Transfer Learning Methods in Renewable Energy Forecasting: Domain Adaptation, Fine-Tuning, and Practical Case Studies

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Abstract

Owing to greenhouse gas emissions caused by human activities, climate change has become a pressing challenge for the global community. For instance, buildings are responsible for approximately a third of global energy consumption and a quarter of CO_2 emissions. Renewable energy is viewed as a key solution to address the challenge of Carbon Neutrality and a pivotal step toward sustainable urban development. In 2022, the annual increase in renewable energy surged, with solar photovoltaic (PV) and wind contributing to nearly 90% of all new renewable installations; the coupling of renewable energy with existing energy systems is an area of focus. However, the integration of solar energy introduces challenges, primarily due to its inherent variability and unpredictability. For instance, Japan has experienced a notable 23% wastage in solar energy utilization, indicating inefficiencies in current usage. To effectively harness solar energy, minimizing wastage and optimizing usage are essential. This necessitates the development of advanced control algorithms for renewable building energy systems, which hinge on accurate solar radiation prediction.

Deep learning models are increasingly applied in the field of solar radiation prediction. However, the substantial demand for labeled data limits their rapid application in newly established systems. Traditional transfer learning employs pre-training and fine-tuning methods to reduce the use of data in the target system. However, it still necessitates a small amount of labeled data for fine-tuning. This results in extensive time and cost for data collection, delaying the deployment of prediction models and optimization algorithms and leading to energy wastage. In this study, we employed the Adversarial Discriminative Domain Adaptation (ADDA) approach to achieve transfer learning under zero-label conditions in the target system, enabling new systems to harness the knowledge from other systems to create predictive models. Using the measured solar

radiation data from Tokyo and Okinawa, two sets of experiments were designed with interchanged source and target domains to validate the efficacy and robustness of the proposed model. The results indicate that compared with the method of directly using the source domain model, transfer learning can enhance the predictive accuracy of the test set by at least 14% in both experiments, exhibiting more stable predictive performance and reduced prediction outliers.