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HYBRID METAHEURISTICS AND MACHINE LEARNING METHODS

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Solving large-scale optimization problems requires approximate methods, particularly metaheuristics, which provide high-quality solutions within reasonable computational times. These methods have demonstrated their efficacy in a wide range of academic and industrial fields, including healthcare, automotive engineering, telecommunications, finance, and energy systems.

Despite their versatility, metaheuristics require manual parameter tuning and problem-specific adaptations, which demand significant expertise. Hybridization with other optimization techniques [1], including exact methods [2], has been explored to improve their performance. However, these approaches remain largely static, relying on predefined rules and empirical configurations, limiting their adaptability across different problem landscapes.

A promising direction is the integration of Artificial Intelligence (AI) and Machine Learning (ML) to make metaheuristics more adaptive, autonomous, and efficient. AI and ML can enhance metaheuristics by automating algorithm selection [3], guiding initialization strategies [4], estimating fitness functions [5], dynamically adjusting parameters [6], and designing adaptive search strategies [7] to improve efficiency and solution quality.

Nevertheless, several fundamental questions remain: How can different approaches be combined dynamically? When should a particular strategy be applied? How can hyperparameters be optimized in real time? How can learning mechanisms improve search efficiency and scalability?

This Ph.D. thesis aims to address these questions by designing next-generation AI-enhanced metaheuristics, capable of self-adaptation, intelligent decision-making, and improved computational performance. The expected outcome is a new class of efficient, scalable, and self-improving optimization methods tailored to tackle complex real-world problems.

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