Doctoral Dissertation
Doctoral Program in Electrical, Electronics and Communications Engineering
(38th cycle)

Deep Learning and Reinforcement Learning for Industrial Microgrid Energy Management

Integrating Interpretable Forecasting, Safety-Oriented Dispatch, and Condition Monitoring

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Summary

The global energy sector is undergoing a profound transformation driven by the depletion of fossil fuel reserves and the urgent need to reduce greenhouse gas emissions. In this transition, microgrids (MGs) play a pivotal role in decentralized energy generation, distribution, and consumption. MGs improve electrical grid resilience, optimize energy management, and enable the large-scale integration of variable renewable energy resources. However, achieving these objectives requires sophisticated control strategies that can adapt to complex and uncertain environments. In this context, this doctoral Thesis advances the state of the art by proposing novel deep learning (DL)- and deep reinforcement learning (DRL)-based methodologies specifically designed to improve forecasting accuracy and optimal dispatch within industrial MGs. The work spans three interdependent functional layers of an energy management system (EMS): prediction, control, and condition monitoring.

The first part of this Thesis addresses forecasting, a fundamental prerequisite for efficient energy management. Multiple approaches for short-term electric load forecasting (STLF) and photovoltaic (PV) generation prediction were developed and compared, including statistical models, recurrent neural networks (RNNs), and Transformer architectures. The Temporal Fusion Transformer (TFT) exhibits superior generalizability and interpretability, while long short-term memory (LSTM) provides the best trade-off between performance and computational costs. This study contributes to building a predictive foundation for advanced EMSs, where interpretability, flexibility, and computational efficiency are crucial to ensure robust performance under volatile meteorological and demand conditions.

Transitioning from forecasting to optimal dispatch, the second research direction is the hourly scheduling of a cogenerator (CHP). The novel application of the partially observable Markov decision process (POMDP) framework to CHP scheduling is proposed to model uncertainty in electric and thermal demands, which is an approach that, to the best of the author's knowledge, has not yet been explored in the literature. Multiple DRL agents were compared with traditional optimization approaches in a real industrial case study. The results highlight that the soft actor-critic (SAC) agent effectively handles uncertainty while achieving a comparable or superior trade-off between economic performance and carbon emissions compared

to conventional methods.

Building on these insights, the third part of the Thesis extends the DRL study to the scheduling of a battery storage system (BSS) in an MG, with a focus on operational safety. A unified safe reinforcement learning (safe RL) framework was developed and evaluated against a model predictive control (MPC) benchmark under partial observability. Central to this contribution is a novel feature extraction module that integrates PV generation and electricity demand forecasting via a pretrained LSTM model. The results show that safe RL methods achieve near-optimal economic performance while significantly reducing safety constraint violations compared to MPC. In particular, the agent that combines reward-shaping and shielding strategies achieves a trade-off between profitability and operational safety.

Finally, this Thesis explores the RNN-based non-invasive identification of the passive parameters of a power electronic converter of a wind turbine via two complementary approaches: a digital twin-based real-time solution, and an ensemble gated recurrent unit (GRU)-based model with derivative approximations. These studies show that RNNs can operate in real time and achieve high predictive performance, extending the role of DL to the condition monitoring layer of MGs.

Overall, the works presented in this Thesis contribute to bridging the gap between interpretable forecasting, uncertainty-aware and safety-oriented control, and condition monitoring in industrial MGs. Through the design, implementation, and validation of DL and DRL models, this Thesis contributes to the development of predictive and control components that can be integrated into next-generation EMSs, supporting the ongoing transformation toward sustainable, autonomous, and resilient energy systems.