Fusion of Microgrid Control with Model-free Reinforcement Learning: Review and Vision

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❑ Introduction

This poster presents a comprehensive review of microgrid control is presented with its fusion of model-free reinforcement learning (MFRL).

- Plotting of **a high-level research map of microgrid control** from the perspective of operation mode, function grouping, timescale, hierarchical structure, communication interface, and control techniques.
- Development of **modularized control blocks** to dive into the fundamental units of microgrids: GFL and GFM inverters.
- Introduction of the **mainstream MFRL algorithms** and summary of MFRL **application guidelines**
- Discussion of the primary challenges associated with adopting MFRL in microgrid control and providing insights for addressing these concerns.

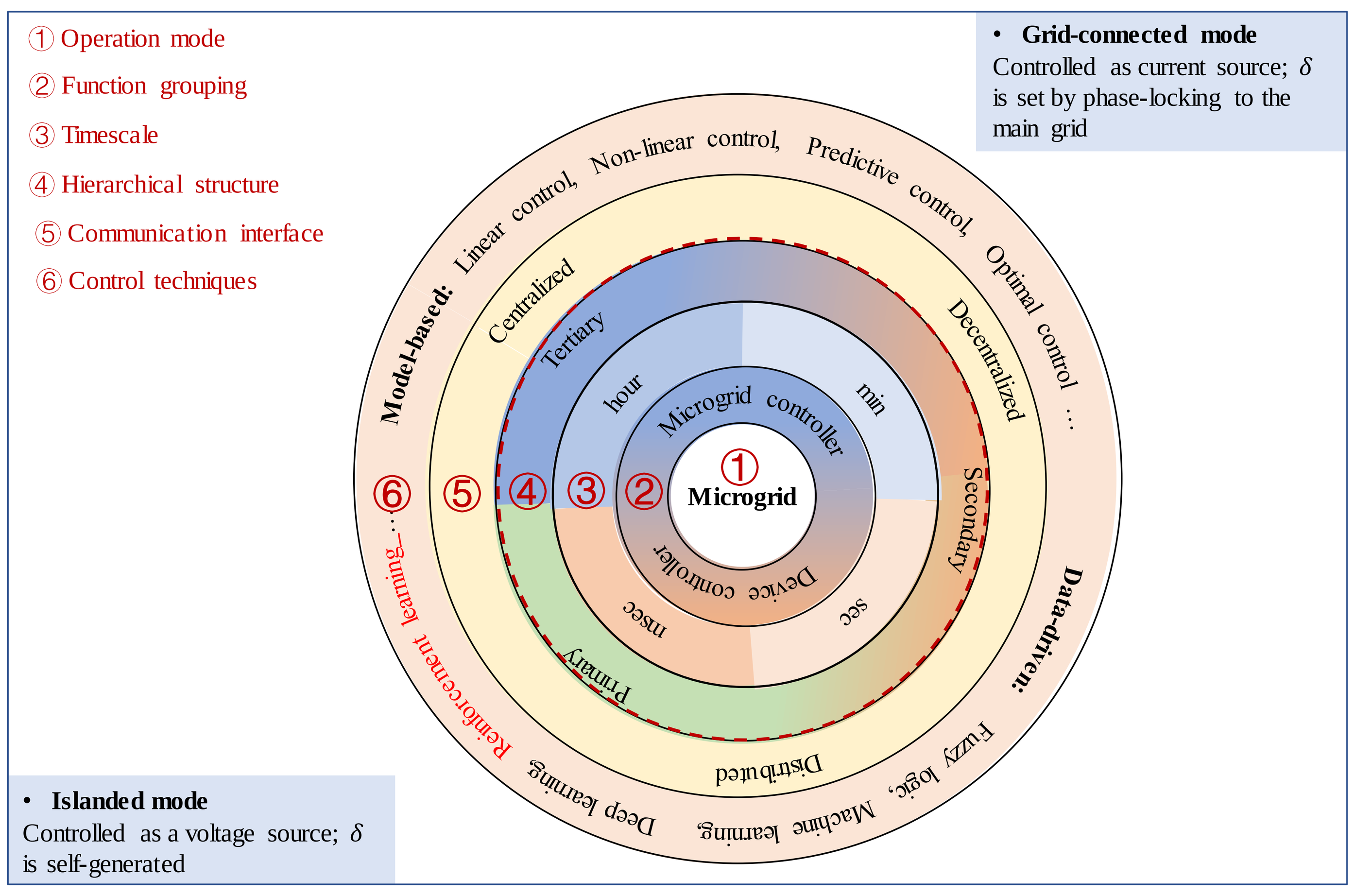

Fig. 1 High-level research map of microgrid control

❑ Microgrid control framework

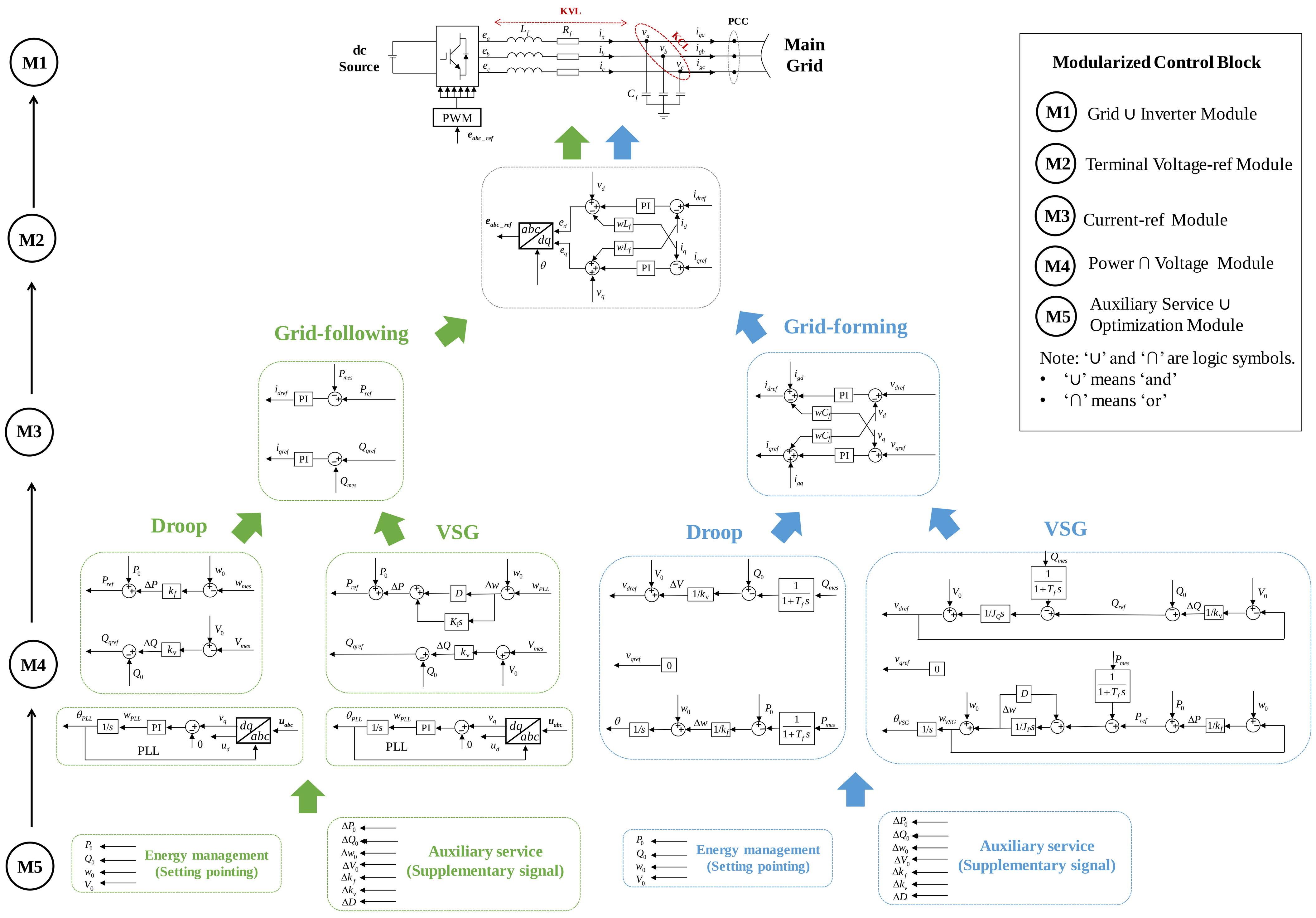

Fig. 2 Modularized control blocks of grid-following and grid-forming inverters

❑ Reinforcement learning

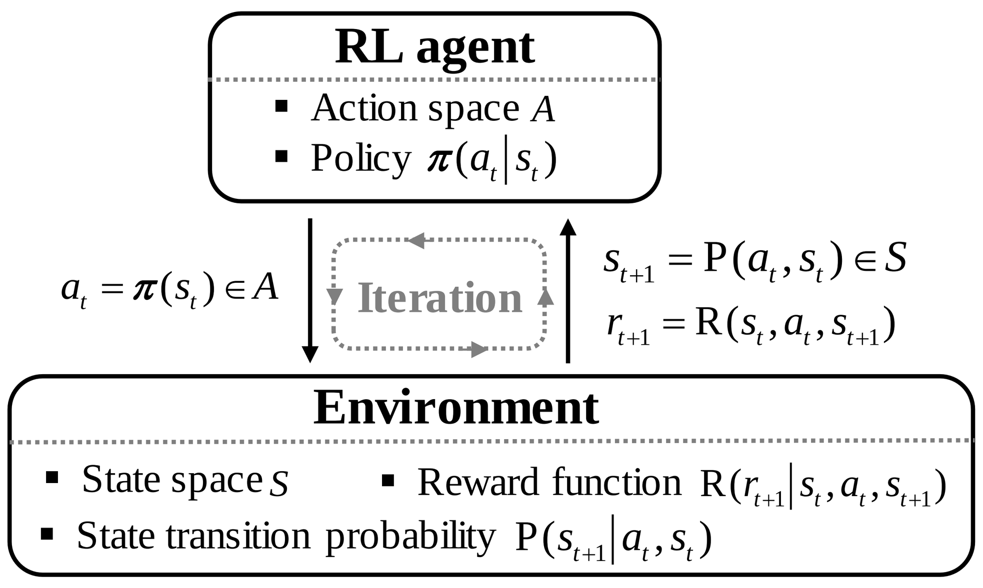

Fig. 3 Diagram of reinforcement learning

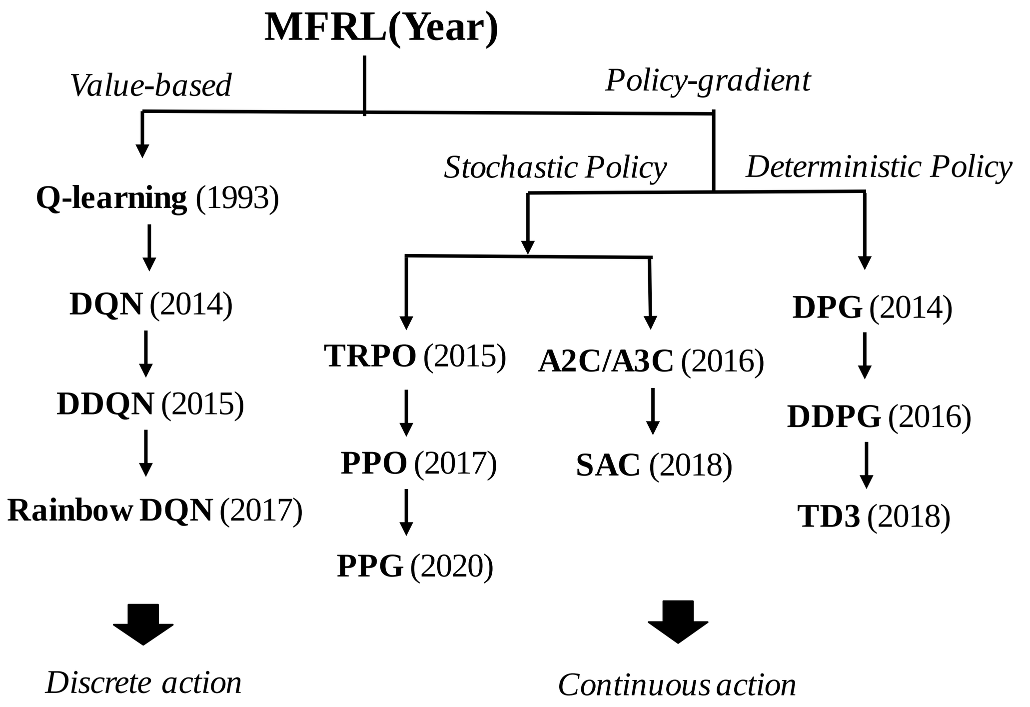

Fig. 4 Mainstream Reinforcement learning algorithm

❑ Fusion of microgrid control with RL

- **Model identification and parameter tuning**
  - Identify the models of the microgrid components
  - Find the optimal parameters for grid components and controllers
    i.e., inertia and damping estimation, PI gain tuning
- **Supplementary signal generation**
  Generate supplementary control signals for existing model-based controller
  i.e., supplementary signal of primary controller for better load sharing
- **Controller substitution**
  Replace the model-based controllers and directly output control actions
  i.e., RL-based dispatching, replace PI controllers with RL agent

❑ Conclusions

- There are three ways of fusing MFRL with the existing model-based controllers, including i). model identification and parameter tuning, ii). supplementary signal generation, and iii). controller substitution.
- The main challenges of employing MFRL in microgrid control are associated with the environment, scalability, generalization, security, and stability, and there are corresponding strategies to address these concerns.

❖ Challenge and Vison

➢ Environment

- Better Numerical simulator: accurate and faster numerical simulator; general power environment like "gym"
- Better Hardware testbed: specialized testbed with protection schemes

➢ Scalability

- Reduce control complexity with domain knowledge
- increase the exploration efficiency: evolutionary RL
- Distributed techniques: federated learning and edge computing

➢ Generalization

- Training scenario generation: representative scenarios; standardized open source data
- Combined with advanced AI techniques: robust RL; long-tail learning; transfer learning

➢ Security

- Constrained RL and Safe RL: respect physical constraints
- Physics-constrained deep learning and Physics-informed deep learning: embeds the knowledge of physical laws into training

➢ Stability

- Integrate model-based criteria: semidefinite programming (SDP), linear matrix inequality (LMI), Lyapunov function
- Enrich training scenarios as much as possible
- Policy validation through time domain simulation