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Contribution of learning algorithms to optimize reconfigurable manufacturing systems

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1 Contribution of Learning Algorithms to Optimize Reconfigurable Manufacturing Systems.

T Uhe optimization of RMS has long been a key research area within the field of industrial engineering. Previous studies have explored various techniques to address the factory layout problem (FLP) and improve the performance of traditional manufacturing systems. Notably, the former Ph.D. thesis successfully employed optimization techniques to tackle FLP, leading to significant advancements in layout design and operational efficiency.

Building upon this foundation, my Ph.D. thesis titled "Contribution of Learning Algorithms to Optimize Reconfigurable Manufacturing Systems" takes a step forward in the field of manufacturing optimization. While the previous thesis utilized optimization methods, namely simulated annealing method, my research explores the integration of artificial intelligence, specifically reinforcement learning, into the optimization of reconfigurable manufacturing systems. Reinforcement learning, a branch of artificial intelligence, provides a promising approach to decision-making in dynamic and uncertain environments. By employing reinforcement learning algorithms, my research aims to develop intelligent optimization strategies for the efficient operation and reconfiguration of RMS.

2 Results and Conclusion

Experimental investigation of Q-learning applied to the factory layout problem has been conducted. Initially, an experiments using a layout scenario involving two machines, with one being reconfigurable. Then, the problem was extended to two reconfigurable machines and RL agent has did well in this front by finding the best solution with the least number of possible actions. Subsequently, we extended the study to encompass a layout scenario with four machines, all of which were reconfigurable.

Firstly, we examined the case where the RL agent aimed to determine the optimal configuration for four machines without the inclusion of the implantation action in the action space. Remarkably, the RL learning agent exhibited proficient performance in identifying the best layout under these circumstances.

Subsequently, we introduced the implantation action into the action space while maintaining the same transportation demand, intending to assess the agent's ability to effectively handle this additional action without being adversely affected. Encouragingly, the RL agent demonstrated commendable competence by generating the same layout as observed in the previous scenario, indicating its successful adaptation to the expanded action space.

Lastly, we altered the transportation demand in a manner that necessitated modifications to the implantation of machines. This change aimed to evaluate the agent's proficiency in utilizing the implantation action effectively. Notably, the RL agent excelled in this regard by skillfully adjusting the implantation of the machines, ultimately identifying the optimal layout. Specifically, it accomplished this by strategically positioning machines M1 and M3 in closer proximity to one another and subsequently determining the most favorable orientations and forms for all machines involved.

Through these three scenarios, we systematically examined the RL agent's capabilities in different contexts, including scenarios with and without the implantation action in the action space, as well as scenarios requiring changes in implantation to optimize the layout. These investigations shed light on the agent's adaptability, effectiveness in utilizing the action space, and ability to leverage the implantation action to achieve superior layouts. Thus far, Q-learning has demonstrated proficiency in addressing the layout problem involving four machines, utilizing a comprehensive action space comprising implantation, reorientation, and form changes. However, when faced with layouts that consist of more than four machines, the increased complexity of the state space poses a challenge for Q-learning. In such cases, the emergence of Deep Reinforcement Learning (DRL) becomes apparent as a potential solution.