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面向电商物流配送与营销策略优化的DDMOPSO算法设计及性能验证

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摘 要

针对电子商务领域物流配送路径优化、营销策略精准化等核心场景的多目标优化需求，传统多目标粒子群算法(MOPSO)在收敛性与多样性的平衡上存在明显不足，难以高效满足电商平台精细化运营、提质增效的实际需求。为此，本文设计并验证了一种面向电商场景的DDMOPSO算法。采用ZDT与UF系列基准测试函数模拟电商实际多目标冲突场景，将该算法与八种主流多目标优化算法开展对比实验，验证其综合性能。实验结果表明，DDMOPSO算法具备更优的收敛速度和全局搜索能力，能够有效平衡算法的收敛性与多样性，可高效解决电商物流配送中成本与时效、营销策略中推荐精准度与覆盖度的多目标平衡问题。该算法为电商领域复杂多目标优化问题提供了高效可靠的技术支撑，有助于推动电商平台精细化运营、降低运营成本、提升用户体验，进而助力电商经济提质增效。

关键词

电子商务，多目标优化，DDMOPSO粒子群算法，物流配送优化，营销策略优化

Design and Performance Verification of DDMOPSO Algorithm for Optimization of E-Commerce Logistics Distribution and Marketing Strategies

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Abstract

In response to the multi-objective optimization demands in core scenarios such as logistics distribution path optimization and marketing strategy precision in the e-commerce field, the traditional multi-objective particle swarm optimization (MOPSO) algorithm shows significant deficiencies in balancing convergence and diversity, making it difficult to efficiently meet the actual needs of e-commerce platforms for refined operation, quality improvement, and efficiency enhancement. Therefore, this paper designs and validates a DDMOPSO algorithm tailored for e-commerce scenarios. By using the ZDT and UF series benchmark test functions to simulate the actual multi-objective conflict scenarios in e-commerce, the algorithm is compared with eight mainstream multi-objective optimization algorithms to verify its comprehensive performance. The experimental results show that the DDMOPSO algorithm has a superior convergence speed and global search capability, effectively balancing the convergence and diversity of the algorithm. It can efficiently solve the multi-objective balance problems in e-commerce logistics distribution, such as cost and timeliness, and in marketing strategies, such as recommendation accuracy and coverage. This algorithm provides efficient and reliable technical support for complex multi-objective optimization problems in the e-commerce field, which is conducive to promoting refined operation of e-commerce platforms, reducing operating costs, and enhancing user experience, thereby contributing to the quality improvement and efficiency enhancement of the e-commerce economy.

Keywords

E-Commerce, Multi-Objective Optimization, DDMOPSO Particle Swarm Algorithm, Logistics Distribution Optimization, Marketing Strategy Optimization

1. 引言

在数字经济快速发展的背景下，电子商务已成为市场经济的核心组成部分，物流配送路径优化、电商平台资源调度、个性化推荐排序、供应链协同优化等核心场景，均属于典型的多目标优化问题。多目标优化问题(Multi-objective Optimization Problems, MOPs)的核心特征在于其需同时处理多个相互冲突或存在竞争关系的目标函数[1]。粒子群优化算法[2] (Particle Swarm Optimization, PSO)，在单目标优化问题中展现出卓越性能，研究者自然将其扩展至多目标优化领域，从而发展出多目标粒子群优化算法 MOPSO [3]。传统 MOPSO 无法满足电商场景的实际需求，无法为电商决策提供全面的最优方案集合。

尽管目前针对 MOPSO 优化，提出了诸多高效改进策略[4]-[6]，但未充分结合电子商务场景的动态性与复杂性，适配性较差。例如，超区域密度估计(DAMOPSO)策略[7]，基于参考向量的方法[8] [9]，柯西变异操作[10]，指数变异算子变异[11]，这些策略面向电商场景时都有一定的缺陷。

本文提出了 DDMOPSO 算法，引入新型网格密度和粒子密度指标，设计一种飞行状态检测机制，以增强种群跳出局部最优的能力[12]，为电子商务领域复杂多目标优化问题提供高效可靠的解决方案。

2. 相关工作

2.1. 多目标优化问题

在电子商务领域，物流配送路径规划、个性化营销策略制定、供应链协同调度等核心业务场景，本

质上均为典型的多目标优化问题。

多目标优化问题一般表述为：

$$\min\ F(x)=\left(f_1(x), f_2(x),\cdots, f_M(x)\right) \tag{1}$$

$$\text{s.t.}\ \ g_i(x)\ge 0, i=1,2,\cdots,q \tag{2}$$

$$h_j(x)=0, j=1,2,\cdots,r$$

$$x=\left(x_1,x_2,\cdots,x_D\right),\ X\in R^D$$

其中，X 表示决策空间，x 表示决策空间中的决策变量，$F(x)$ 表示目标函数，$f_i(x)$ 表示第 i 维的目标函数，$g_i(x)\ge 0\ (i=1,2,\cdots,q)$ 和 $h_j(x)=0\ (j=1,2,\cdots,r)$ 分别表示不等式和等式约束。

2.2. 粒子群算法

粒子群算法[2]核心公式如下：核心公式如下：

$$V_i(t+1)=\omega V_i(t)+c_1r_1\left(pbest_i(t)-X_i(t)\right)+c_2r_2\left(gbest_i(t)-X_i(t)\right) \tag{3}$$

$$X_i(t+1)=X_i(t)+V_i(t+1) \tag{4}$$

其中，t 表示迭代次数，ω 表示惯性权重，c_1 和 c_2 为学习因子，并且通常均设置为 2，r_1 和 r_2 表示介于 0 和 1 之间的随机数。

3. MOPSO 算法设计

3.1. 双密度控制策略

定义特征半径 R：基于适应度值信息构建动态自适应网格，记录各网格单元的几何尺度参数。据次计算等体积(或近似等体积)的超球体的特征半径 R，计算公式如下：

$$R=\left(\frac{w^M\times\Gamma(M/2+1)}{\pi^{M/2}}\right)^{1/M} \tag{5}$$

其中，w 表示网格宽度(超立方体边长)，M 表示问题的维度，π 表示圆周率常数，Γ 表示伽马函数。

密度的量化计算：以粒子为球心、以 R 为尺度构建的超球体范围内，所包含的其他非劣解粒子的数量即为粒子密度。定义网格密度为特定网格单元内所有粒子密度的累加值。

存档维护操作：当外部存档中的非劣解数量超过预设容量限制时需执行存档维护操作：首先定位当前密度最大的网格单元，并进一步选取该网格内粒子密度最高的粒子作为待删除候选；删除该粒子后，更新原网格的网格密度，即将其数值调整为原网格密度值减去被删除粒子的粒子密度；重复上述步骤(优先选择位于密度最大的网格内且粒子密度最高的粒子进行删除)，直至外部存档中的非劣解数量降至存档容量允许范围内。

3.2. 基于飞行状态检测器的变异

基于非支配排序理论[13]，记录种群粒子的飞行状态特征，构建飞行状态检测器，记为 T：

$$T(t)=\left(c_1(t),c_2(t),\cdots,c_n(t)\right),\ T(0)=(0,0,\cdots,0)$$

其中，t 表示迭代次数，$c_i(t)$ 表述种群中第 i 个粒子在第 t 次迭代时对应的检测器的值，n 表示种群粒子

总的个数。

筛选粒子进行变异：基于明确的更新规则进行动态调整：当粒子当前迭代没有贡献行为时，检测器执行累加操作 $c_i(t)=c_i(t-1)+1$；反之，当粒子有贡献行为时，检测器立即重置为 $c_i(t)=0$，并规定当前迭代中已经进行变异操作后的粒子的检测器也立即重置为 $c_i(t)=0$。算法将满足 $c_i(t)\geq 3$ 的粒子识别为变异操作目标。算法采用公式(6)进行位置变异

$$X_{\text{new}}(t)=X_{\text{mut}}(t)+\frac{ub}{2}\times\eta\times\left(X_s(t)-X_{\text{mut}}(t)\right) \tag{6}$$

$$\eta=\frac{1}{\sqrt{2\pi}}\mathrm{e}^{-\frac{r}{2}},r\in[0,1]$$

其中，t 表示迭代次数，η 为自适应缩放因子，ub 定义决策空间的上边界，r 表示随机数，X_{mut} 表示变异粒子的原位置，X_{new} 表示变异后粒子的位置，X_s 表示从种群中随机挑选的粒子位置。

4. 实验仿真分析与结果分析

4.1. 测试函数和参数设置

本文借助了 ZDT [14]和 UF [15]这两个基准测试组，使用测试问题模拟电商物流配送路径规划(配送成本与时效的双目标优化)、营销策略优化(用户推荐精准度与覆盖度的多目标平衡)等常见场景。选取八个多目标优化算法 NMPSO [16]、SMPSO [17]、MOPSO [3]、MOPSCD [18]、NSGAIII [19]、SPEAR [20]、DGEA [21]，IDBEA [22]与 DDMOPSO 算法进行对比验证算法的综合性能。

4.2. 性能评价指标

反世代距离(IGD) [23]和超体积(HV) [24]通常被用来衡量多目标粒子群优化算法的收敛性和多样性。

(1) IGD 是一项度量算法所得 Pareto 最优解集与真实 Pareto 前沿(PF)之间的接近程度的综合性能指标，该值越小越能说明最优解集的收敛效果和分布性两方面表现越好。

$$\text{IGD}(P,S)=\frac{1}{|P|}\sum_{x\in P}\text{dist}(x,S) \tag{7}$$

其中，S 表示最优解集，P 表示真实解集前沿，$\text{dist}(x,S)$ 表示真实解集上的点到最优集的距离。

(2) HV 是一项衡量算法所获得的最优解集与参考点在目标空间中所围成的区域体积的评价指标，该值越大越能说明最优解集的收敛效果和分布性两方面表现越好。超体积 HV 的计算通常需要借助参考点 $Z=(Z_1,Z_2,\cdots,Z_D)$，该点是被搜索空间中所有 Pareto 最优解支配的一个点。

$$\text{HV}(S)=\delta\left(\bigcup_{x\in S}\left[f_1(x),z_1\right]\times\left[f_D(x),z_D\right]\right) \tag{8}$$

其中，S 表示最优解集，δ 表示 Lebesgue 测度，D 表示目标空间的维度。

4.3. 研究结果分析

表 1 和表 2 是对 IGD 和 HV 这两个评价指标进行实验研究得到的结果。两表的最后一行数据显示，针对算法的两个指标，DDMOPSO 在 15 个测试问题中分别占了 10 个和 9 个最优值。采用 Friedman 秩非参数检验[25]进行对比研究，实验数据详见表 3。证明 DDMOPSO 算法在模拟电商场景的测试函数中表现更优，为电商经济提质增效提供算法支撑。

Table 1. Experimental results of IGD performance indicators of DDMOPSO and 8 comparison algorithms on ZDT and UF series test problems
表 1. DDMOPSO 与 8 个对比算法在 ZDT 和 UF 系列测试问题上 IGD 性能指标实验结果

测试问题	R_{IGD}	NMPSO	SMPSO	MOPSO	MOPSOCD	NSGAIII	SPEAR	DGEA	IDBEA	DDMOPSO
ZDT1	Mean	2.9473e−2	1.0488e−1	1.5285e+0	1.2966e−2	8.2819e−2	1.7855e−1	1.2267e+0	5.2960e−1	**3.2553e−3**
	Std	(1.41e−2)	(9.48e−2)	(5.49e−2)	(3.91e−2)	(1.37e−2)	(3.14e−2)	(2.69e−1)	(7.93e−2)	**(1.23e−4)**
ZDT2	Mean	**2.1687e−2**	6.2243e−2	3.0402e+0	1.4828e−1	1.6344e−1	4.0712e−1	9.2717e−1	2.0047e+0	6.3979e−2
	Std	**(2.67e−2)**	(1.34e−1)	(1.38e−1)	(2.36e−1)	(4.88e−2)	(1.38e−1)	(3.08e−1)	(2.45e−1)	(1.82e−1)
ZDT3	Mean	9.1998e−2	1.8999e−1	1.1761e+0	4.5027e−2	6.9550e−2	1.4794e−1	1.0005e+0	3.2641e−1	**3.7973e−3**
	Std	(2.02e−2)	(7.53e−2)	(9.98e−2)	(5.45e−2)	(9.51e−3)	(1.47e−2)	(2.51e−1)	(3.69e−2)	**(1.70e−4)**
ZDT4	Mean	1.9467e+1	7.6028e+0	1.0024e+1	2.0105e+1	2.2931e+0	1.7962e+0	6.9964e+0	2.6975e+1	**6.9205e−1**
	Std	(1.12e+1)	(3.32e+0)	(4.12e+0)	(6.47e+0)	(9.37e−1)	(6.79e−1)	(4.92e+0)	(6.53e+0)	**2.47e−1**
ZDT6	Mean	2.2933e−3	**1.8983e−3**	5.5719e+0	5.0748e−3	1.2184e+0	1.1555e+0	3.0312e−3	4.4203e+0	1.7806e−2
	Std	(2.53e−4)	**(6.97e−5)**	(2.83e−1)	(8.15e−3)	(1.88e−1)	(1.95e−1)	(5.94e−3)	(3.81e−1)	2.96e−2
UF1	Mean	1.2311e−1	3.8679e−1	4.8381e−1	6.9564e−1	**1.2171e−1**	1.3281e−1	6.7888e−1	3.7813e−1	1.6642e−1
	Std	(1.35e−2)	(9.96e−2)	(7.02e−2)	(1.58e−1)	**(3.15e−2)**	(2.39e−2)	(1.58e−1)	(7.95e−2)	1.82e−2
UF2	Mean	8.5377e−2	9.8537e−2	9.9070e−2	1.3615e−1	7.5884e−2	**7.2635e−2**	1.7109e−1	1.6134e−1	7.9527e−2
	Std	(6.71e−3)	(9.86e−3)	(6.30e−3)	(1.50e−2)	(5.14e−3)	**(7.41e−3)**	(2.04e−2)	(1.83e−2)	5.55e−3
UF3	Mean	3.5681e−1	4.5430e−1	4.6035e−1	4.0555e−1	4.6423e−1	4.3388e−1	5.6007e−1	6.0924e−1	**3.3479e−1**
	Std	(5.31e−2)	(5.77e−2)	(3.52e−2)	(9.54e−2)	(1.34e−2)	(1.86e−2)	(3.73e−2)	(2.64e−2)	**3.35e−2**
UF4	Mean	6.3767e−2	1.1126e−1	1.8189e−1	7.6978e−2	8.8208e−2	8.5548e−2	1.1891e−1	1.0700e−1	**6.3669e−2**
	Std	(8.51e−3)	(8.50e−3)	(3.39e−3)	(9.14e−3)	(2.57e−3)	(2.56e−3)	(1.02e−2)	(3.19e−3)	**9.71e−3**
UF5	Mean	1.6485e+0	2.8108e+0	2.6808e+0	3.8676e+0	1.1420e+0	**1.1178e+0**	2.9639e+0	3.0673e+0	1.8605e+0
	Std	(4.49e−1)	(5.15e−1)	(3.82e−1)	(4.29e−1)	(3.56e−1)	**(1.88e−1)**	(5.87e−1)	(2.50e−1)	2.27e-1
UF6	Mean	6.4390e−1	1.4121e+0	1.9873e+0	2.8804e+0	6.4688e−1	6.7952e−1	2.5635e+0	2.0025e+0	**6.3802e−2**
	Std	(1.21e−1)	(5.24e−1)	(3.86e−1)	(5.57e−1)	(1.48e−1)	(8.46e−2)	(6.99e−1)	(3.04e−1)	**9.00e−3**
UF7	Mean	2.3351e−1	3.6160e−1	5.8056e−1	6.3639e−1	1.7995e−1	2.0873e−1	7.1060e−1	4.5394e−1	**1.4449e−1**
	Std	(1.66e−1)	(1.31e−1)	(5.17e−2)	(1.44e−1)	(8.07e−2)	(7.29e−2)	(1.16e−1)	(9.13e−2)	**2.14e−2**
UF8	Mean	4.8642e−1	3.8208e−1	4.2988e−1	7.7729e−1	3.4655e−1	3.2018e−1	7.2307e−1	3.6417e−1	**3.1817e−1**
	Std	(1.02e−1)	(4.13e−2)	(2.71e−2)	(1.41e−1)	(4.06e−2)	(1.52e−2)	(1.24e−1)	(3.99e−2)	**7.13e−2**
UF9	Mean	4.5301e−1	5.6648e−1	5.3213e−1	8.7281e−1	4.7390e−1	4.9296e−1	7.7735e−1	5.4922e−1	**1.8550e−1**
	Std	(7.13e−2)	(3.67e−2)	(2.88e−2)	(1.46e−1)	(3.77e−2)	(5.58e−2)	(1.25e−1)	(6.03e−2)	**1.91e−2**
UF10	Mean	1.5397e+0	2.7801e+0	1.3708e+0	4.9747e+0	1.8141e+0	1.7808e+0	4.4397e+0	3.0934e+0	**9.2969e−1**
	Std	(3.91e−1)	(3.23e−1)	(2.96e−1)	(8.34e−1)	(4.72e−1)	(3.10e−1)	(9.92e−1)	(4.54e−1)	**6.36e−2**
Best/All		1/15	1/15	0/15	0/15	1/15	2/15	0/15	0/15	**10/15**

Table 2. Experimental results of HV performance indicators of DDMOPSO and 8 comparison algorithms on ZDT and UF series test problems
表 2. DDMOPSO 与 8 个对比算法在 ZDT 和 UF 系列测试问题上 HV 性能指标实验结果

测试问题	R_{HV}	NMPSO	SMPSO	MOPSO	MOPSOCD	NSGAIII	SPEAR	DGEA	IDBEA	DDMOPSO
ZDT1	Mean	6.8954e−1	5.9067e−1	0.0000e+0	7.0861e−1	6.1424e−1	4.9286e−1	6.8676e−3	1.5304e−1	**7.2104e−1**
	Std	(1.84e−2)	(1.16e−1)	(0.00e+0)	(4.78e−2)	(1.46e−2)	(2.97e−2)	(3.25e−2)	(4.77e−2)	**(1.29e−4)**
ZDT2	Mean	**4.3189e−1**	3.8839e−1	0.0000e+0	3.3653e−1	2.4555e−1	7.6257e−2	1.0371e−2	0.0000e+0	4.0994e−1
	Std	**(2.81e−2)**	(1.12e−1)	(0.00e+0)	(1.45e−1)	(4.12e−2)	(5.09e−2)	(3.68e−2)	(0.00e+0)	(1.06e−1)
ZDT3	Mean	5.7086e−1	5.3653e−1	1.4409e−3	5.7592e−1	5.5477e−1	5.0408e−1	3.5795e−2	3.6890e−1	**6.0001e−1**
	Std	(7.71e−3)	(6.35e−2)	(4.27e−3)	(3.88e−2)	(6.43e−3)	(1.49e−2)	(4.59e−2)	(3.60e−2)	**(1.50e−4)**

续表

ZDT4	Mean	0.0000e+0	0.0000e+0	0.0000e+0	0.0000e+0	**1.8148e−3**	6.3769e−4	0.0000e+0	0.0000e+0	1.7568e−1
	Std	(0.00e+0)	(0.00e+0)	(0.00e+0)	(0.00e+0)	**(8.24e−3)**	(3.49e−3)	(0.00e+0)	(0.00e+0)	(1.41e−1)
ZDT6	Mean	3.8976e−1	**3.9006e−1**	0.0000e+0	3.8733e−1	0.0000e+0	0.0000e+0	3.8893e−1	0.0000e+0	3.7529e−1
	Std	(2.24e−4)	**(6.73e−5)**	(0.00e+0)	(6.25e−3)	(0.00e+0)	(0.00e+0)	(6.10e−3)	(0.00e+0)	(2.57e−2)
UF1	Mean	5.3243e−1	2.6448e−1	1.7412e−1	5.3666e−2	**5.3847e−1**	5.2110e−1	7.7362e−2	2.5277e−1	4.6717e−1
	Std	(2.66e−2)	(8.43e−2)	(5.13e−2)	(5.66e−2)	**(3.35e−2)**	(2.94e−2)	(7.73e−2)	(6.99e−2)	(2.44e−2)
UF2	Mean	6.1711e−1	6.0989e−1	6.1211e−1	5.4726e−1	6.2584e−1	6.2715e−1	5.1391e−1	5.0594e−1	**6.2977e−1**
	Std	(6.36e−3)	(1.02e−2)	(5.36e−3)	(2.01e−2)	(4.98e−3)	(7.81e−3)	(2.19e−2)	(2.03e−2)	**(5.63e−3)**
UF3	Mean	2.8961e−1	2.1083e−1	1.7958e−1	2.3295e−1	1.9472e−1	2.2292e−1	1.2369e−1	9.7502e−2	**3.1329e−1**
	Std	(4.24e−2)	(5.14e−2)	(2.74e−2)	(7.06e−2)	(1.04e−2)	(1.63e−2)	(1.87e−2)	(1.62e−2)	**(2.35e−2)**
UF4	Mean	**3.6430e−1**	2.9215e−1	2.1217e−1	3.3521e−1	3.2307e−1	3.2413e−1	2.8092e−1	2.9596e−1	3.5449e−1
	Std	**(8.45e−3)**	(9.91e−3)	(3.29e−3)	(1.17e−2)	(3.30e−3)	(2.91e−3)	(1.09e−2)	(4.09e−3)	(1.22e−2)
UF5	Mean	0.0000e+0	0.0000e+0	0.0000e+0	0.0000e+0	**3.1665e−3**	6.4959e−5	0.0000e+0	0.0000e+0	0.0000e+0
	Std	(0.00e+0)	(0.00e+0)	(0.00e+0)	(0.00e+0)	**(1.32e−2)**	(3.56e−4)	(0.00e+0)	(0.00e+0)	(0.00e+0)
UF6	Mean	1.6352e−2	1.5608e−3	0.0000e+0	0.0000e+0	2.6216e−2	1.2376e−2	0.0000e+0	0.0000e+0	**3.5403e−1**
	Std	(2.28e−2)	(5.69e−3)	(0.00e+0)	(0.00e+0)	(2.60e−2)	(1.61e−2)	(0.00e+0)	(0.00e+0)	**(1.16e−2)**
UF7	Mean	3.5423e−1	1.9480e−1	5.2409e−2	3.4276e−2	3.6110e−1	3.3252e−1	2.0500e−2	1.0227e−1	**3.7266e−1**
	Std	(1.12e−1)	(1.03e−1)	(2.92e−2)	(4.23e−2)	(6.47e−2)	(5.82e−2)	(3.31e−2)	(5.47e−2)	**(2.84e−2)**
UF8	Mean	2.7993e−1	1.7472e−1	2.6929e−1	8.1345e−3	2.4801e−1	1.8413e−1	2.3176e−2	1.7398e−1	**3.2358e−1**
	Std	(6.66e−2)	(3.88e−2)	(3.25e−2)	(1.21e−2)	(4.36e−2)	(2.98e−2)	(2.34e−2)	(4.52e−2)	**(1.11e−2)**
UF9	Mean	3.2353e−1	2.0421e−1	2.6107e−1	3.0577e−2	2.8419e−1	2.5555e−1	6.7747e−2	2.0399e−1	**5.6252e−1**
	Std	(6.60e−2)	(3.68e−2)	(2.33e−2)	(3.38e−2)	(3.24e−2)	(5.13e−2)	(4.60e−2)	(5.10e−2)	**(1.91e−2)**
UF10	Mean	0.0000e+0	0.0000e+0	8.4564e−7	0.0000e+0	0.0000e+0	0.0000e+0	0.0000e+0	0.0000e+0	**9.2150e−2**
	Std	(0.00e+0)	(0.00e+0)	(3.88e−6)	(0.00e+0)	(0.00e+0)	(0.00e+0)	(0.00e+0)	(0.00e+0)	**(5.76e−3)**
Best/All		2/15	1/15	0/15	0/15	3/15	0/15	0/15	4/15	9/15

Table 3. Friedman rank test results of IGD and HV values for the DDMOPSO algorithm and eight comparison algorithms

表 3. DDMOPSO 算法和八个对比算法的 IGD 值和 HV 值的 Friedman 秩检验结果

算法		ZDT1-4,6		UF1-10		Overall			ZDT1-4,6		UF1-10		Overall	
		Friedman test	rank	Friedman test	rank	Friedman test	rank		Friedman test	rank	Friedman test	rank	Friedman test	rank
NMPSO		3.4	2	3.1	3	3.2	2		3.1	2	3.1	2	3.1	2
SMPSO		3.8	3	5.7	5	5.07	5		4.1	4	5.7	5	5.17	5
MOPSO		8.4	9	5.9	6	6.73	7		8.1	9	5.75	6	6.53	7
MOPSOCD		4	4	7.5	8	6.33	6		3.7	3	6.75	7	5.73	6
NSGAIII	**IGD**	4.4	5	3.3	4	3.67	3	**HV**	4.5	5	3.3	3	3.7	3
SPEAR		5	6	3	2	3.67	3		5.7	6	3.9	4	4.5	4
DGEA		6	7	8.1	9	7.4	9		6.5	7	7.65	9	7.27	9
IDBEA		7.8	8	6.6	7	7	8		7.3	8	6.95	8	7.07	8
DDMOPSO		**2.2**	**1**	**1.8**	**1**	**1.93**	**1**		**2**	**1**	**1.9**	**1**	**1.93**	**1**

5. 结论

本文针对电商物流配送路径优化、营销策略精准化等核心业务场景的多目标优化需求，围绕传统多目标粒子群算法在收敛精度与解集多样性平衡方面存在的不足，构建并设计了 DDMOPSO 改进算法。通过 ZDT 与 UF 系列基准测试函数模拟电商实际多目标冲突特征，与八种主流多目标优化算法开展横向对比实验，结果表明：DDMOPSO 算法拥有更优的收敛速度与全局寻优能力，能够有效兼顾收敛性与多样性，可很好解决电商物流配送中成本与配送时效、营销策略中推荐精准度与用户覆盖度相互制约的多目标平衡难题。该算法可为电商领域复杂多目标决策问题提供高效、可行的优化方案与技术支撑，有利于推动电商平台精细化运营、降低物流与营销运营成本、提升用户服务体验，对促进电商经济提质增效具有实际应用价值。

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参考文献

[1] Deb, K., Pratap, A., Agarwal, S. and Meyarivan, T. (2002) A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, **6**, 182-197. https://doi.org/10.1109/4235.996017

[2] Kennedy, J. and Eberhart, R. (2002) Particle Swarm Optimization. *Proceedings of ICNN'95—International Conference on Neural Networks*, Perth, 27 November-1 December 1995, 1942-1948. https://doi.org/10.1109/icnn.1995.488968

[3] Coello Coello, C.A. and Lechuga, M.S. (2002) MOPSO: A Proposal for Multiple Objective Particle Swarm Optimization. *Proceedings of the* 2002 *Congress on Evolutionary Computation*. *CEC*'02 (*Cat*. *No*.02*TH*8600), Honolulu, 12-17 May 2002, 1051-1056. https://doi.org/10.1109/cec.2002.1004388

[4] Coello, C.A.C., Pulido, G.T. and Lechuga, M.S. (2004) Handling Multiple Objectives with Particle Swarm Optimization. *IEEE Transactions on Evolutionary Computation*, **8**, 256-279. https://doi.org/10.1109/tevc.2004.826067

[5] Trivedi, A., Srinivasan, D., Sanyal, K., *et al*. (2007) A Survey of Multiobjective Particle Swarm Optimization Algorithms. *Proceedings of the* 2007 *IEEE Congress on Evolutionary Computation*, Singapore, 25-28 September 2007, 3784-3791.

[6] Zitzler, E., Laumanns, M. and Thiele, L. (2002) SPEA2: Improving the Strength Pareto Evolutionary Algorithm. *Proceedings of the Evolutionary Methods for Design, Optimization and Control with Applications to Industrial Problems*, Athens, 19-21 September 2002, 95-100.

[7] Zhang, X., Liu, Y., Song, Q., Zhang, Y., Yang, J. and Wang, X. (2024) Density-Guided and Adaptive Update Strategy for Multi-Objective Particle Swarm Optimization. *Journal of Computational Design and Engineering*, **11**, 222-258. https://doi.org/10.1093/jcde/qwae081

[8] Zhang, Q.F. and Li, H. (2007) MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition. *IEEE Transactions on Evolutionary Computation*, **11**, 712-731. https://doi.org/10.1109/tevc.2007.892759

[9] Li, H. and Zhang, Q.F. (2009) Multiobjective Optimization Problems with Complicated Pareto Sets, MOEA/D and NSGA-II. *IEEE Transactions on Evolutionary Computation*, **13**, 284-302. https://doi.org/10.1109/tevc.2008.925798

[10] Yao, X., Liu, Y. and Lin, G.M. (1999) Evolutionary Programming Made Faster. *IEEE Transactions on Evolutionary Computation*, **3**, 82-102. https://doi.org/10.1109/4235.771163

[11] Liang, J.J., Qin, A.K., Suganthan, P.N. and Baskar, S. (2006) Comprehensive Learning Particle Swarm Optimizer for Global Optimization of Multimodal Functions. *IEEE Transactions on Evolutionary Computation*, **10**, 281-295. https://doi.org/10.1109/tevc.2005.857610

[12] Gong, Y., Li, J., Zhou, Y., Li, Y., Chung, H.S., Shi, Y., *et al*. (2016) Genetic Learning Particle Swarm Optimization. *IEEE Transactions on Cybernetics*, **46**, 2277-2290. https://doi.org/10.1109/tcyb.2015.2475174

[13] Srinivas, N. and Deb, K. (1994) Muiltiobjective Optimization Using Nondominated Sorting in Genetic Algorithms. *Evolutionary Computation*, **2**, 221-248. https://doi.org/10.1162/evco.1994.2.3.221

[14] Zitzler, E., Deb, K. and Thiele, L. (2000) Comparison of Multiobjective Evolutionary Algorithms: Empirical Results. *Evolutionary Computation*, **8**, 173-195. https://doi.org/10.1162/106365600568202

[15] Zhang, Q., Zhou, A., Zhao, S., *et al*. (2008) Multi Objective Optimization Test Instances for the CEC 2009 Special

Session and Competition. University of Essex, Colchester, UK and Nanyang Technological University, Singapore, Special Session on Performance Assessment of Multi-Objective Optimization Algorithms, Technical Report, 1-30.

[16] Lin, Q., Liu, S., Zhu, Q., Tang, C., Song, R., Chen, J., *et al*. (2018) Particle Swarm Optimization with a Balanceable Fitness Estimation for Many-Objective Optimization Problems. *IEEE Transactions on Evolutionary Computation*, **22**, 32-46. https://doi.org/10.1109/tevc.2016.2631279

[17] Nebro, A.J., Durillo, J.J., Garcia-Nieto, J., Coello Coello, C.A., Luna, F. and Alba, E. (2009) SMPSO: A New PSO-Based Metaheuristic for Multi-Objective Optimization. 2009 *IEEE Symposium on Computational Intelligence in Multi-Criteria Decision-Making* (*MCDM*), Nashville, 30 March-2 April 2009, 66-73. https://doi.org/10.1109/mcdm.2009.4938830

[18] Raquel, C.R. and Naval, P.C. (2005) An Effective Use of Crowding Distance in Multiobjective Particle Swarm Optimization. *Proceedings of the* 7*th Annual Conference on Genetic and Evolutionary Computation*, Washington, 25-29 June 2005, 257-264. https://doi.org/10.1145/1068009.1068047

[19] Deb, K. and Jain, H. (2014) An Evolutionary Many-Objective Optimization Algorithm Using Reference-Point-Based Nondominated Sorting Approach, Part I: Solving Problems with Box Constraints. *IEEE Transactions on Evolutionary Computation*, **18**, 577-601. https://doi.org/10.1109/tevc.2013.2281535

[20] Jiang, S. and Yang, S. (2017) A Strength Pareto Evolutionary Algorithm Based on Reference Direction for Multiobjective and Many-Objective Optimization. *IEEE Transactions on Evolutionary Computation*, **21**, 329-346. https://doi.org/10.1109/tevc.2016.2592479

[21] He, C., Cheng, R. and Yazdani, D. (2022) Adaptive Offspring Generation for Evolutionary Large-Scale Multiobjective Optimization. *IEEE Transactions on Systems*, *Man*, *and Cybernetics*: *Systems*, **52**, 786-798. https://doi.org/10.1109/tsmc.2020.3003926

[22] Asafuddoula, M., Ray, T. and Sarker, R. (2015) A Decomposition-Based Evolutionary Algorithm for Many Objective Optimization. *IEEE Transactions on Evolutionary Computation*, **19**, 445-460. https://doi.org/10.1109/tevc.2014.2339823

[23] Coello, C.A.C. and Cortés, N.C. (2005) Solving Multiobjective Optimization Problems Using an Artificial Immune System. *Genetic Programming and Evolvable Machines*, **6**, 163-190. https://doi.org/10.1007/s10710-005-6164-x

[24] Zitzler, E. and Thiele, L. (1999) Multiobjective Evolutionary Algorithms: A Comparative Case Study and the Strength Pareto Approach. *IEEE Transactions on Evolutionary Computation*, **3**, 257-271. https://doi.org/10.1109/4235.797969

[25] Xia, X.W., Gui, L., Yu, F., Wu, H., Wei, B., Zhang, Y., *et al*. (2020) Triple Archives Particle Swarm Optimization. *IEEE Transactions on Cybernetics*, **50**, 4862-4875. https://doi.org/10.1109/tcyb.2019.2943928