Guest Editorial
Special Issue on Deep Reinforcement Learning for Optimization: Methods and Application

Nothing at all takes place in the universe that maximum or minimum does not appear.

—Euler

OPTIMIZATION is an old research topic, which widely exists in many engineering problems. Till now loads of methods have been proposed to handle complex optimization problems, amongst which evolutionary algorithms have attracted a great deal of attentions due to their robustness to the underlying problem characteristics. However, evolutionary algorithms which simulate the evolution of nature is an iterative optimizer, causing high computational effort to approximate the optima. That is, such methods may not be applicable on online or real-time optimization.

Deep reinforcement learning (DRL), implementing deep learning architecture with reinforcement learning algorithms, is capable of creating a powerful model that can learn to make decisions and scale to previously unsolvable problems. In recent years, several new methods emerge on the surface that solve combinatorial optimization problems via DRL techniques, e.g., [1], [2], [3], [4]. They are significantly faster than traditional solvers, e.g., evolutionary algorithms, and able to generalize either to larger problems or to different unseen problems from the same class of the optimization task. Deep reinforcement learning for optimization is an emerging topic over the recent years and has shown promising results. However, a number of research issues remain to be explored. There is a need to explore novel methods to handle constrained, continuous, complex large-scale and multi/many-objective optimization problems using DRL techniques.

This special issue aims to promote emerging computational intelligence theories and methodologies of deep reinforcement learning for optimization. Six papers were accepted by a rigorous review that considers the relevance, originality, novelty and presentation of these papers. The selected articles cover a wide range of recent advances in theory, algorithm development and applications of deep reinforcement learning developed for complex optimization. We introduce the selected manuscripts in details as follows.

The first paper, titled "Deep Reinforcement Learning Based Optimization Algorithm for Permutation Flow-Shop Scheduling" by Pan et al., proposes a DRL method for solving permutation flow-shop scheduling problem (PFSP) to minimize the maximum completion time. A new deep neural network (PFSPNet) is designed for the PFSP to achieve the end-to-end output, and is trained using an actor-critic method. In addition, an improvement strategy is designed to refine the solution provided by the PFSPNet. Experimental results show that their proposed method can obtain better results than the existing heuristics in similar computational time.

The paper titled "Influence Maximization in Complex Networks by Using Evolutionary Deep Reinforcement Learning" by Ma et al., propose an evolutionary deep reinforcement learning algorithm (EDRL-IM) for Influence maximization (IM) in complex networks. First, the IM problem is modelled as a continuous weight parameter optimization of deep Q network (DQN). Then, they combine an evolutionary algorithm (EA) and a deep reinforcement learning algorithm (DRL) to evolve the DQN. Systematic experiments on both benchmark and real-world networks show the superiority of EDRL-IM over the state-of-the-art IM methods in finding seed nodes.

The paper titled "RL-CSL: A Combinatorial Optimization Method Using Reinforcement Learning and Contrastive Self-Supervised Learning" by Yuan et al., proposes a method based on reinforcement learning and contrastive self-supervised learning to solve combinatorial optimization problems. This method uses an attention model to learn a policy for generating solutions and combines a contrastive self-supervised learning model to learn the attention encoder in the way of node-by-node. Experimental results demonstrate the good performance of the proposed method on various combinatorial optimization problems.

The paper titled "Structural Parameter Space Exploration for Reinforcement Learning via a Matrix Variate Distribution" by Wang et al., propose a novel structural parameter space noise exploration method, where structural weight uncertainty brought by noise dramatically enhances the exploration for reinforcement learning. By generating the noise via a matrix variate distribution, the noisy exploration in the method is based on the entire weight matrix of a layer in the neural network rather than an isolated weight point. Extensive experiments have shown that matrix variate noise exploration outperforms fully factorized noisy exploration on most Atari tasks and Super Mario Bros tasks and is competitive to the state-of-the-art methods.

The paper titled "Knowledge-Based Reinforcement Learning and Estimation of Distribution Algorithm for Flexible Job Shop Scheduling Problem" by Du et al., proposes a hybrid multi-objective optimization algorithm of estimation of distribution algorithm (EDA) and deep Q-network (DQN) to solve a flexible job shop scheduling problem with time-of-use electricity

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price constraint. 34 state features and 9 actions are designed to enhance the exploitation abilities of the DQN component. A problem-based EDA component is embedded in the algorithm to enhance the exploration abilities. The results on wide-range scale instances show that the proposed method is efficient and effective at solving the integrated flexible job shop scheduling problem.

The last paper, titled "Deep Reinforcement Learning Based Adaptive Operator Selection for Evolutionary Multi-Objective Optimization" by Tian et al., proposes a novel operator selection method based on reinforcement learning during the search process in evolutionary algorithms (EAs). In the proposed method, the decision variables are regarded as states and the candidate operators are regarded as actions. By using deep neural networks to learn a policy that estimates the Q value of each action given a state, the proposed method can determine the best operator for each parent that maximizes its cumulative improvement. The proposed method is verified to be more effective than the state-of-the-art ones on challenging multi-objective optimization problems.

Overall, the selected articles are of high quality and provide a set of emerging computational intelligence theories and methods on deep reinforcement learning for optimization. Guest editors would like to thank all authors for submitting their original works to this special issue. We also would like to thank all reviewers for their constructive suggestions and recommendations. We specially thank the Editor-in-Chief, Prof Yew-Soon Ong, and all editorial team members for their support and guidance. We sincerely expect that this special issue would prompt further studies on this promising research perspective.

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