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Opportunities and Developmental Dilemmas Brought by AI Intervention in the Construction of Renewable Energy Microgrids

Qianmingxi Xu

Engineering and Information Technology, University of Technology, 2008, Sydney, Australia

Abstract: Renewable energy-based microgrids are viewed as a fundamental solution to the energy transition. However, throughout operation they are under double strain of production change and lack of economic efficiency. Based on the public statistics and existing research literature, this study studies the application performance of artificial intelligence in the fields of prediction, scheduling, operation and maintenance and power trading. The operating data of the existing project reveals that, under certain conditions, standard artificial intelligence can reduce prediction mistakes, minimise unplanned downtime and boost trade profits. But the scale of these benefits is strongly dependent on the availability of high-quality data and local optimisation, and limited by external institutional obstacles including data silos, the absence of market regulations, and unclear legal responsibilities and rights. The existing power system has not set up a proper institutional basis. Simply deploying technology is hard to overcome the current obstacles without the backing of a well-matched system. When combining numerous local optimisations, it might cause system concerns, such as over-limit grid power flow and voltage instability. The research shows that the future development direction should be to limit the quest of single technical indicators and to move toward the coordinated evolution of technology, data and system, promoting microgrids from demonstration and verification to large-scale commercial implementations.

Keywords: Artificial intelligence, renewable energy, microgrid, electricity market, institutional bottlenecks.

1. Introduction

The energy structure of the world is still moving forward in transition. The National Energy Administration released data in January 2026, showing that at the end of 2025, China's cumulative installed wind and photovoltaic power capacity exceeded 1.4 billion kilowatts, five years ahead of the initial objective. The fast growing installed capacity has not necessarily relieved the burden of grid connectivity and system stability. Microgrid integrates distributed power sources, energy storage devices and load consumption, and can provide autonomous operation and flexible access in the local region. This, in principle, solves the above problem. Based on the operation data of several projects that have been put into operation, the real utilisation rate of renewable energy is low, the overall operating expenses are high, and the investment payback period is often long. The marketing of microgrids has been gradual and there is a considerable gap to broad-scale use.

The reasons for this gap are numerous but theoretically speaking, the optimisation process of microgrids is a high-dimensional nonlinear dynamic decision making problem. Traditional physical model scheduling approaches are hard to achieve the overall optimisation in the face of many uncertainties. Attention has consequently been attracted to Artificial Intelligence. Deep learning has the advantages of fitting nonlinear relationships, and reinforcement learning has the advantages of sequence decision-making, which create new technical possibilities for output prediction, operation scheduling, and equipment maintenance [1]. Operational data from domestic and overseas demonstration projects over the last two years reveal that some initiatives have achieved efficiency improvements and cost reductions under certain situations. However, these improvements are often relied on specialised data gathering techniques, extended model tuning cycles, and costly initial expenditure. When transferred to other sites, or enlarged to a greater extent of operation, the impact is much less.

This means that the application effect of AI in microgrid is not necessarily obvious. AI's relevant premise and boundary conditions need to be clearly specified. This paper reviews existing practices and evaluates the actual contributions of AI in each link. Focusing on the institutional environment and structural factors that constrain the release of its effectiveness, this paper tries to go beyond a purely technical perspective and provide a reference for subsequent policy formulation.

2. Enhancement of Prediction Accuracy: The Distance from Technical Feasibility to Economic Feasibility

Accurate prediction of wind power and solar power output is important for the stable operation of microgrid. In case the output estimate is wrong the system has to reserve extra reserve capacity which will increase the operating cost instantaneously and the integration of renewable energy would also be affected. The traditional physical model with statistical adjustment is well suited under typical settings, but performs poorly in extreme cases such as local temperature change or rapid cloud generation and dispersion. The model's generalisation abilities can not keep up [2].

In this sense, AI is just using data to mimic complex non-linear interactions in high-dimensional systems that are hard to capture in physics-based models. Long Short-Term Memory networks and Transformer-based time series models can combine satellite cloud imaging, ground meteorological observations and numerical weather forecasts as well as

historical output data into a framework to determine an end-to-end prediction process. The statistical error is substantially diminishing [3]. AI offers an edge over conventional methodologies in terms of mean square root error and mean absolute percentage error for ultra-short term and short term forecasting of photovoltaic electricity. Some literature shows the error reduction is 20 per cent to 30 per cent. The numbers are mind-boggling.

But don't get too excited yet, there is a long way between the improvement in statistical correctness and the increase in real money earnings. If you want to use the AI model in a real project, you need a complete supporting framework. We need someone to organise clean historical data. Model parameters need to be updated repeatedly according to local conditions. Training and operation require a team knowledgeable with data, models and microgrids. But such eye-catching upfront investments might be paid by fiscal cash in demonstration programs. But it is an independent commercial venture which needs to take the profit or loss. Every dime has to come out of the books. It is a massive sunk cost. The concern is that a model trained in one place would normally perform poorly at a new site with different climate variables and geographic environments. This "one scenario-one model" customisation approach therefore indicates an essentially no possibility of marginal cost reduction, unless there is a method for data sharing and model reuse at the industry level. The glitter of scientific progress is definitely beautiful, but before it can shine in reality it must first cross the threshold of economic feasibility. Once it passes this level the leap in forecast accuracy is pretty huge.

3. Scheduling Optimization: The Tension Between Local Optimum and System Optimum

The microgrid has a question at the scheduling level when reliable predictions of electricity output are available: How to allocate the power reasonably among the power producing units, energy storage devices and loads? This is a challenge on numerous time scales and there are various constrains there is a lot of non-linear interaction. In such a complexity, the conventional linear programming or heuristic algorithms could only provide a reasonable solution but not close to the true optimal solution [4].

Another technique is deep reinforcement learning. The agent interacts often with the simulation environment, or the real system, and tries and changes until a more perfect strategy is approached, without having to simplify the system too much. These methods are helpful to coordinate various devices, deal with uncertainties, and deal with multiple limitations. The pace of photovoltaic power absorption surpasses the conventional rule-based methods on the microgrid scheduling.

However, the difficulty is that much of the available research confines the scope of optimisation to a single microgrid, trying to improve the economic efficiency or self-consumption rate of the local system. This is fine in isolation, but when several microgrids are connected to the same distribution network at the same time and charge and discharge according to their own optimal techniques, their behaviours will conflict at certain times. For example, during noon when the photovoltaic output is maximal, there are several microgrids providing power to the grid concurrently and the risk of reverse overload happens in the distribution sub-area. With the vast scale integration of distributed energy, the problem of "multi-agent independent decision making and lack of coordination" is becoming more and more frequent.

The "black box" aspect of the reinforcement learning algorithms poses trust-related problems in the power scheduling business. It is impossible to guess the reasons for the orders of charging and discharging given by the algorithm, if the duty engineer sees it. If the instructions are not consistent with his long accumulated operating knowledge, manual intervention is unavoidable [5]. The automated scheduling rate generally cannot reach the desired level after being put into practice in the laboratory. Lastly, an ideal strategy that works effectively on one node without the support of trust mechanism and system level coordination framework would lose the effectiveness when implemented in a real operational setting. But if we ignore the shortcomings of multi-node collaborative governance, even if the local scheduling optimisation is truly simple, it may increase the operational risks of the whole system. And the daily maintenance level also influences the equipment to appropriately respond to the scheduling directions.

4. Operation and Maintenance Transformation: Data Annotation Bottleneck and Cross-Brand Barriers

The execution effect of dispatching decision relies on the healthy operation of equipment. There are scattered wind and photovoltaic equipment, and the operational environment is difficult. Also the roof components and the wind turbines in the Gobi are exposed to different temperature, humidity, sand and dust conditions. The typical manual inspection and routine maintenance wastes a lot of people and time and it is hard to find the early warning signals of defect. Losses have already been incurred as difficulties develop, affecting power generation or even causing equipment to cease [6].

Artificial intelligence (AI) technology is transforming operations and maintenance practices. Infrared camera-equipped drones hover over the site area and convolutional neural networks analyse the photos in real time. Automatically detects defects including hot spots, fractures and weld strip detachment. Multi-dimensional data like bearing and gearbox vibration spectra and temperature can be used to capture the wear trend before the critical value is reached. Major equipment manufacturers Trina Solar and Goldwind Technology have rolled out AI-based inspection and defect prediction products. All the power stations that have adopted such systems have reduced the unscheduled shutdowns and operation and maintenance costs to different extents.

But in real promotion, the growth of technology is faced with two limits. The first limitation is data foundation. Deep learning models are trained using labelled fault cases. Normal and faulty samples have to be clearly distinguished and, ideally, the kind and amount of fault must also be labelled. The collecting of such labelled data is limited: through equipment disassembly examination to verify, or through long-term accumulated historical fault records. The failure data available for training in newly launched micro grid systems is rather small. Under these conditions, the diagnostic models trained usually have a greater false alarm rate and missed detection rate in actual operation than the laboratory test results [7].

The second barrier consists of the technological obstacles between the equipment makers. The communication methods and data formats of different manufacturers are not interoperable, making it extremely difficult to construct a uniform diagnostic model across brands and generations. Most of the present AI operation and maintenance solutions are for single-brand equipment. In the case of a micro-grid project with equipment from several manufacturers, the operation and maintenance team may only maintain numerous incompatible diagnostic systems in concurrently, which actually increases the management burden. Regardless of the advancement of intelligent diagnosis, the scale effect of operation and maintenance transformation can not be released if the data interoperability and sharing mechanism is not developed at the institutional level.

5. Market Transactions: Technological Exploration in the Absence of Institutional Frameworks

Cost reduction alone is not sufficient for microgrids to become financially self-sustainable. They need to participate in the external electricity market to be able to make money. The development of the electrical spot market has made the application of AI to forecast the price of electricity and optimise the trading strategy a hot topic in the industry [8].

In 2024, the Guangdong Electricity Trading Center included microgrids in the spot market trading companies. This change allows them the legal ability to be a part of the market trading. Several trial programs have merged reinforcement learning of bidding techniques with deep learning of power price predictions. Compared with manual experience-based bidding, the income of energy generation has been improved, preliminarily proving the practicability of AI for trade decisions [9]. The international institutional environment and market maturity are different, and the exploration speed is faster. Australian energy company AGL Energy has announced autonomous trading agency services for industrial and commercial energy storage and virtual power plants. The relevant information is posted on their official website and investor briefings. The Tesla Autobidder platform offers automated bidding trading functionalities for user-side energy storage, and has been deployed in several regions including the United States, Australia and the United Kingdom. The platform's service concept is described on the Tesla official website.

However, there are still a number of restrictions to implementation in these circumstances in China. The electricity spot market is still in the construction phase, with a high proportion of medium and long-term transactions, insufficient market liquidity, and limited room for AI strategies to play a role. The predictive advantages are difficult to be fully released given that there are limited trading opportunities. In different provinces, the standards are different for the certification of participating participants in transactions, measurement regulations, settlement procedures and information dissemination. The difficulty of adapting a universal AI trading system to such a dispersed institutional design considerably reduces the model transfer ability and generalisation effect. Some existing laws prevent automated programs from immediately placing orders. That means the artificial intelligence systems can produce suggestions for traders to look at and act upon. The time benefit of implementing a strategy is lost altogether and the decision making chain is slowed down and becomes inefficient. The real efficacy of AI trading techniques primarily rely on a market environment with adequate liquidity, transparent rules, and permitting programmatic involvement. Such conditions do not yet exist in the present electrical power grid. The institutional hurdles can lead to very little actual value from the technical advantages of trading algorithms. It is difficult to obtain good returns on the significant investment in research and development with the restrictions imposed by rules.

6. Structural Challenges: Constraints from Data, Institutional Frameworks, and Law

The application of AI to the four parts of prediction, scheduling, operation and maintenance and transactions has a commonality in the real application: the incremental benefits brought by AI are always restrained by some external factors. This limiting force is not due to the lack of algorithm skills or the lack of processing capacity but rather the institutional level.

The first limitation is about the data. Microgrid operational data are spread across equipment makers, property owners, electrical grid corporations and operation service providers. Sharing data is rarely a wish of either side, whether for commercial goals or for safety reasons. The training effect of the AI model is closely related to the amount of data and the quality of annotation. No cross-industry collaboration system and the data of each project is generally not enough Within that project the model's capabilities can only be limited, the strategy needs to be reconstructed in a different scenario. Without data circulation, the reusability value of AI is significantly weakened.

The second constraint is within the power system itself. The power system has centralised dispatching authority in the existing operation design, and the underlying logic is the uniform balance of the enormous power grid. The aim of a microgrid is local autonomy and the dispatching algorithms improved by AI are for this too. There is no connecting process in between the two and each follows its own logic. The disparities accumulate up to a certain degree, the coordination of the distribution network will be much more challenging. This friction cannot be overcome by the optimisation algorithm itself.

Thirdly, the restriction is on the legal and ethical level. But if the AI is making decisions about schedules and transactions that result in equipment damage or power outages, who is responsible? The legal rights and obligations of algorithm authors, equipment operators, on-site engineers and microgrid owners have still to be written. The imprecision of rights and obligations allows operators to restrict the use of AI to less risky areas and to keep the fundamental choices in human hands [10]. Therefore, the role space of the AI in the microgrid is confined to the perimeter.

These three limitations are incorporated. The model cannot be fully built without data sharing. Without a sophisticated model, the dispatching technique can not be tuned to the needs of the system. People are reluctant to give AI any authority because there are no clear legal definitions. Each relaxation of a constraint must be complemented by a progression of the other two [11]. This means the full use of AI in microgrids will not happen soon, it is only possible bit by bit. There is a huge disparity between what is technically

doable and what is institutionally possible.

7. Conclusion

The technological viability of AI has been demonstrated in four key areas of microgrids: forecasting, scheduling, operation and maintenance, and trading. In some cases, it can reduce prediction error of the power output, improve the operating efficiency of the equipment, reduce unexpected downtime and bring some benefits in the power trade. But these achievements are mostly on the level of local improvement, which have not produced a structural shift in the operation style of the microgrid.

The rationale is that the release of AI efficiency is highly contingent on the availability of external institutional circumstances. AI requires availability of data, openness of the market and clarification of legal duties as prerequisites to work. In several respects the existing electricity grid is badly lagging behind: 1) Data resources are isolated and difficult to flow between multiple parties; 2) The spot market is still under construction, the trading depth is not enough; 3) There is no clear legal concept of liability for accidents. These structural restrictions render AI, if technically feasible, difficult in getting into the practical functioning phase. Another key worry is that many microgrids, without a coordinating mechanism, pursue local optimal scheduling strategies which may lead to additional disorder in the distribution grid level.

In this sense, this paper understands that the focus of subsequent promotion will shift from technical verification to institutional alignment. First, formulate industry data sharing standards to create conditions for model cross-scenario reuse. Second, accelerate the construction of the electricity spot market, and build a unified trading rule system as soon as possible to provide an expected operating space for AI strategies. Third, the distribution network dispatching architecture should make forward-looking arrangements for the access of high proportion of distributed intelligent entities, and the legal level also needs to clearly define the responsibility and authority boundaries of AI-assisted decision-making. These three working traits are mutually restrictive, and should be cultivated in a coordinated way. Finally, the relevance of AI in the microgrid field is not the marginal improvement of the algorithm correctness, but how much space the institutional framework can leave to apply the technology.

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