frontiers | Frontiers in Energy Research

OPINION
published: 19 May 2022
doi: 10.3389/fenrg.2022.916495

Artificial Intelligence Early Warnings of Agricultural Energy Internet

Xueqian Fu[1,2,3,4]* *and Feifei Yang*[1,2,3,4]

[1]College of Information and Electrical Engineering, China Agricultural University, Beijing, China, [2]National Innovation Center for Digital Fishery, China Agricultural University, Beijing, China, [3]Key Laboratory of Smart Farming Technologies for Aquatic Animal and Livestock, Ministry of Agriculture and Rural Affairs, Beijing, China, [4]Beijing Engineering and Technology Research Center for Internet of Things in Agriculture, Beijing, China

Keywords: agricultural energy internet, security risk, intelligent early warning, artificial intelligence, internet of things

OPEN ACCESS

Edited by:
Bo Yang,
Kunming University of Science and Technology, China

Reviewed by:
Wei Dai,
Guangxi University, China
Yixun Xue,
Taiyuan University of Technology, China

Correspondence:
Xueqian Fu
fuxueqian@cau.edu.cn

Specialty section:
This article was submitted to Smart Grids, a section of the journal Frontiers in Energy Research

Received: *09 April 2022*
Accepted: *19 April 2022*
Published: *19 May 2022*

Citation:
Fu X and Yang F (2022) Artificial Intelligence Early Warnings of Agricultural Energy Internet. Front. Energy Res. 10:916495. doi: 10.3389/fenrg.2022.916495

INTRODUCTION

Electrification in agriculture is an effective way for China to build modern agriculture, and it brings significant environmental and economic benefits (Fu and Yang, 2022). With the increasingly obvious trend of cross-integration of energy internet and modern agriculture, the park-level agricultural energy internet (AEI) has become one of the trends in the development of smart agriculture. AEI is a new concept that has originated from Energy Internet to realize renewable-energy-based electrification goals in rural energy systems. On the physical side, AEI is a multienergy system integrating heating, gas, and power networks. On the information side, AEI requires the public sharing of agricultural information and energy information to the control center of agricultural energy systems. AEI supports the development of new energy industries, empowers modern agriculture, and is a new driving force for rural revitalization (Fu et al., 2021a). The distribution system adopts standardized communication to collect voltage, current, fault, and power quality data and conduct real-time safety analysis in intelligent management and control systems (Song et al., 2013). The operation and management of the existing facility agricultural environment monitoring system and the agricultural energy supply system are independent of each other. They are operated and managed by different companies. There is a lack of linkage mechanism and unified control. It is difficult to prevent and control the linkage risks between agricultural production and energy systems, and it is impossible to cope with the demand for power outages in rural greenhouses and the overloading of agricultural energy loads. It brings dual challenges to the implementation of AEI applications. The intelligent early warning of AEI is the premise of safe agricultural production and the safe operation of agricultural energy supply systems. This research has theoretical guiding significance for protecting facility plants from cold weather and agricultural drought. The existing intelligent early warning methods mainly include the multisource data fusion technology and the security risk assessment and prediction method. In terms of multisource data fusion technology, it is an effective tool for greenhouse environment monitoring, positioning, and navigation to optimize calculation to improve accuracy in agriculture, and it is introduced into load forecasting, fault diagnosis, etc., in the energy system. Mancipe et al. proposed a data fusion strategy to predict environmental variables in precision agriculture (Mancipe-Castro and Gutiérrez-Carvajal, 2022). Erfani et al. fused robot sensor data based on Dempster–Shafer evidence theory and Kalman filtering to achieve optimal localization estimation in unstable agricultural environments (Erfani et al., 2019). Jiang et al. combined the long short-term memory and convolutional neural network to form a hybrid multitask framework for short-term prediction of household energy consumption (Jiang et al., 2021). Jiao et al. proposed a transmission line fault location model on the basis of fuzzy multisensor data fusion to improve the fault location accuracy (Jiao and Wu, 2018). Security risk assessment is necessary to detect the growth status and predict the environmental parameters in agriculture. Security risk assessment is often used to evaluate the security of power supply in real-time and predict the power generation and energy consumption in energy systems. Xu et al. proposed

FIGURE 1 | Intelligent early warning of AI-powered AEI.

a multiclassification model on the basis of support vector machines and artificial neural networks to warn an occurrence of frost disasters (Xu et al., 2021). Yang et al. proposed a hybrid wind speed prediction method based on data-processing strategies, which makes full use of artificial intelligence algorithms (Yang and Wang, 2018). Larsen et al. developed a comprehensive and flexible framework to assess power supply security (Larsen et al., 2017). Garshasbi et al. predicted the hourly energy consumption and power generation of net-zero energy buildings using a hybrid genetic algorithm and the Monte Carlo method (Garshasbi et al., 2016). However, most of the current research on agricultural systems and energy systems is limited to its respective field, and there is almost no research on the park-level AEI. It is urgent to deepen the research on the theory and method of intelligent early warnings of AEI. The main purpose of this research is to ensure the safe operation of the park-level AEI *via* cross-integrating agricultural science, information science, and electricity science, and we explore a way of comprehensive utilization of energy data and agricultural data. It can realize double early warnings of agricultural ecology environment and energy systems, and then the safe operation of the park-level AEI can be guaranteed.

TECHNOLOGY METHODOLOGIES

This section includes two parts. First, the concept of the intelligent early warning of the park-level AEI is proposed in **section 2.1**. Second, the key technologies are analyzed in **section 2.2**.

Concept

To realize the intelligent early warning of agricultural ecology environment and energy systems, AEI is used as the research object. The risk information in the measurement data of agricultural environmental sensors and energy meters is fully mined, and information science theories, such as information conservation, multisource heterogeneous data fusion, model and data fusion drive, and the association rule mining algorithm (Fu et al., 2021b), are adopted. The schematic diagram of the intelligent early warning of the park-level AEI is shown in **Figure 1**. It can monitor the whole of greenhouse environmental parameters, crop physiological states, state variables, and energy supply margins of park-level energy systems based on environmental sensors, energy meters, cameras, and other equipment, combined with agricultural energy security indicators. To realize the early warning of AEI, the dynamic planting conditions of facility agriculture, the observation data of greenhouse microclimate, and the measurement data of park-level energy systems are obtained in real-time, relying on environmental sensors and energy meters based on JavaEE technology framework, service-oriented architecture cloud service, and artificial intelligence (AI) technologies. Knowledge of the safe operation of facility agriculture and energy systems is summarized through calculating and studying big data of facility agriculture and park-level energy systems. Expert knowledge rules related to multiple factors such as crops, environment, and energy are developed and constructed. In addition, knowledge rules suitable for the safe operation of facility agriculture and park-level energy systems can be quickly found by data matching. The distributed energy and agricultural equipment is controlled by the AI scheduling software in the park-level AEI. The control of agricultural load requires synergistic consideration of the safety and economic requirements of both agricultural ecology environment and energy systems.

Key Technologies of Intelligent Early Warning

The realization of intelligent early warnings of AEI relies on agricultural smart sensors, energy meters, communication networks, and AI-powered monitoring systems. Agricultural smart sensors include illuminance sensors, light integrators, sunshine hour sensors, photosynthetically active radiometers, air temperature sensors, time–temperature integrators, soil temperature sensors, humidity sensors, soil moisture meters, carbon dioxide sensors, atmospheric pressure sensors, wind speed and direction sensors, cameras, RGB cameras, depth cameras, 3D laser scanners, imaging spectrometers, and fluorescence imagers. Energy meters include smart meters, gas meters, and calorimeters. Data collected by agricultural smart sensors are transmitted to the security risk monitoring system through the 5G wireless communication network. The system evaluates the environmental safety of facility agriculture and predicts energy consumption (i.e., load forecasting), relying on artificial intelligence technology such as statistical machine learning (Fu, 2022).

By combining agricultural load forecast results and data collected by energy meters, the security risk monitoring system can evaluate the security situation of the energy system. First, we use machine vision to study the data from plant phenotype-monitoring devices and judge the physiological state of crops. Second, we use multitask learning algorithms to study the physiological state of crops and environmental sensor data, and the energy consumption of facility agriculture can then be predicted. Finally, we use deep learning algorithms to predict transformer loads according to history energy meter data and predict agricultural energy consumption. When the predicted transformer loads are brought into the distribution network model for power flow calculation, the security index of the energy system can be predicted.

Industry has higher requirements for power supply safety than agriculture and also requires high power quality. A sudden power outage will result in a large number of waste products in the factory and cause great economic losses. Dual power supply is adopted for industrial consumers, and uninterruptible power supply is also installed to ensure power safety. The growth of crops is a slow process, so the impact of short-term power outage is small. However, with the development of agricultural informatization and the construction of unmanned farms, agricultural production will realize industrialization. When power outage occurs, the unmanned farm will be shut down, resulting in losses far greater than that of agriculture with a low level of automation and informatization.

DISCUSSION

Differences Between AEI and IoT

The differences between AEI, Internet of Things (IoT) in agriculture, and IoT in power are concluded as follows. 1) AEI not only assesses the information on the perception layer of the agricultural IoT, especially the information related to energy consumption, but also needs to assess the information on the perception layer of IoT in power. 2) AEI includes technologies in both the physical layer and the information side. The physical layer realizes the coupling optimization of multienergy and agricultural production. The information side realizes the perception and control of the physical environment and can realize the precise prediction of agricultural power generation and power consumption so as to accurately control the environmental factors of facility agriculture. However, IoT in agriculture can only perform automatic management based on the monitoring of the crop environment and physiological parameters, ignoring the possibility of out-of-limit voltage; IoT in power only involves power science and information science and cannot regulate the facility agricultural environment.

Bottleneck Analysis of Intelligent Early Warning

The bottlenecks in the development of intelligent early warnings of the park-level AEI are concluded as follows. 1) Existing modeling methods cannot accurately describe the dynamic relationship between the agriculture ecology environment and energy systems. The interaction between agricultural and energy systems is enhanced, and failures can propagate between systems to form cascading failures. Energy flow and material flow restrict and transform each other in AEI, and agricultural material and energy are in a state of circulation. Hence, the high energy consumption of modern agriculture tests the bearing capacity of the power grid, and the energy operation status is related to the normal operation of agricultural equipment. 2) It is difficult to construct an early warning indicator system for the coordinated safety of the agricultural ecology environment and energy systems. The security warning indicators of facility agriculture should fully consider the differences in crop species, developmental periods, and corresponding physiological characteristics. The security warning indicators of the park-level energy system should fully reflect the environmental regulation load changes of facility agriculture caused by physiological differences in crops. In addition, the time scales are different in generating the security of the agricultural ecology environment and energy systems. This makes it difficult to characterize the synergistic security between facility agriculture and energy systems at the same time. 3) The variability in weather brings challenges to the security early warning of AEI. The change in weather directly affects the facility environment, and bad weather threatens the crop growth environment. In addition, renewable energy such as photovoltaic power generation is directly affected by the weather, and power generation becomes uncertain due to the variability in weather. Therefore, the weather brings great disturbance to both sides of the source and load in the agricultural energy system, increasing the complexity of safety early warnings.

CONCLUSION

AI-powered unmanned farming is an inevitable trend in Chinese agriculture and an effective way to solve rural pollution and lack of agricultural labor. AI application in an agriculture energy system is the core technology of unmanned farm construction, and intelligent early warnings can assist agricultural production. Agricultural electrification and informatization have further promoted the development of the IoT and formed the AEI based on IoT in agriculture and IoT in power. The combination of IoT in agriculture and IoT in power significantly improved the integration of energy data and agricultural environment monitoring data, based on which advanced artificial intelligence technology can realize dual early warnings of agricultural ecology environment and energy systems to ensure the safe operation of park-level AEI. With the integration of renewable energy and agriculture, carbon emission will be further reduced, which also brings higher security risks than before. It can be concluded that AI warnings of AEI will become one of the most impactful technologies of agricultural automation.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

FUNDING

This study is supported by the National Natural Science Foundation of China under Grant 52007193 and the 2115 Talent Development Program of China Agricultural University.

REFERENCES

Erfani, S., Jafari, A., and Hajiahmad, A. (2019). Comparison of Two Data Fusion Methods for Localization of Wheeled Mobile Robot in Farm Conditions. *Artif. Intell. Agric.* 1, 48–55. doi:10.1016/j.aiia.2019.05.002

Fu, X. (2022). Statistical Machine Learning Model for Capacitor Planning Considering Uncertainties in Photovoltaic Power. *Prot. Control Mod. Power Syst.* 7 (1), 51–63. doi:10.1186/s41601-022-00228-z

Fu, X., and Yang, F. (2022). Viewpoints on the Theory of Agricultural Energy Internet. *Front. Energy Res.* 10, 871772. doi:10.3389/fenrg.2022.871772

Fu, X., Yang, F., Zhou, Y., and Wei, Z. (2021b). Intelligent Early Warning Theory of the Facility Agricultural Energy Internet: Review and Prospect. *Trans. Chin. Soc. Agric. Eng. Trans. CSAE)* 37 (21), 24–33. doi:10.11975/j.issn.1002-6819.2021.21.004

Fu, X., Zhou, Y., Yang, F., Ma, L., Long, H., Zhong, Y., et al. (2021a). A Review of Key Technologies and Trends in the Development of Integrated Heating and Power Systems in Agriculture. *Entropy* 23 (2), 260. doi:10.3390/e23020260

Garshasbi, S., Kurnitski, J., and Mohammadi, Y. (2016). A Hybrid Genetic Algorithm and Monte Carlo Simulation Approach to Predict Hourly Energy Consumption and Generation by a Cluster of Net Zero Energy Buildings. *Appl. Energy* 179, 626–637. doi:10.1016/j.apenergy.2016.07.033

Jiang, L., Wang, X., Li, W., Wang, L., Yin, X., and Jia, L. (2021). Hybrid Multitask Multi-Information Fusion Deep Learning for Household Short-Term Load Forecasting. *IEEE Trans. Smart Grid* 12 (6), 5362–5372. doi:10.1109/TSG.2021.3091469

Jiao, Z., and Wu, R. (2019). A New Method to Improve Fault Location Accuracy in Transmission Line Based on Fuzzy Multi-Sensor Data Fusion. *IEEE Trans. Smart Grid* 10 (4), 4211–4220. doi:10.1109/TSG.2018.2853678

Larsen, E. R., Osorio, S., and van Ackere, A. (2017). A Framework to Evaluate Security of Supply in the Electricity Sector. *Renew. Sustain. Energy Rev.* 79, 646–655. doi:10.1016/j.rser.2017.05.085

Mancipe-Castro, L., and Gutiérrez-Carvajal, R. E. (2022). Prediction of Environment Variables in Precision Agriculture Using a Sparse Model as Data Fusion Strategy. *Inf. Process. Agric.* 9 (2), 171–183. doi:10.1016/j.inpa.2021.06.007

Song, I.-K., Yun, S.-Y., Kwon, S.-C., and Kwak, N.-H. (2013). Design of Smart Distribution Management System for Obtaining Real-Time Security Analysis and Predictive Operation in Korea. *IEEE Trans. Smart Grid* 4 (1), 375–382. doi:10.1109/TSG.2012.2233769

Xu, J., Guga, S., Rong, G., Riao, D., Liu, X., Li, K., et al. (2021). Estimation of Frost Hazard for Tea Tree in Zhejiang Province Based on Machine Learning. *Agriculture* 11 (7), 607. doi:10.3390/agriculture11070607

Yang, Z., and Wang, J. (2018). A Hybrid Forecasting Approach Applied in Wind Speed Forecasting Based on a Data Processing Strategy and an Optimized Artificial Intelligence Algorithm. *Energy* 160, 87–100. doi:10.1016/j.energy.2018.07.005

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors, and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.