainty descriptions were also provided.

Fig. 7 shows that a 3.36% cost reduction using our optimal battery operating sequence (shown in Fig. 8). The corresponding electricity price, PV generation and load forecast are shown in Fig. 9a – c respectively, with all uncertainties considered.

E. Results – Client #2

Let us consider the following example from our customer in Guangzhou, China [3]:

Battery Capacity: 300kW / 500kWh

Depth of Discharge: 90%

Efficiency: 90%

Electricity Price (RMB/kWh): Peak (1.033), Normal (0.638), Off-Peak (0.334)

- Peak Period: 14:00-17:00 / 19:00-22:00 (red)
- Normal Period: 8:00-14:00 / 17:00-19:00 / 22:00-24:00 (green)
- Off-Peak: 0:00-8:00 (blue)

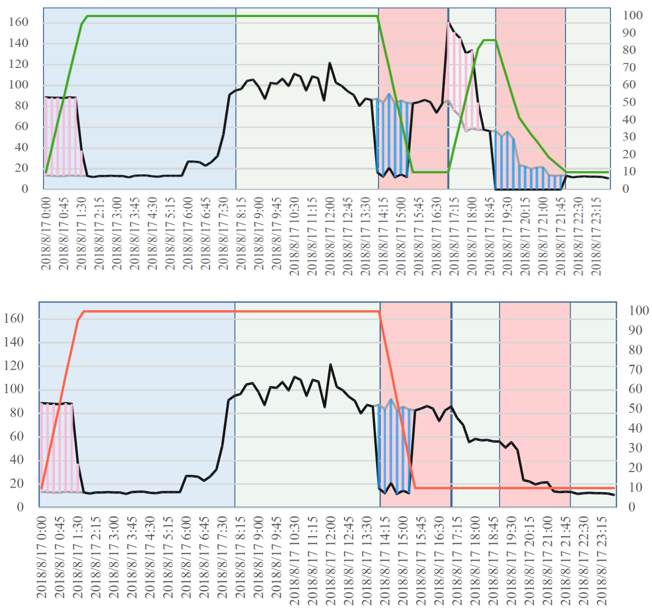

Fig. 10. (a) Savings of a typical day with our optimal battery operation; (b) Savings of a typical day with the baseline 1-charge-1discharge battery operation.

Fig. 10a and 10b shows our optimal battery operation and the baseline 1-charge-1-discharge battery operation respectively. The left y-axis shows the load (in kWh) while the right y-axis shows the State of Charge (SOC, in %) of the battery while the x-axis shows the timestamp of a typical day. The three colored zones (blue, green, red) represent three electricity price period (Off-Peak, Normal, Peak) respectively. The battery SOC is between minimum of 10% to maximum of 100%. The black line shows the load of the building if it follows our optimal battery operation (green line). The blue strips show the energy being discharged from the battery to the building (save money) while the red strips show the other way (cost money). The optimal operation can make 396.6 RMB compared to the baseline performance of 281.4 RMB via 1-charge-1-discharge operation on a typical with additional 115.2 RMB gain (~41%).

V. Conclusion

It has been clearly demonstrated that our work can be beneficial to the developed countries to help save money by improving efficiency and reducing operation and maintenance costs for the industrial parks and development zone. It is revolutionary to the developing countries by making energy more accessible and reliable for off-grid end-customers not by simple grid expansion, but by digital solution at low cost and low carbon, and also very scalable for future development. The success of the Future Smart Grid relies heavily on the participation of the edge partners across equipment, facility, power generation sources, storage system, etc.

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