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# List of Abbreviations

<b>Abbreviation</b>	<b>Description</b>
A2CS	Advantage Actor Critic Strategy
ACO	Ant Colony Optimization
ADB	Deadline and Budget Constrained Archimedes Optimization
AI	Artificial Intelligence
ANOVA	Analysis of Variance
AOA	Archimedes Optimization Algorithm
CPOP	Critical Path on a Processor
CPU	Central Processing Unit
DAG	Directed Acyclic Graph
DDPG	Deep Deterministic Policy Gradient
DQN	Deep Q Network
EARES	Energy Aware Reliability Enhancement Scheduling
FCFS	First Come First Serve
FPA	Flower Pollination Algorithm
GA	Genetic Algorithm
GWO	Grey Wolf Optimization
HEFT	Heterogenous Earliest Finish Time
LEO	Local Escaping Operation
MDP	Markov Decision Process
MFGA	Modified Fuzzy Genetic Algorithm
MI	Million Instructions
MIPS	Million Instructions Per Second

## LIST OF ABBREVIATIONS

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<b>Abbreviation</b>	<b>Description</b>
ML	Machine Learning
MLEAO	Modified Local Escaping Archimedes Optimization
MLP	Multi Layer Perceptron
MLPOA	Multi Layer Perceptron Optimized Archimedes Approach
MRFO	Manta Ray Foraging Optimization
MRFOBL	Opposition-Based Learning Enhanced Manta Ray Foraging
MVO	Multi Verse Optimizer
NNRL	Neural Network-based Reinforcement Learning
OBL	Opposition Based Learning
PE	Processing Element
PSO	Particle Swarm Optimization
QoS	Quality of Service
ReLU	Rectified Linear Unit
RL	Reinforcement Learning
SIPHT	Three Dimensional
SJF	Shortest Job First
SLA	Service Level Agreement
SLR	Systematic Literature Review
SOS	Symbiosis Organisms Search
SOTA	State-of-the-Art
VM	Virtual Machine