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SPECIAL TOPIC ARTICLE

Optimizing smart grid operations from the demand side

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Abstract
As demand for electricity grows in China, the existing power grid is coming under increasing pressure. Expansion of power generation and delivery capacities across the country requires years of planning and construction. In the meantime, to ensure safe operation of the power grid, it is important to coordinate and optimize the demand side usage. In this paper, we report on our experience deploying an artificial intelligence (AI)–empowered demand-side management platform – the Power Intelligent Decision Support (PIDS) platform – in Shandong Province, China. It consists of three main components: 1) short-term power consumption gap prediction, 2) fine-grained Demand Response (DR) with optimal power adjustment planning, and 3) Orderly Power Utilization (OPU) recommendations to ensure stable operation while minimizing power disruptions and improving fair treatment of participating companies. PIDS has been deployed since August 2018. It is helping over 400 companies optimize their power usage through DR, while dynamically managing the OPU process for around 10,000 companies. Compared to the previous system, power outage under PIDS due to forced shutdown has been reduced from 16% to 0.56%.

INTRODUCTION

Increases in economic activities, seasonal changes in weather, natural disasters, and migration of populations can cause short-term imbalances in the demand and supply of electricity, putting transient pressure on the power grid (Li et al. 2019). Currently, many provinces in China rely primarily on coal to generate electricity. As the coal supply limits the electric power generation (Meng et al. 2019), the existing power grid lacks the ability to rapidly respond to fluctuations in demand. This can cause fluctuations in electricity prices and sometimes forced power outages, thereby negatively affecting the stability and safe operation of the power grid.

To address this challenge, there are currently two main approaches (Colak et al. 2016): (1) on the supply side, intelligent power grid scheduling can be performed; and (2) on the demand side, consumer usage coordination can be performed. As the power generation adjustment flexibility of China's mostly coal fired power plants is limited, there is not much room for optimization on the supply side. Thus, the focus of existing power management systems in China is generally through demand side coordination in order to maintain safe operation (Zhou and Yang, 2015).

Currently, power grid demand-side usage coordination in China is carried out according to the following general steps:

1. Performing short-term power consumption gap prediction: this step is typically performed by experts based on domain knowledge. In the case of Shandong province, the 3-day moving average values of previous power demand and supply are used as the basis for predicting the power consumption gaps during the next 5 days. If the predicted usage gap is larger than a predefined threshold value, the power consumption adjustment operations will be triggered.
2. Drafting a hierarchical power consumption adjustment plan: based on the predicted power consumption gap, the experts will decide on a specific period of time for power consumption adjustment, and divide the total amount of over-supply or shortage of power among the cities and counties in a province in a hierarchical fashion according to pre-defined rules. The adjusted power consumption quota allocated to each city/county will, in turn, be divided among companies located in the region which have signed agreements to participate in such operations.
3. Circulating the plan to participating companies and gathering feedback: the current plan will then be forwarded to each of the eligible companies which are selected to participate in this round of power consumption adjustment for confirmation. If some of these companies prefer not to participate in this round (e.g., due to production scheduling conflicts), the plan will be manually adjusted to the extent allowed by the current situation for another round of confirmation.
4. Submitting the plan for official approval: the finalized plan is then submitted for approval by the provincial power management authority and archived.
5. Executing the plan: execute the approved plan for power adjustment, either in the form of Demand Response (DR) (Strasser et al. 2015) by adjusting electricity prices, or Orderly Power Utilization (OPU) (Srivastava et al. 2016) through planned forced shutdown during a given period for the selected companies.

Steps 1 and 2, which are key to the performance of a power consumption management system, used to be performed manually by domain experts. Not only is this approach inefficient and unable to handle complex power consumption adjustment situations, it is also prone to human errors which might lead to accidents in production or unfair treatment of certain participating companies. Thus, the previously used system was unable to achieve rapid response to fluctuations in power demand and supply while minimizing disruption to economic activities.

In order to address this important limitation, we developed an artificial intelligence (AI)-empowered power consumption decision support system - the Power Intelligent Decision Support (PIDS) platform. A novel short-term load forecasting model based on Wavelet Decomposition and Long Short-Term Memory (WD-LSTM) is incorporated into its AI Engine. It combines influencing factor analysis, wavelet decomposition feature extraction, third order exponential smoothing (Holt-Winters) time series analysis and Long Short-Term Memory (LSTM) networks to improve power consumption gap prediction. Based on the improved prediction results, PIDS computes an optimal power consumption adjustment plan which enables fine-grain adjustment of power consumption through joint objective constraint optimization to ensure safe operation while minimizing power disruptions and providing fair treatment of participating companies (Yu et al. 2019b; Zheng et al. 2019), with detailed analytics for enhanced transparency in decision support.

The PIDS platform has been deployed in Shandong Province since August 2018. It has significantly improved short-term power consumption prediction accuracy compared to the previous approach used in the province, and is helping over 400 companies optimize their power consumption through DR while dynamically managing the OPU process for around 10,000 companies. Compared to the previous system, planned shutdown under PIDS has

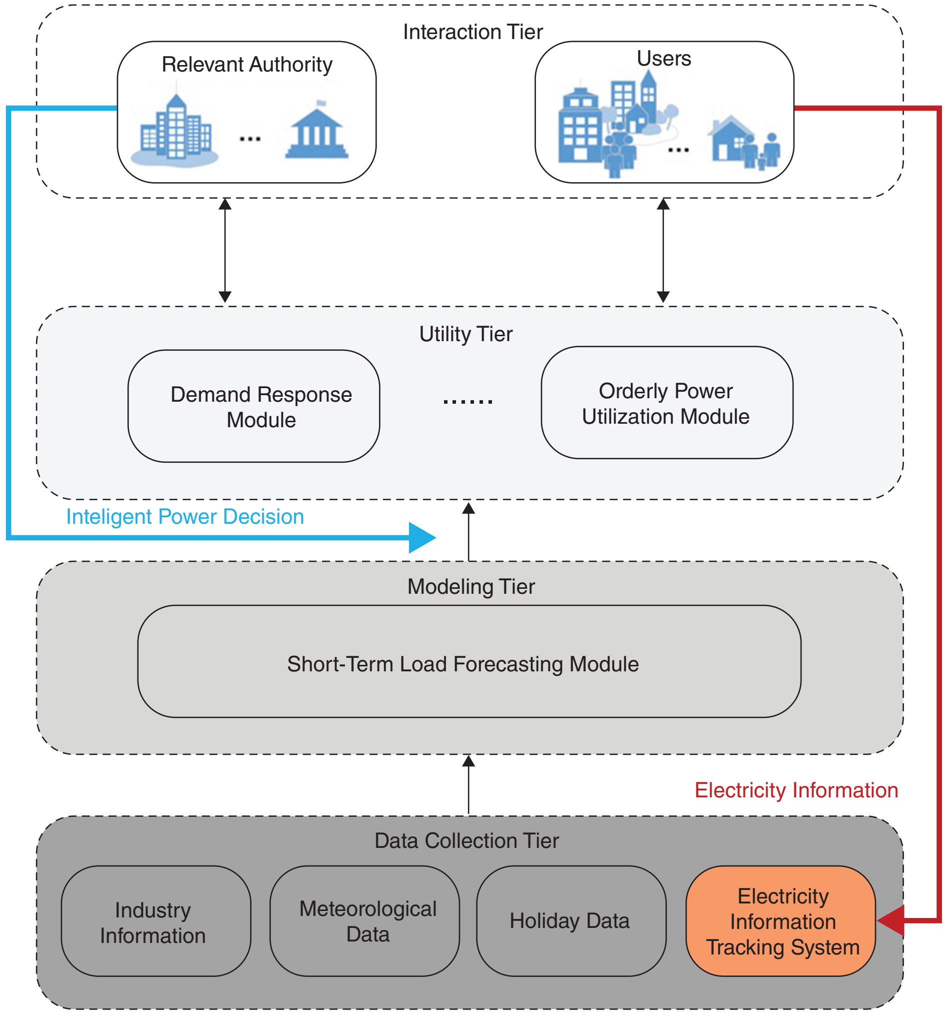

FIGURE 1 The architecture of the PIDS platform

been reduced from 16% to 0.56%, minimizing disruption to economic activities.

METHOD

We first describe the existing demand-side power usage coordination operations in China, and explain which parts of the operations the proposed approach optimizes.

The PIDS platform

The system architecture of PIDS is shown in Figure 1. It comprises of four tiers:

1. The Data Collection tier aggregates relevant data from multiple sources. These include load data and user profile information from the Electricity Information Collection System, meteorological data from the China Meteorological Data Service Center, and holiday data from public holiday calendars.
2. The Modeling tier performs short-term load forecasting, which is the basis for subsequent power consumption adjustment. Its accuracy will affect the effectiveness of subsequent steps. The proposed WD-LSTM model can achieve the accuracy needed for our purposes.
3. The Utility tier includes DR and OPU. Based on the results of short-term load forecasting, this tier computes the optimal power consumption adjustment quota for participating companies and sends out DR invitations to them. It is also responsible for recommending OPU operations to the authority in case DR alone is not enough to ensure safe operation.
4. In the Interaction tier, users can query their historical power consumption behavior analysis reports. They can also accept/reject invitations to the DR operations. The confirmed power consumption adjustment amounts are delivered to the Electricity Information Collection System as feedback. The relevant authority can audit the processes of OPU and DR through the system with human interpretable explanations generated

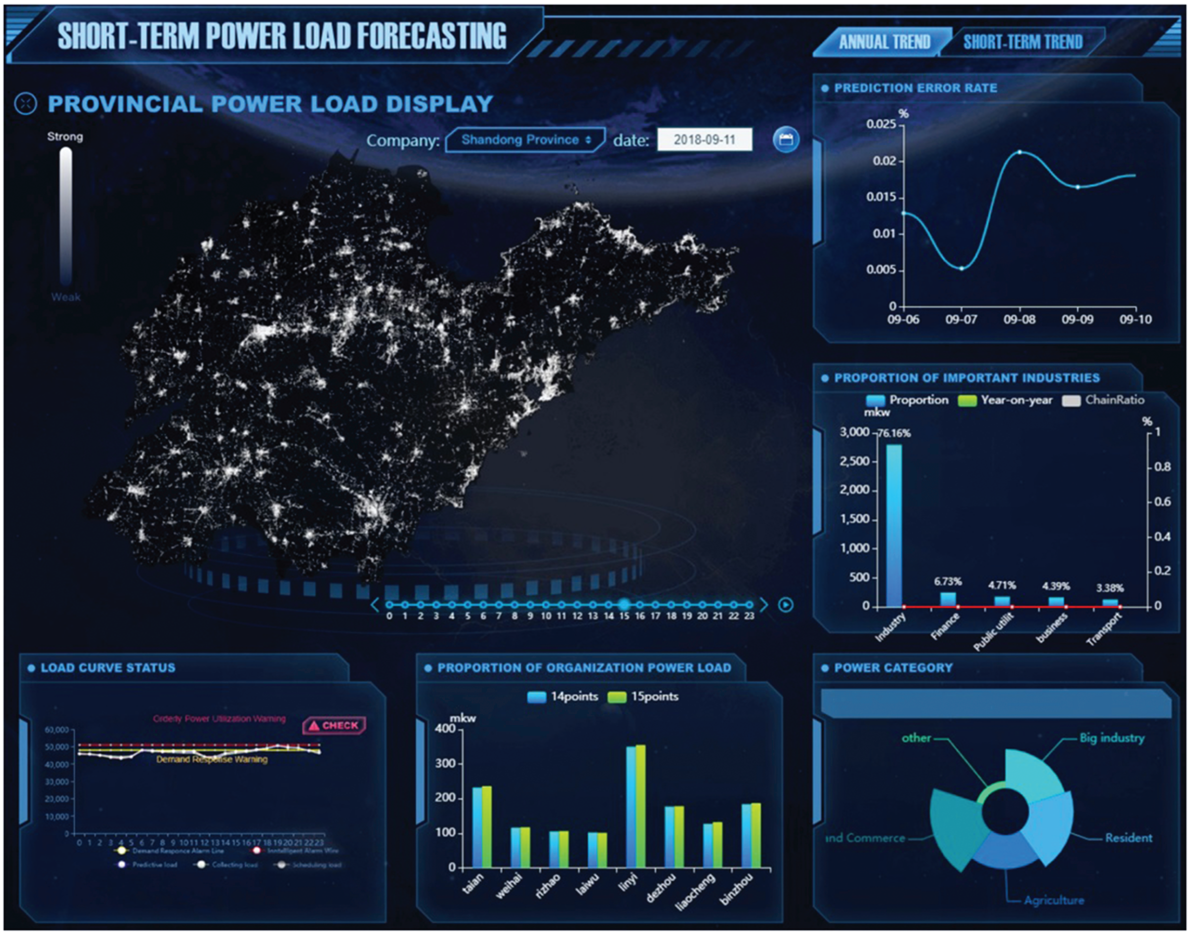

FIGURE 2 The PIDS user interface showing the predicted power consumption gap and related analysis results (Zheng et al. 2019)

by the AI Engine, and modify future policies based on these results.

The user interface through which PIDS displays the predicted power consumption gap and related analysis for the administrators of the power grid in Shandong Province is shown in Figure 2. This is a translated version as the actual deployed system uses a Chinese language user interface. In this example, captured on September 11, 2018, the WD-LSTM model predicted a near-term power consumption gap on September 15, 2018 that would exceed the pre-defined safe operation parameters. It issued an alert in the Load Curve Status panel. Detailed breakdowns of the year-to-date power consumption by different types of customers are shown in different panels. The historical prediction error rates are also plotted in the Prediction Error Rate panel at the top-right hand corner of the screen. The additional analysis is shown to provide transparency and help the administrators make informed decisions on whether to act on the given alerts. PIDS displays recommendations for selected companies to participate in a round of demand response operation, as well as a summary of compliance by these companies (Figure 3). In this instance, due to poor compliance from the selected companies for DR, forced power shutdown through OPU was activated.

AI technologies are used in PIDS mainly for performing two key tasks: (1) predicting the short-term power consumption gap, and (2) optimizing the selection of companies to join DR and OPU.

Short-term load forecasting

Accurate prediction of the short-term usage gap of power consumption is important for the subsequent DR and OPU operations, in order to ensure safe operation of the power grid. However, in power consumption management systems, the following challenges must be addressed to produce accurate predictions on short-term load on the power grid:

Missing data: there are many possible causes for this problem. For example, hardware or software faults during data collection, the data collection mechanism cannot

FIGURE 3 The PIDS user interface showing decision support functions related to demand response optimization (02-Apr-2019)

keep up with the speed of data being generated during peak usage periods, and high cost of data collection. A method for complementing the missing data is thus required.

Noisy data: the collection of massive amounts of power consumption data over time may be affected by random noise and environmental conditions. This negatively impacts the analysis of factors influencing the power load when data are viewed as a time series. Denoising is thus required during feature extraction.

External influencing factors: power consumption can be affected by many factors external to the power grid (e.g., temperature which affects heating and cooling needs, public holidays which affect power needs of certain geographic locations and industries, and natural disasters). The accuracy of short-term power consumption gap prediction can be significantly improved by explicitly taking such factors into account.

Our short-term load forecasting model—WD-LSTM (Liu et al. 2019; Zheng et al. 2019)—is incorporated into the AI Engine of the PIDS platform to solve these problems. The conceptual framework of WD-LSTM is shown in Figure 4. It combines influencing factor analysis, wavelet decomposition feature extraction, third order exponential smoothing (Holt-Winters) time series analysis and Long Short-Term Memory (LSTM) networks. Wavelet decomposition is used to extract the main features of the load data. WD-LSTM then analyzes feature correlation with other influencing factors including temperature, public holidays and industries involved, and then constructs the corresponding adjustment factors.

To deal with the problem of noisy power consumption data, a 3-layer wavelet decomposition and reconstruction method is used in WD-LSTM. The four resulting sub-sequences and data concerning temperature, public holidays and industry specific information are used to perform correlation analysis to obtain the set of power load features and related influencing factors. Then, for each influencing factor, variance assessment based on the ARIMA-GARCH model (Tan et al. 2010) is performed to compute the adjustment values. The preliminary forecast for each feature subsequence is obtained using the Holt-Winters algorithm (Gelper et al. 2010). Finally, the forecasting result and the adjustment values are used as the input to the LSTM network (Gers et al. 1999) to perform regression forecasting and wavelet inverse transformation to obtain the best forecasting results.

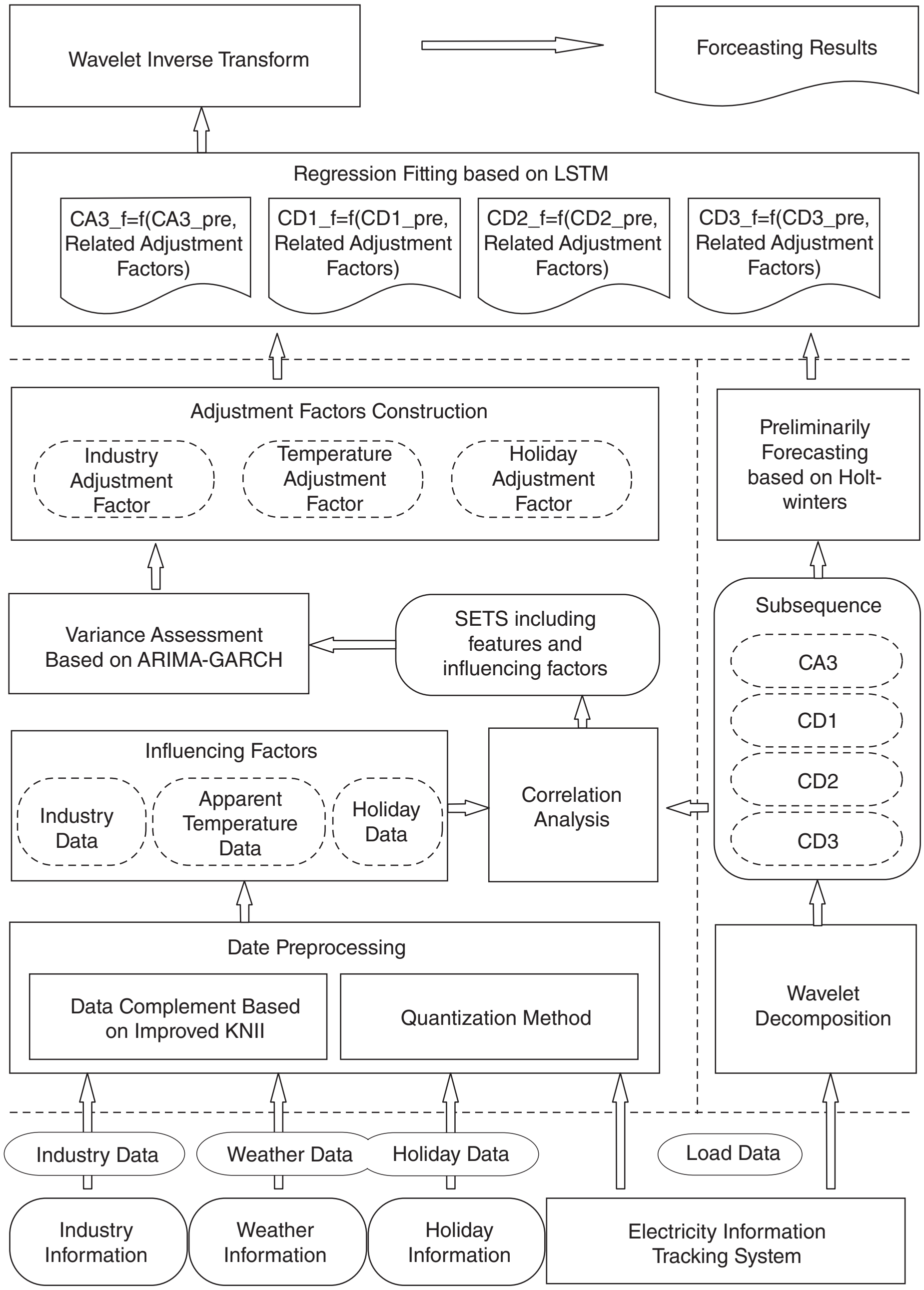

FIGURE 4 The conceptual framework of WD-LSTM

Dynamic power consumption adjustment

Under PIDS, a set of N companies have signed contracts with the provincial government agreeing to participate in power consumption adjustment operations in the following year in exchange for preferential electricity rates. The actual amount of concessions received depends on the level of participation by these companies.

Power consumption adjustments can be divided into two levels: (1) demand response (DR) and (2) orderly power utilization (OPU), as shown in Figure 5. DR can be used to reduce power demands during peak periods, or increase power demands during trough periods. Under DR, a user reduces (or increases) its power consumption by an agreed amount over a specific period of time (e.g., through partially shutting down operations or boosting production activities) in exchange for a lower electricity price during the DR period. During peak periods, if the amount of power consumption reduction in a given round of DR operation is not enough to bridge the power demand-supply gap, OPU will be triggered. PIDS will then select some target companies to be forcibly powered down during the specific period in order to ensure safe operation of the power grid. The selection of companies for DR and OPU must not only satisfy safety constraints, but also

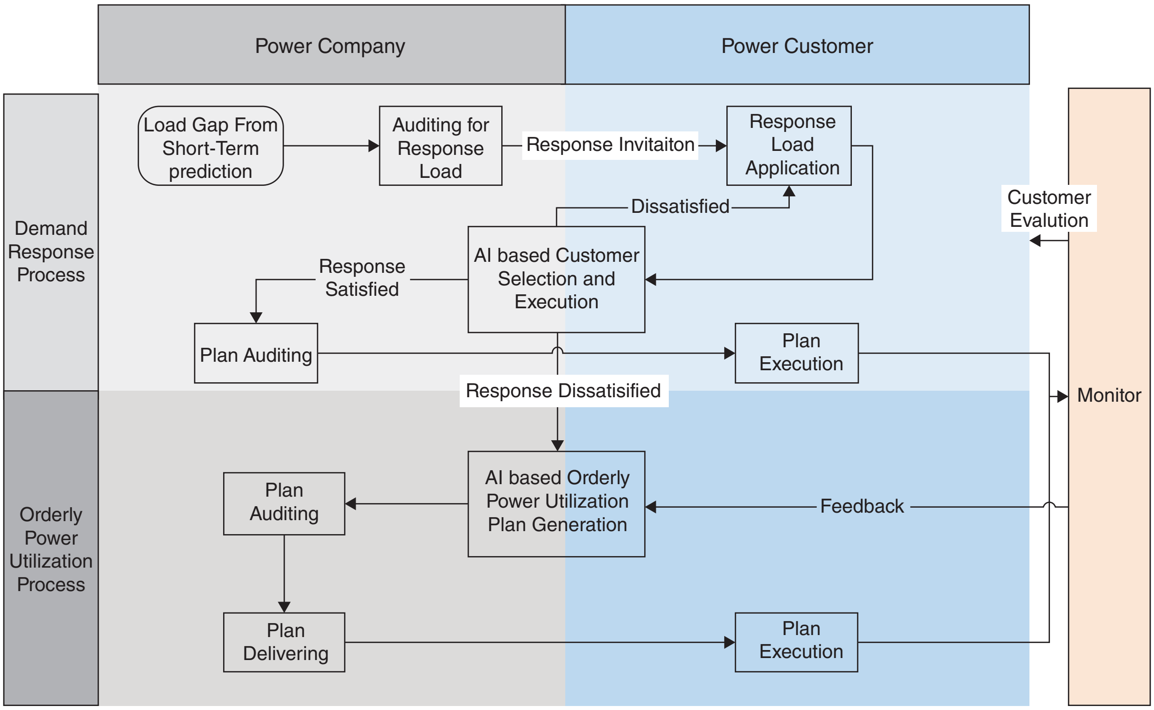

FIGURE 5 The two phases of the power consumption adjustment process

minimize economic loss and ensure fair treatment of the participating companies.

Demand response (DR)

In order to achieve these objectives, we have extended our framework in (Yu et al. 2013a, 2015, 2016, 2017), which has been deployed in our social insurance service provision platform (Zheng et al. 2018, 2020), to enable PIDS to dynamically allocate power consumption adjustment quotas among participating companies. It minimizes variations in the allocated power consumption adjustments among the companies in order to achieve two aspects of fair treatment: (1) the distribution of sacrifice among companies within each round is even, and (2) the fluctuations in the sacrifices made by the companies over time remain small. PIDS also takes into account the economic impact on the companies when prioritizing which companies shall join DR in a given round.

The PIDS platform coordinates the allocation of power consumption adjustment quotas by sending messages to selected companies and gathering their responses. If a power disruption to a company results in a low economic cost, and the company has not made much sacrifice by participating in recent rounds of DR operations, the priority for the company to join the current round of DR operation is increased. If some companies decline this round of invitation, PIDS repeats the optimization process, with all the companies which have accepted or declined the invitations excluded from the eligible solution set, to compute a new solution for DR. Since the authority only informs the AI Engine of high level preferences through setting key DR parameters without necessarily approving each AI recommendation, the nature of AI operations in this part is *human-over-the-loop* (Yu et al. 2019).

Intelligent orderly power utilization (OPU)

Following the DR process, if PIDS cannot find a feasible solution to bridge the predicted gap between power demand and supply, PIDS will trigger the OPU operation. It generates a preliminary proposal for selected companies to completely shut down their operations during the predicted power consumption gap period based on the load characteristics of the companies which have signed contracts with the provincial authority to participate in OPU. This proposal is submitted to the Commission of Economy and Information Technology for approval.

The administrators from the Commission of Economy and Information Technology logs into the PIDS platform, and enters the government department management interface to review the OPU plan. Since the recommendations for performing OPU are made based on only predicted power consumption gaps, the authority needs to make the final decision on whether to approve such recommendations. Thus, the nature of AI operations in this part is *human-in-the-loop* (Yu et al. 2019). If the OPU plan is approved, the execution of the OPU plan will be managed by PIDS.

IMPACT

PIDS has been deployed across Shandong Province, China since August 2018. The province consists of 16 prefectures, 140 counties and 1,941 townships with a total population of around 100 million[1]. PIDS has been used by the provincial authority to manage the demand side electricity usage by industrial users. At the time of submission of this paper, over 400 companies have signed agreements to participate in DR operations, and over 10,000 companies have signed agreements to participate in OPU operations through PIDS. In this section, we discuss the impact of the PIDS platform. We compare the performance achieved by PIDS with data from the previous power consumption management system used by Shandong Province during the period from August 2017 to July 2018. The performance data of PIDS were gathered from August 2018 to July 2019.

With WD-LSTM, the PIDS platform achieved a root mean square error (RMSE) of less than 2.5% when predicting the short-term power consumption gap during the 1 year period of deployment. This represents a large reduction of 86.40% compared to the RMSE of 18.38% achieved by the 3-day moving average-based prediction approach adopted by the previous power consumption management system.

The first round of province-wide DR operation occurred in August 2018. A total of 264 companies received DR invitations to bridge the power consumption gap of 555 MW. Eventually, 201 companies accepted the invitations and adjusted their power consumption by 439 MW through DR (accounting for 79% of the power gap). The remaining power gap was bridged through OPU.

Another round of province-wide DR operation occurred in December 2018. A total of 188 companies boosted their power consumption at noon time (12:00 pm to 13:00 pm) to bring the power demand trough up by 291 MW. Then, on the same day, 327 companies reduced their power consumption from 17:00 pm to 18:00 pm to bring the power demand peak down by 641 MW. This round of power consumption adjustment reduced the difference between the peak and trough of the power demand by 15.74% (from 5,566 MW to 4,690 MW), thereby significantly smoothing the power demand curve.

With the help of PIDS, an average of 76% of participating companies did not experience significant disruptions to their power consumption on the day of power consumption adjustment. This is an improvement of more than 58% compared to the average of only 48% of participating companies which managed to achieve this under the previous system.

With the help of PIDS, participating companies only had to reduce their power consumption by an average of 0.56% on the day of power consumption adjustment. In contrast, under the previous system, the corresponding figure was 16%.

Under PIDS, within the week after the power consumption adjustment operation, participating companies can recoup the reduction in power consumption safely, thereby minimizing the negative impact on economic activities. In contrast, an average of 8% of production output was permanently lost due to power consumption adjustment under the previous system. Overall, PIDS has achieved a much better performance compared to the previous system over the 1 year period it was deployed.

CONCLUSIONS

In this article, we reported on our experience using AI to address the challenges of dynamically managing industrial electric power consumption in Shandong Province, China. We developed the PIDS platform to provide data-driven intelligent power consumption adjustment decision support for the provincial authority. By improving the accuracy of the short-term power consumption gap prediction and dynamically optimizing the selection of companies to join demand response and orderly power utilization operations, PIDS provides fine-grain adjustment of the power demand curve in order to ensure safe operation while minimizing power disruptions and providing fair treatment to participating companies.

Since its deployment, PIDS has helped over 400 companies in Shandong Province optimize their power consumption through DR while dynamically managing the OPU process for around 10,000 companies. The platform has provided significant benefits in terms of improving the management of the power grid with minimal impact on economic activities compared to the previous system. Further plans to deploy PIDS in other parts of China have been put in place. The experience gained is being analyzed to help revise related policies in China.

In subsequent work, we will investigate how to incorporate Stackelberg game theory into PIDS to enable the dynamic pricing of electric power. In this way, the platform may be able to make use of price signals to better motivate companies to participate in power consumption adjustment operations. We are also looking into applying explainable AI approaches (Fan and Toni, 2015; Zeng et al. 2019) to automatically generate explanations for the AI recommendations to help administrators better understand the reasoning processes in order to improve user acceptance and trust in AI (Yu et al. 2013b, 2018).

In addition, as smart meters start to be incorporated into the power grid infrastructure in Shandong Province, massive amounts of usage behavior data will be generated by companies and households. Not only is it expensive to transmit and store such data, but private information such as patterns in people's daily life might be inferred from such data as well. We will investigate how to apply privacy-preserving machine learning techniques such as federated learning (Gao et al. 2019; Yang et al. 2019) in PIDS so as to enable collaboration across power companies in compliance with privacy-protection laws such as the General Data Protection Regulation (GDPR) (Voigt and Bussche, 2017).

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ENDNOTE

[1] https://en.wikipedia.org/wiki/Shandong

REFERENCES

Colak, I., S. Sagiroglu, G. Fulli, M. Yesilbudak, and C. F. Covrig. 2016. "A Survey on the Critical Issues in Smart Grid Technologies." *Renewable and Sustainable Energy Reviews* 54: 396–405.

Fan, X., and F. Toni. 2015. "On Computing Explanations in Argumentation." In *Proceedings of the 29th AAAI Conference on Artificial Intelligence (AAAI-15)*, 1496–502.

Gao, D., Y. Liu, A. Huang, C. Ju, H. Yu, and Q. Yang. 2019. "Privacy-Preserving Heterogeneous Federated Transfer Learning." In *Proceedings of the 2019 IEEE International Conference on Big Data (IEEE BigData'19)*, 2552–59.

Gelper, S., R. Fried, and C. Croux. 2010. "Robust Forecasting with Exponential and HoltWinters Smoothing." *Journal of Forecasting* 29, 285–300.

Gers, F. A., J. Schmidhuber, and F. A. Cummins. 1999. "Learning to Forget: Continual Prediction with LSTM." In *Proceedings of the 9th International Conference on Artificial Neural Networks (ICANN'99)*, 850–55.

Li, Y., W. A. Pizer, and L. Wu. 2019. "Climate Change and Residential Electricity Consumption in the Yangtze River Delta, China." *Proceedings of the National Academy of Sciences (PNAS)* 116, 472–77.

Liu, Y., K. Zhang, S. Zhen, Y. Guan, and Y. W. R. L. Shi. 2019. "A Combined Model for Short-Term Load Forecasting." In *Proceedings of the 3rd International Joint Conference on Web and Big Data (APWeb-WAIM'19)*, 35–42.

Meng, W., Q. Zhong, Y. Chen, H. Shen, X. Yun, K. R. Smith, B. Li, et al. 2019. "Energy and Air Pollution Benefits of Household Fuel Policies in Northern China." *Proceedings of the National Academy of Sciences (PNAS)* 116: 16773–780.

Srivastava, A. K., A. S. Pandey, and D. Singh. 2016. "Short-Term Load Forecasting Methods: A Review." In *Proceedings of the 2016 International Conference on Emerging Trends in Electrical Electronics and Sustainable Energy Systems (ICETEESES'16)*, 130–38.

Strasser, T. F., J. Kathan, C. Cecati, C. Buccella, P. Siano, P. Leito, G. Zhabelova, V. Vyatkin, and P. Vrba. 2015. "A Review of Architectures and Concepts for Intelligence in Future Electric Energy Systems." *IEEE Transactions on Industrial Electronics* 62, 2424–38.

Tan, Z., J. Zhang, J. Wang, and J. Xua. 2010. "Day-Ahead Electricity Price Forecasting using Wavelet Transform Combined with ARIMA and GARCH Models." *Applied Energy* 87: 3606–10.

Voigt, P., and A. V. D. Bussche. 2017. *The EU General Data Protection Regulation (GDPR): A Practical Guide*. Springer Publishing Company.

Yang, Q., Y. Liu, T. Chen, and Y. Tong. 2019. "Federated Machine Learning: Concept and Applications." *ACM Transactions on Intelligent Systems and Technology* 10. 1–12:19.

Yu, H., C. Miao, B. An, C. Leung, and V. R. Lesser. 2013a. "A Reputation Management Model for Resource Constrained Trustee Agents." In *Proceedings of the 23rd International Joint Conference on Artificial Intelligence (IJCAI'13)*, 418–24.

Yu, H., Z. Shen, C. Leung, C. Miao, and V. R. Lesser. 2013b. "A Survey of Multi-Agent Trust Management Systems." *IEEE Access* 1: 35–50.

Yu, H., C. Miao, Z. Shen, C. Leung, Y. Chen, and Q. Yang. 2015. "Efficient Task Sub-delegation for Crowdsourcing." In *Proceedings of the 29th AAAI Conference on Artificial Intelligence (AAAI-15)*, 1305–11.

Yu, H., C. Miao, C. Leung, Y. Chen, S. Fauvel, V. R. Lesser, and Q. Yang. 2016. "Mitigating Herding in Hierarchical Crowdsourcing Networks." *Scientific Reports* 6. https://doi.org/10.1038/s41598-016-0011-6.

Yu, H., C. Miao, Y. Chen, S. Fauvel, X. Li, and V. R. Lesser. 2017. "Algorithmic management for improving collective productivity in crowdsourcing." *Scientific Reports* 7. https://doi.org/10.1038/s41598-017-12757-x.

Yu, H., Z. Shen, C. Miao, C. Leung, V. R. Lesser, and Q. Yang. 2018. "Building Ethics into Artificial Intelligence." In *Proceedings of the 27th International Joint Conference on Artificial Intelligence (IJCAI'18)*, 5527–33.

Yu, H., Y. Liu, X. Wei, C. Zheng, T. Chen, Q. Yang, and X. Peng. 2019a. "Fair and Explainable Dynamic Engagement of Crowd Workers." In *Proceedings of the 28th International Joint Conference on Artificial Intelligence (IJCAI'19)*, 6575–77.

Yu, H., C. Miao, Y. Zheng, L. Cui, S. Fauvel, and C. Leung. 2019b. "Ethically Aligned Opportunistic Scheduling for Productive Laziness." In *Proceedings of the 2nd AAAI/ACM Conference on AI, Ethics, and Society (AIES-19)*, 45–51.

Zeng, Z., C. Miao, C. Leung, Z. Shen, and J. J. Chin. 2019. "Computing Argumentative Explanations in Bipolar Argumentation Frameworks." In *Proceedings of the 33rd AAAI Conference on Artificial Intelligence (AAAI-19)*, 10079–80.

Zheng, Y., H. Yu, L. Cui, C. Miao, C. Leung, and Q. Yang. 2018. "SmartHS: An AI Platform for Improving Government Service Provision." In *Proceedings of the 30th AAAI Conference on Innovative Applications of Artificial Intelligence (IAAI-18)*, 7704–12.

Zheng, Y., H. Yu, L. Cui, C. Miao, C. Leung, Y. Liu, and Q. Yang. 2020. "Addressing the Challenges of Government Service Provision with AI." *AI Magazine* 41: 33–43.

Zheng, Y., H. Yu, K. Zhang, Y. Shi, C. Leung, and C. Miao. 2019. "Intelligent Decision Support for Improving Power Management." In *Proceedings of the 28th International Joint Conference on Artificial Intelligence (IJCAI'19)*, 6587–89.

Zhou, K., and S. Yang. 2015. "Demand Side Management in China: The Context of China's Power Industry Reform." *Renewable and Sustainable Energy Reviews* 47: 954–65.

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