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Energy-efficient trajectory planning for a multi-UAV-assisted mobile edge computing system

Key words: Multiple unmanned aerial vehicles; Mobile edge computing; Trajectory planning; Differential evolution; *k*-means clustering algorithm; Greedy method

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Motivation

1. To plan trajectories of unmanned aerial vehicles (UAVs), we need to know how many stop points (SPs) are suitable and where they are located, which UAV is assigned to visit the given SP, and how to visit SPs in turn for each UAV.

2. Since the number of SPs is unknown a priori, the length of individuals in conventional evolutionary algorithms (EAs) is not fixed. However, the commonly used crossover and mutation operators are designed for fixed-length individuals. Thus, it would be ineffective to use conventional EAs directly.

Main idea

1. The trajectories of UAVs at each iteration are planned through three phases: update of the deployment of SPs, generation of the association between UAVs and SPs, and construction of the order of SPs.

2. A differential evolution (DE) algorithm with a variable population is adopted to update the number and locations of SPs at the same time.

Method

1. An energy-efficient trajectory planning algorithm, called TPA, is proposed to tackle the trajectory planning problem.

2. A DE algorithm with a variable population is first adopted to optimize the deployment of SPs. Then, the *k*-means clustering algorithm is used to group the given SPs into several clusters. Finally, a greedy method is proposed to construct the order of SPs in each cluster.

Method (Cont'd)

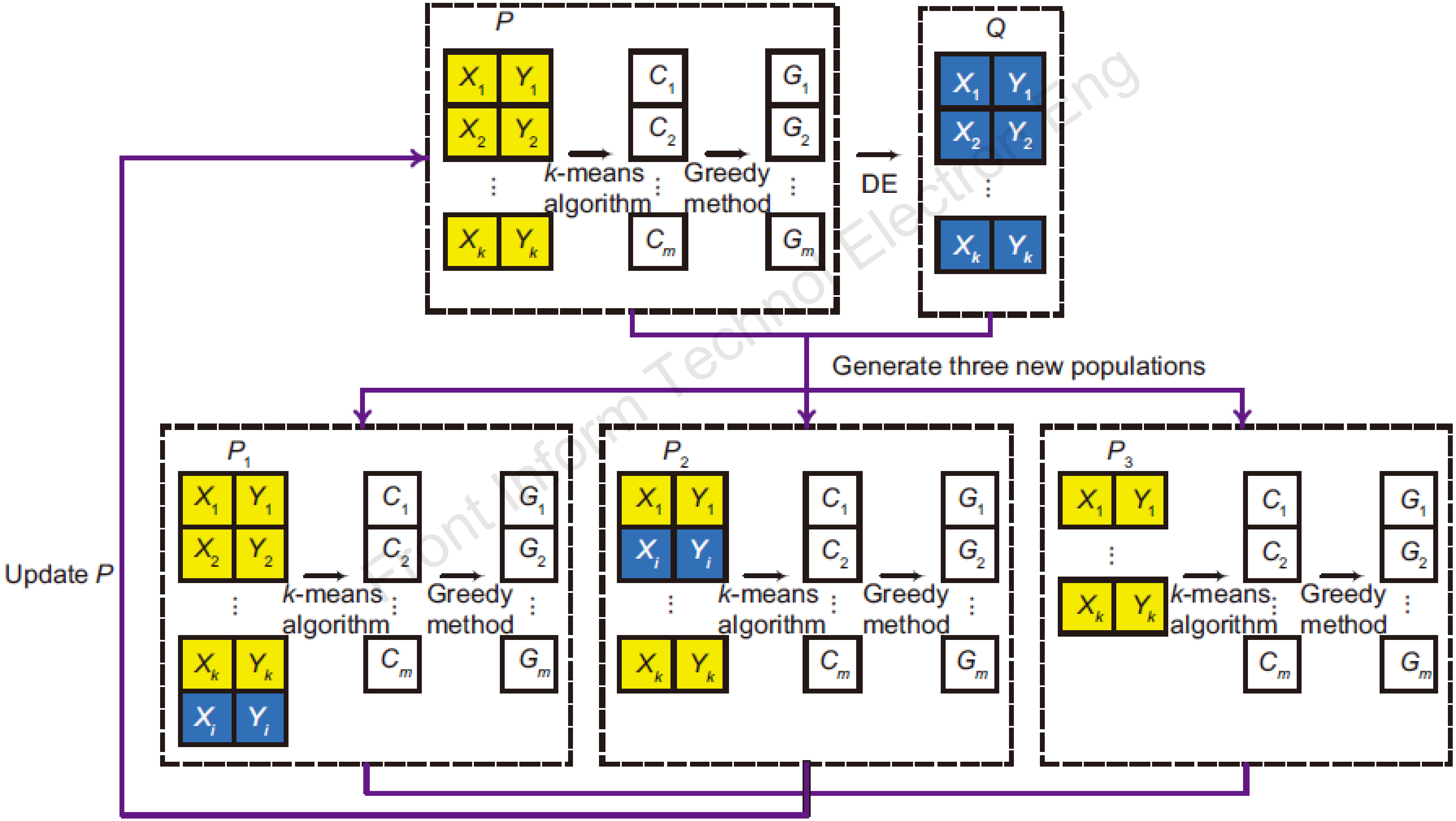


Fig. 3 Overall framework of trajectory planning algorithm

Major results

Table 1 Experimental results of TPA-VLGA, TPA-JGGA, TPA-DEEM, and TPA in terms of average energy consumption (EC) (J) over 20 runs

n	Mean (standard deviation)			Feasibility rate
	TPA-VLGA	TPA-JGGA	TPA	TPA-DEEM
60	$1.57e+6$ $(2.33e+4)$ ↑	$1.53e+6$ $(2.47e+4)$ ↑	$1.40e+6$ $(2.03e+4)$	90% ↑
80	$2.36e+6$ $(4.20e+4)$ ↑	$2.22e+6$ $(2.33e+4)$ ↑	$2.06e+6$ $(2.68e+4)$	95% ↑
100	$3.07e+6$ $(3.41e+4)$ ↑	$2.94e+6$ $(2.79e+4)$ ↑	$2.68e+6$ $(3.73e+4)$	90% ↑
120	$3.28e+6$ $(3.54e+4)$ ↑	$3.12e+6$ $(2.74e+4)$ ↑	$2.82e+6$ $(6.29e+4)$	80% ↑
140	$4.31e+6$ $(4.39e+4)$ ↑	$4.09e+6$ $(3.59e+4)$ ↑	$3.71e+6$ $(3.03e+4)$	70% ↑
160	$5.03e+6$ $(6.89e+4)$ ↑	$4.77e+6$ $(2.59e+4)$ ↑	$4.21e+6$ $(5.21e+4)$	75% ↑
180	$5.63e+6$ $(6.06e+4)$ ↑	$5.39e+6$ $(3.87e+4)$ ↑	$4.83e+6$ $(4.17e+4)$	85% ↑
200	$6.27e+6$ $(1.00e+5)$ ↑	$6.07e+6$ $(3.86e+4)$ ↑	$5.35e+6$ $(4.20e+4)$	80% ↑
↑ / ↓ / ≈	7/0/0	7/0/0		7/0/0

“↑,” “≈,” and “↓” represent that TPA performed significantly better than, equivalent to, and worse than its competitor, respectively.

Major results (Cont'd)

Table 2 Experimental results of TPA-WoK, TPA-RAN, TPA-GA, and TPA in terms of average energy consumption (EC) (J) over 20 runs

n	Mean (Standard deviation)			
	TPA-WoK	TPA-RAN	TPA-GA	TPA
60	$1.60e+6$ $(5.74e+4)$ ↑	$1.56e+6$ $(1.97e+5)$ ↑	$1.43e+6$ $(5.87e+4)$ ↑	$1.40e+6$ $(2.03e+4)$
80	$2.29e+6$ $(6.89e+4)$ ↑	$2.48e+6$ $(3.14e+5)$ ↑	$2.27e+6$ $(3.14e+4)$ ↑	$2.06e+6$ $(2.68e+4)$
100	$2.99e+6$ $(4.88e+4)$ ↑	$3.63e+6$ $(4.02e+5)$ ↑	$3.18e+6$ $(1.72e+5)$ ↑	$2.68e+6$ $(3.73e+4)$
120	$3.15e+6$ $(5.29e+4)$ ↑	$4.33e+6$ $(1.71e+5)$ ↑	$3.71e+6$ $(1.96e+5)$ ↑	$2.82e+6$ $(6.29e+4)$
140	$4.06e+6$ $(4.88e+4)$ ↑	$5.51e+6$ $(2.29e+5)$ ↑	$4.90e+6$ $(1.24e+5)$ ↑	$3.71e+6$ $(3.03e+4)$
160	$4.66e+6$ $(6.71e+4)$ ↑	$6.61e+6$ $(1.83e+5)$ ↑	$5.94e+6$ $(1.05e+5)$ ↑	$4.21e+6$ $(5.21e+4)$
180	$5.22e+6$ $(6.71e+4)$ ↑	$7.60e+6$ $(1.45e+5)$ ↑	$6.69e+6$ $(1.07e+5)$ ↑	$4.83e+6$ $(4.17e+4)$
200	$5.85e+6$ $(8.88e+4)$ ↑	$8.51e+6$ $(2.38e+5)$ ↑	$7.72e+6$ $(2.62e+5)$ ↑	$5.35e+6$ $(4.20e+4)$
↑ / ↓ / ≈	7/0/0	7/0/0	7/0/0	

"↑," "≈," and "↓" represent that TPA performed significantly better than, equivalent to, and worse than its competitor, respectively.

Major results (Cont'd)

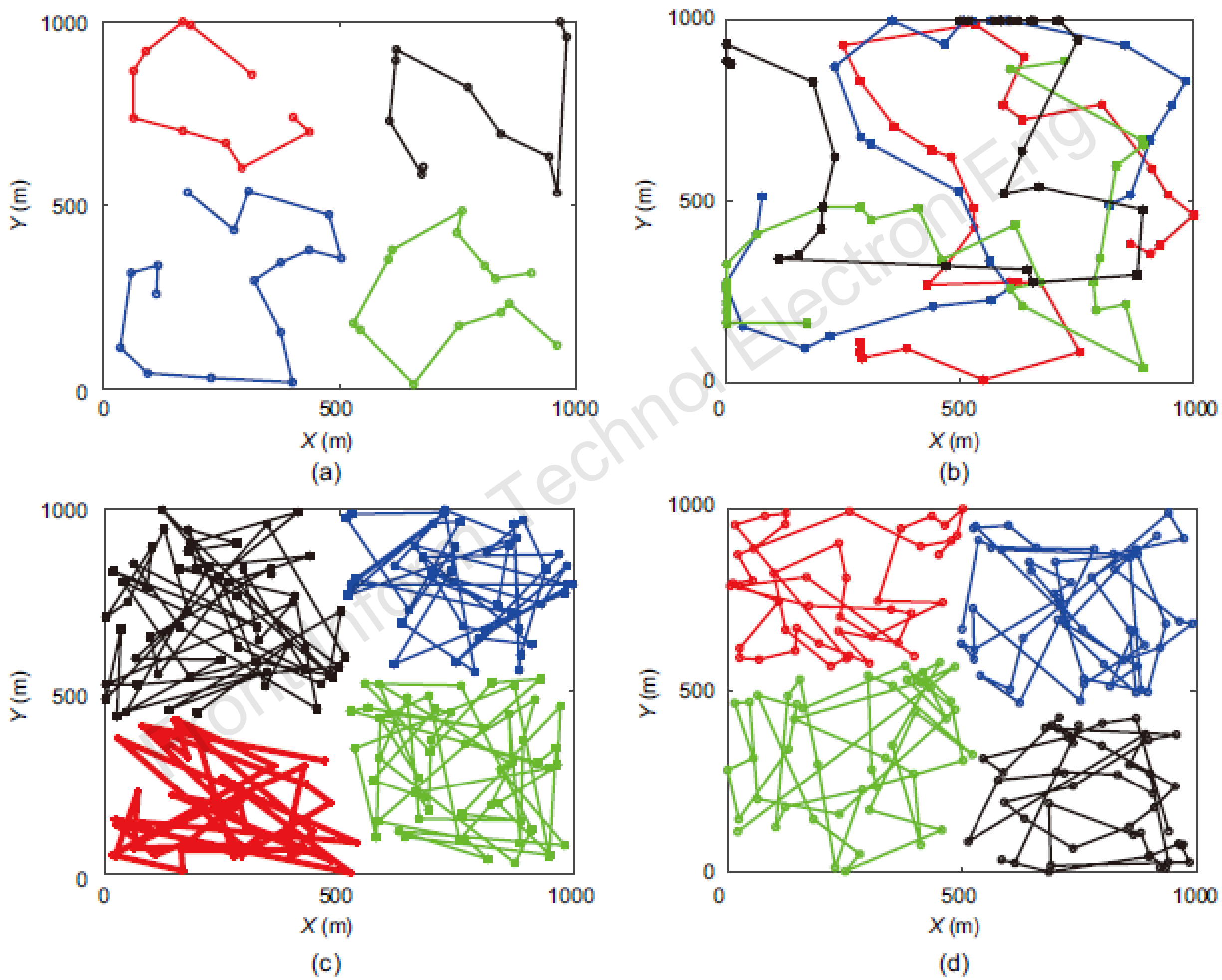


Fig. 6 Trajectories of UAVs obtained by TPA (a), TPA-WoK (b), TPA-RAN (c), and TPA-GA (d) when $n = 200$

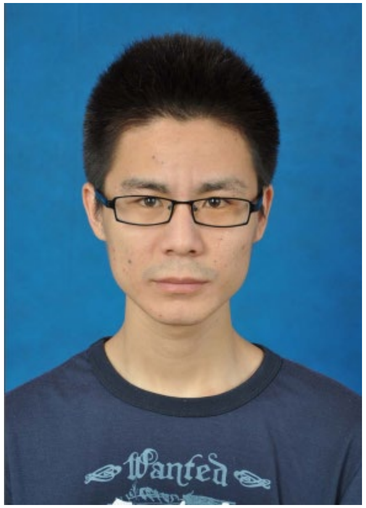
Red, green, blue, and black lines indicate trajectories $\mathcal{G}_1$, $\mathcal{G}_2$, $\mathcal{G}_3$, and $\mathcal{G}_4$, respectively. References to color refer to the online version of this figure

Conclusions

1. A trajectory planning problem in a multi-UAV-assisted MEC system was formulated, containing three coupled sub-problems: the deployment of stop points, the association between UAVs and SPs, and the order of stop points.

2. To solve the trajectory planning problem, we proposed a three-phase trajectory planning algorithm, called TPA.

3. The experimental results showed that on a set of instances at different scales, TPA can save much energy compared with other algorithms.



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