Special Session VII

Special Session Basic Information:

专栏题目 Session Title	中文：抽水蓄能系统在现代储能系统中的作用 英文：The Role of Pumped Hydro Storage System in Modern Energy Storage Systems
专栏介绍和征稿主题 Introduction and topics	

中文：
抽水蓄能（Pumped hydro storage, PSH）是目前应用最广泛的储能技术，约占全球公用事业级储能容量的 96%和储能总量的 99%。抽水蓄能的工作原理是利用需求低谷期的富余电力，将水从下水库抽送到上水库，从而将电能转化为势能。在用电高峰期间，释放蓄水以发电。抽水蓄能支持电网服务，包括峰值负荷管理、频率调节、可再生能源并网、应急备用以及整体电网稳定性。抽水蓄能的关键组件包括水库、压力管道和可逆式泵水轮机组。
尽管技术已趋成熟，抽水蓄能仍面临优化与经济可行性方面的挑战。水库容量受计划放水、自然径流、蒸发、降水、温度及土壤渗透率等多种因素影响，这些因素之间存在复杂的非线性关系。这种复杂性使得传统统计方法难以进行准确预测。此外，抽水蓄能调度是一个高维问题，具有非线性性能特征和多重约束，包括为保护设备免受磨损和故障而需规避的振动区。诸如等增量法和动态规划等传统优化方法不适用于这些复杂的非线性系统，而智能算法则可能表现出不稳定性和不可靠性。
机器学习（Machine learning, ML）领域的最新进展提供了潜在的解决方案。卷积神经网络（Convolutional neural networks, CNN）擅长从时间序列数据中提取模式，而长短期记忆（Long Short-Term Memory, LSTM）网络（包括其双向变体 bidirectional LSTM, BiLSTM）则能同时捕捉短期和长期的时间依赖性。注意力机制（如挤压与激发机制，Squeeze-and-Excitation, SE）通过动态权重特征来提升模型性能，从而提高预测精度。深度强化学习（Deep reinforcement learning, DRL）将深度学习与决策相结合，使智能体能够学习最优调度策略。诸如深度确定性策略梯度（Deep Deterministic Policy Gradient, DDPG）等算法特别适用于连续控制问题，如 PSH 机组调度与调度优化。
近期研究探索了适用于 PSH 的混合神经网络架构。例如，基于斯皮尔曼相关系数处理输入特征的多分支注意力-卷积神经网络-BiLSTM（Multi-Branch Attention-CNN-BiLSTM）模型，在水库容量预测精度方面取得了显著提升，误差减少幅度最高达 2%，水量误差减少 14-17 立方米。同样，经过原子轨道搜索（Atomic Orbital Search, AOS）优化的 LSTM 模型在预测流量特性曲线方面表现优于传统方法。通过将这些高精度模型与基于 DDPG 的调度相结合，已实现最高 2.36%的用水量削减，并提升了避震区控制效果。随着光伏和风能等可再生能源日益深度并网，抽水蓄能系统必须应对可再生能源输出波动及自然入流量带来的不确定性。将入流量预测与风险量化相结合的条件风险感知强化学习框架，使之预测精度在均方误差上提高了 18.9%，在均绝对误差上提高了 58.8%。
当前研究通常将水库预测与调度分离，从而错失了集成优化的机会。鲜有框架能将这两个方面整合为统一方法，利用预测不确定性来指导调度决策。本研究提出了一种基于 DRL 的混合多分支注意力-卷积神经网络- BiLSTM 框架，用于动态水库容量预测和优化调度。研究目标是提高预测精度 15%-20%，降低用水量 1.5%-3.0%，并将振动区运行减少 90%以上。本研究为储能、可再生能源并网等领域的 AI 应用做出了贡献，并支持可持续发展目标 7（经济适用的清洁能源）、9（工业、创新和基础设施）以及 13（气候行动）。
英文：
Introduction
Pumped hydro storage (PSH) is the most widely deployed energy storage technology, representing ~96% of global utility-scale energy storage capacity and 99% of stored energy. PSH operates by using excess electricity during low demand periods to pump water from a lower to an upper reservoir, converting electrical energy into potential energy. During peak demand, the stored water is released to generate electricity. PSH supports grid services such as peak load management, frequency regulation, renewable energy integration, emergency backup, and overall grid stability. Key components of PSH include reservoirs, pressure conduits, and reversible pump-turbine units.
Despite its technological maturity, PSH faces challenges related to optimization and economic viability. Reservoir capacities are affected by various factors like scheduled releases, natural inflows, evaporation, precipitation,

temperature, and soil permeability, which exhibit complex, nonlinear relationships. This complexity makes accurate forecasting difficult using traditional statistical methods. Additionally, PSH scheduling is a high-dimensional problem with nonlinear performance characteristics and multiple constraints, including vibration zone avoidance to protect equipment from wear and failure. Traditional optimization methods like the Equal Incremental Rate method and Dynamic Programming are unsuitable for these complex, nonlinear systems, while intelligent algorithms may exhibit instability and unreliability.

Recent advancements in machine learning (ML) offer potential solutions. Convolutional neural networks (CNNs) are effective at extracting patterns from time-series data, and Long Short-Term Memory (LSTM) networks, including their bidirectional variants (BiLSTM), capture both short- and long-term temporal dependencies. Attention mechanisms, like the Squeeze-and-Excitation (SE) mechanism, enhance model performance by dynamically weighting features for improved prediction accuracy. Deep reinforcement learning (DRL) integrates deep learning with decision-making, allowing agents to learn optimal scheduling policies. Algorithms such as Deep Deterministic Policy Gradient (DDPG) are particularly suited for continuous control problems like PSH unit commitment and dispatch.

Recent studies have explored hybrid neural network architectures for PSH. For example, Multi-Branch Attention-CNN-BiLSTM models, which process input features based on Spearman correlation, have achieved improvements in reservoir capacity forecasting accuracy, reducing errors by up to 2% and 14-17 cubic meters. Similarly, Atomic Orbital Search (AOS)-optimized LSTM models have outperformed traditional methods in predicting flow characteristic curves. By combining these high-precision models with DDPG-based scheduling, water consumption reductions of up to 2.36% and improved vibration zone avoidance have been achieved. As renewable energy sources like photovoltaics and wind become more integrated into the grid, PSH must address uncertainties related to renewable output variability and natural inflows. Conditional risk-aware reinforcement learning frameworks that combine inflow prediction with risk quantification have improved forecasting accuracy by 18.9% in mean square error and 58.8% in mean absolute error.

Current research typically separates reservoir forecasting from scheduling, missing opportunities for integrated optimization. Few frameworks exist that combine both aspects into a unified approach that informs scheduling decisions with forecast uncertainty. This research proposes a hybrid Multi-Branch Attention-CNN-BiLSTM framework with DRL for dynamic reservoir capacity forecasting and optimized scheduling. The goals are to improve forecasting accuracy by 15-20%, reduce water consumption by 1.5-3.0%, and decrease vibration zone operations by over 90%. This work contributes to AI applications in energy storage, renewable energy integration, and supports Sustainable Development Goals 7 (Affordable and Clean Energy), 9 (Industry, Innovation, and Infrastructure), and 13 (Climate Action).

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Organizer’s Brief Biography

中文：现任天津大学电气自动化与信息工程学院副教授，新疆师范大学物理与电子学院副院长，长期从事储能、机器学习领域研究。作为项目负责人，主持国家自然科学基金、面上项目及省部级、企业横向合作等各类科研项目十余项，累计经费超过 500 万元。近年来，以第一作者或通讯作者在国内外重要学术期刊上累计发表 SCI 论文 50 余篇，其中 JCR Q1 区论文 10 余篇，获得省部级奖励两项。

英文：Feng Renhai is currently an Associate Professor at the School of Electrical and Information Engineering, Tianjin University, and Vice Dean of the School of Physics and Electronics, Xinjiang Normal University. He has long been engaged in research in the fields of energy storage and machine learning. As a principal investigator, he has led more than ten research projects, including grants from the National Natural Science Foundation of China, as well as provincial/ministerial-level projects and industry-academia collaborations, with total funding exceeding 5 million yuan. In recent years, he has published over 50 SCI-indexed papers as first or corresponding author in leading domestic and international academic journals, including more than 10 papers in JCR Q1-ranked journals, and has received two provincial and ministerial-level awards.