Supplementary Material for "Cooperative Coevolution Genetic Programming for Dynamic Joint Workflow Scheduling and Container Scaling in Cloud-Fog Computing"

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Appendix A
Related Work

The integration of cloud and fog computing has emerged as a critical solution to meet the demands of the rapidly growing IoT, which requires low-latency and high-efficiency computing. Cloud computing provides massive computing and storage resources, while fog computing extends these capabilities to the network edge, better serving real-time and latency-sensitive applications [1], [2]. However, achieving efficient workflow scheduling in the cloud/fog computing environment is a significant challenge due to the heterogeneity of resources, the dynamism of systems, and the complex and often conflicting objectives of workflows.

Workflow/Task Scheduling in Cloud-Fog Environments. These challenges manifest primarily in the fundamental problem of resource allocation and task offloading: deciding whether to execute tasks on resource-limited but low-latency fog nodes or on powerful but distant cloud servers. Several works in the literature proposed meta-heuristic algorithms to address workflow scheduling in cloud/fog computing environments [3], [4], [5], [6]. For instance, Singh and Chaturvedi [4] designed a hybrid genetic algorithm-modified particle swarm optimization for workflow scheduling in cloud-fog environment to balance makespan, cost, and energy consumption. Ali et al. [5] applied a multi-objective Harris Hawks Optimization algorithm for task scheduling in cloud-fog environments to minimise delay and energy, generating a set of trade-off solutions via a Pareto-optimal front. Nazemi and Khorsand [6] combined a Chaotic Krill Herd algorithm with an improved Cuckoo Search to enhance global search capabilities for workflow scheduling in fog computing to minimise makespan and energy. Karami et al. [3] proposed a hybrid approach for the static workflow scheduling problem in cloud-fog computing. Different from the methods mentioned above, they employed Non-Dominated Sorting Genetic Algorithm (NSGA) to optimise the execution order of tasks and utilised heuristic rule designed with a scoring function based on completion time and energy consumption to map tasks to resources. These meta-heuristic algorithms have strong global search capabilities and can be adapted to various scheduling problems via customised encoding and decoding schemes. However, they struggle to adapt to the inherent resource elasticity and dynamism of cloud environments due to their reliance on fixed-length encodings or explicit task-to-resource mappings.

Consequently, researchers are actively exploring alternative scheduling methods, including rule-based heuristics [7], [8], [9], [10], hyper-heuristics [11], [12], [13], [14], and machine learning [15], [16], [17], to better address these modern challenges. Among rule-based heuristics, Stavrinides and Karatza [7] proposed a rule-based scheduling heuristic for real-time workflow in a fog environment to balance performance and monetary cost by utilising a weighted score function that combines Estimated Finish Time and Estimated Monetary Cost. In a subsequent work [8], they introduced a data-aware dynamic scaling mechanism that prevents data loss during scale-in actions by ensuring VMs holding necessary intermediate workflow data are not terminated. Taghinezhad-Niar and Taheri [10] proposed two scheduling algorithms for real-time multi-workflow scheduling in compute-continuum environments to optimise for rental cost, energy consumption, and reliability, employing a 'Reliability Guard' with task duplication to satisfy reliability constraints. In the area of hyper-heuristics, Yang et al. [12] developed dual-tree genetic programming method for the dynamic workflow scheduling in cloud computing to minimise the rental fee and deadline violation penalty by automatically evolving VM selection rule and task selection rule. In the area of machine learning, Goudarzi et al. [16] developed a distributed deep reinforcement learning framework for service offloading in fog computing environments to minimise execution time by using a distributed actor-critic architecture where parallel actors accelerate the learning process. Although these methods show great promise for adaptive scheduling, they often focus on performance optimisation and do not fully integrate the many-objective challenges of the problem with the fine-grained management of container resources.

Container-based Workflow/Task Scheduling. Container-based virtualisation has become a pivotal technology in cloud-fog computing due to its lightweight nature and efficient resource management capabilities. The elasticity of containers, both horizontal and vertical, offers significant advantages for dynamic resource allocation and task scheduling [18]. However, some studies utilised containers in a limited capacity. Rodriguez et al. [19] and Ye et al. [20] assumed containers inherited fixed resource configurations from their host VMs, while Sun et al. [21] considered static CPU and memory configurations for tasks. These models, while leveraging containers for faster deployment than VMs, did not fully exploit their dynamic potential. Some studies utilised the lightweight and fast deployment capabilities of containers. Ranjan et al. [22] proposed an energy-efficient workflow scheduling scheme for software-defined data centers to minimise energy consumption, which migrated the containers within the VMs among different data centers. Yin et al. [23] proposed a container-based task scheduling model for fog computing in smart manufacturing to improve the number of concurrent tasks and reduce delay. To manage containers at a higher level, Tuli et al. [17] developed the COSCO framework for container orchestration, which utilises co-simulation and a gradient-based optimization strategy to make intelligent placement and migration decisions that optimise QoS. Although these methods show great promise for adaptive scheduling, they often focus on performance optimization and do not fully integrate the many-objective challenges of the problem with the fine-grained management of container resources.

The aforementioned studies primarily focus on horizontal scaling, which involves managing the placement, migration, and number of container instances. However, the dynamic jointly workflow scheduling and container scaling (including both horizontal scaling and vertical scaling) problem remains a significant and underexplored research area.

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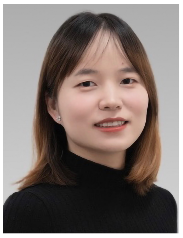

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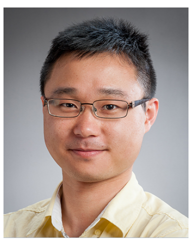

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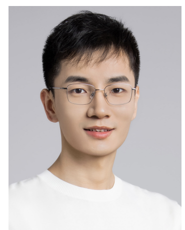

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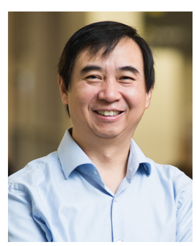

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