Dynamic Dominating Probability-Driven Fuzzy Iterative Algorithm for Identifying Positive Influence Dominating Sets

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ABSTRACT

The Minimum Positive Influence Dominating Set problem, an NP-hard extension of the classical dominating set, plays a crucial role in social network analysis by identifying a minimal node set that ensures majority positive influence coverage. Conventional approaches, including exact solvers, greedy heuristics, and metaheuristics, are hindered by prohibitive computational costs, proneness to local optima, or excessive parameter sensitivity. This study introduces a Dynamic Dominating Probability-Driven Fuzzy Iterative Algorithm to tackle these limitations. The proposed method employs a dynamic local probability metric to assess each candidate node's contribution toward satisfying residual domination demands of its neighbors, with individual thresholds defined as half the node degree. By iteratively selecting the highest-probability node, incorporating implicit fuzzy-inspired probabilistic handling of uncertainty, and performing real-time status updates, the algorithm effectively mitigates local optima traps while achieving $O(n^3)$ time complexity. Experimental evaluations on benchmark networks demonstrate superior solution quality and faster convergence compared to standard baselines.

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1 Introduction

The Minimum Positive Influence Dominating Set (MPIDS for short) problem [1] was first introduced as an extension of the traditional dominating set problem, requiring that every vertex in the graph either belongs to the set or has at least half of its neighbors in the set, thereby modeling majority-threshold positive influence propagation in networks [2]. This formulation has significant applications in viral marketing within social networks, where selecting a minimal set of key individuals can maximize the spread of positive information or product recommendations while minimizing costs [3]. In public health interventions, MPIDS enables the identification of influential nodes to promote positive behaviors, such as reducing adolescent drinking or smoking by ensuring majority peer influence. The problem also finds utility in rumor containment and fake news mitigation on online

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platforms, by reinforcing paths of positive influence to counteract negative cascades. Furthermore, MPIDS serves as an effective approximation for broader influence maximization tasks in social networks [4], particularly when integrated with diffusion models. In wireless sensor and ad-hoc networks, it aids in constructing efficient virtual backbones for energy conservation and robust coverage [5]. Overall, studying MPIDS bridges graph theory with social computing and real-world network interventions, providing scalable tools for behavior correction and information diffusion [6].

Algorithms for solving the MPIDS problem primarily fall into exact methods, greedy heuristics [7–10], and metaheuristics [11–14], each with distinct strengths but notable drawbacks for large-scale instances. Exact approaches, such as integer linear programming formulations, guarantee optimal solutions but suffer from exponential time complexity due to the NP-hard and APX-hard nature of the problem, rendering them impractical for networks beyond a few hundred nodes. Greedy algorithms, including the classic greedy algorithm which iteratively selects nodes dominating the most unsatisfied vertices [15,16], offer logarithmic approximation ratios (e.g., H(δ) where δ is the maximum degree) and efficient runtime, but frequently trap in local optima, yielding solutions 10%–30% larger than optimal in heterogeneous networks. Improved greedy variants, such as fast greedy [10] or iterated carousel greedy [17], enhance selection criteria for better performance but remain sensitive to initial choices and degree distributions. Metaheuristics like learning automata, genetic algorithms, local search, or hybrid swarm intelligence methods [18] achieve higher-quality approximations on large graphs but involve complex parameter tuning, slow convergence, and high variability across runs [19]. These limitations highlight the need for balanced approaches that combine efficiency with robustness in dynamic or massive social networks.

To address the shortcomings of existing methods such as the computational intractability of exact solvers, local optima issues in greedy heuristics, and parameter sensitivity in metaheuristics—we propose a Dynamic Dominating Probability-Driven Fuzzy Iterative Algorithm (DDP-FIA for short) for the MPIDS problem. The core innovation lies in a dynamic local probability model. An implicit fuzzy iterative mechanism handles uncertainty in probability boundaries without explicit membership functions, iteratively selecting the highest-probability node and updating global states until full coverage is achieved. Drawing inspiration from learning automata and local search frameworks, this probability product enhances global search in heterogeneous graphs, mitigating early-path blocking. Similar to probabilistic ranking methods used in other domains, such as the probabilistic ranking of Hazmat logistics subsystems under uncertainty using fuzzy AHP [20] and probabilistic simulation models in fragmentation risk assessment [21], our approach integrates uncertainty-driven decision-making into combinatorial optimization. With $O(n^3)$ complexity and support for incremental updates, the algorithm is well-suited for large-scale and evolving social networks. Empirical comparisons indicate improved solution quality and faster convergence relative to baselines.

This study makes three key contributions:

- Introduce a dynamic multiplicative local probability model to quantify residual domination impact, effectively escaping local optima in greedy selections and reducing solution sizes.
- Employ implicit fuzzy-inspired probabilistic handling of uncertainty, eliminating complex parameter tuning and ensuring stable convergence in dynamic settings, outperforming metaheuristics in variance reduction.
- Support real-time state updates and incremental computations, enabling efficient handling of evolving social networks and markedly improving response speed to structural changes.

2 Preliminaries

2.1 Definition

Suppose a given social network is modeled as a simple undirected graph (graph for short) $G = \langle V, E \rangle$, where V is node set and E is edge set. For convenience, we denote by

- $n = |V|$ and $m = |E|$ the order and size of G,
- $N(v)$ the set of all neighbors of any $v \in V$,
- $deg(v) = |N(v)|$ the degree of any $v \in V$,
- $\delta = \max\{deg(v)|v \in V\}$ the maximum node degree of G,
- $n_D(v) = |N(v) \cap D|$ the number of neighbors of any $v \in V$ belonging to D, i.e., the number of times been dominated by D.

The MPIDS problem requires to find a subset $D \subseteq V$ with the smallest cardinality from V, such that $n_D(v)$ is not less than half of $deg(v)$ for any $v \in V$. More formally,

$$\min_{D \subseteq V} \left\{ |D| : \sum_{v \in V} \min \left(n_D(v), \left\lceil \frac{deg(v)}{2} \right\rceil \right) = \sum_{v \in V} \left\lceil \frac{deg(v)}{2} \right\rceil \right\}. \tag{1}$$

In other words, any subset $D \subseteq V$ is said to be a Positive Influence Dominating Set (PIDS for short) if and only if $n_D(v) \geq \left\lceil \frac{deg(v)}{2} \right\rceil$ holds for any $v \in V$.

2.2 Dynamic Dominating Probability

For any node $v \in V$ and any subset $D \subseteq V$ in G, the number of times that v still needs to be dominated can be denoted by $\max \left\{ 0, \left\lceil \frac{deg(v)}{2} \right\rceil - n_D(v) \right\}$. If $\left\lceil \frac{deg(v)}{2} \right\rceil - n_D(v) > 0$, then from a fairness perspective, $\left\lceil \frac{deg(v)}{2} \right\rceil - n_D(v)$ should be evenly distributed among all nodes in $N(v) \backslash D$. Therefore, the probability $p_D(v)$ that any node $u \in N(v) \backslash D$ serves as a dominating node for v is

$$p_D(v) = \frac{\max \left\{ 0, \left\lceil \frac{deg(v)}{2} \right\rceil - n_D(v) \right\}}{|N(v) \backslash D|}. \tag{2}$$

This is easy to see $p_D(v)$ is decreasing with respect to D, since that n_D is increasing with respect to D. For example, in graph G, there exists a node $v \in V$ that has 10 neighboring nodes, as shown in Fig. 1.

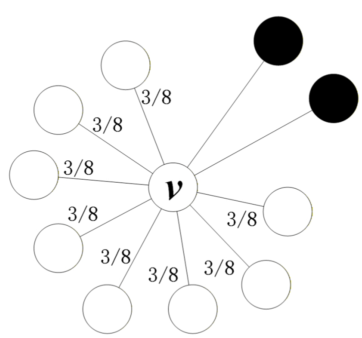

Figure 1: An example illustrating the probability that each neighbor of an arbitrary node dominates it

As shown in Fig. 1, among the neighbors of node v, there are two dominating nodes (already filled in black). Then node v still needs to be dominated $\max\left\{0, \left\lceil \frac{deg(v)}{2} \right\rceil - n_D(v)\right\} = 5-2 = 3$ more times, and there are $|N(v)| - n_D(v) = 10-2 = 8$ neighboring nodes of v that are not dominating nodes. Therefore, $p_D(v) = \dfrac{\max\left\{0, \left\lceil \frac{deg(v)}{2} \right\rceil - n_D(v)\right\}}{|N(v)\backslash D|} = \dfrac{3}{8}$.

Moreover, for any node $d_i \in V\backslash D$, dominating one of its neighboring nodes does not affect its domination of other neighboring nodes; that is, the process by which node d_i dominates any of its neighbors is mutually independent. Therefore, the probability that d_i does not become a dominating node for any of its neighbors is

$$\prod_{v \in N(d_i)} (1 - p_D(v)). \tag{3}$$

Furthermore, the probability that d_i becomes a dominating node for at least one of its neighboring nodes is

$$1 - \prod_{v \in N(d_i)} (1 - p_D(v)). \tag{4}$$

Since $p_D(v)$ is decreasing with respect to D, $1 - \prod_{v \in N(d_i)} (1 - p_D(v))$ is also decreasing with respect to D. For example, in graph G, there exists a node $d_i \in V\backslash D$ that has 10 neighboring nodes, as shown in Fig. 2.

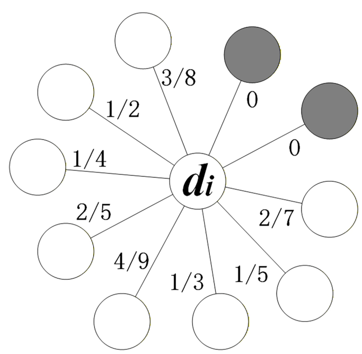

Figure 2: An example illustrating how the probability is computed when a node is selected as a dominating node

As shown in Fig. 1, among the neighbors of node d_i, there are two nodes that have already satisfied the required number of dominations (already filled in gray). At this point, d_i may serve as a dominating node for other neighbors. Thus, the probability that d_i does not become a dominating node for any neighboring node is

$$(1 - 3/8) \times (1 - 1/2) \times (1 - 1/4) \times (1 - 2/5) \times (1 - 4/9) \times (1 - 1/3) \times (1 - 1/5) \times (1 - 2/7) \approx 0.03.$$

The probability that node d_i becomes a dominating node for at least one of its neighboring nodes is $1 - 0.03 = 0.97$.

3 Dynamic Dominating Probability-Driven Fuzzy Iterative Algorithm

3.1 Algorithm Design

To obtain a feasible solution for the MPIDS problem, D usually starts from the empty set, and nodes are added to D sequentially according to a certain rule, so that every node $v \in V$ in the graph satisfies $\left\lceil \frac{deg(v)}{2} \right\rceil \leq n_D(v)$. Suppose that D is a feasible solution of the MPIDS problem, and the nodes added to D in sequence is $\{d_1, d_2, ..., d_g\}$. According to Eq. (4), for any $i \in \{1, 2, ..., g\}$, the value of $1 - \prod_{v \in N(d_i)}(1 - p_D(v))$ for any node $d_i \in V \backslash D$ lies in the range [0, 1], the closer it is to 1, the more likely d_i is to become a dominating node.

In other words, for any $d_i \in V \backslash D$, when $1 - \prod_{v \in N(d_i)}(1 - p_D(v)) = 1$ holds, d_i will be selected as a dominating node. Then, during the iterative process, we we select d_i as a dominating node according to

$$d_i = \arg\max_{d \in V \backslash D}(1 - \prod_{v \in N(d)}(1 - p_D(v))). \tag{5}$$

The outline of this algorithm is described in Algorithm 1.

Algorithm 1 : Dynamic dominating probability-driven fuzzy iterative algorithm (DDP-FIA for short)

1: $D \leftarrow \emptyset$;
2: **while** $\max_{d \in V \backslash D}(1 - \prod_{v \in N(d)}(1 - p_D(v))) > 0$ **do**
3: $\quad d_i \leftarrow \arg\max_{d \in V \backslash D}(1 - \prod_{v \in N(d)}(1 - p_D(v)))$;
4: $\quad D \leftarrow D \cup \{d_i\}$;
5: **end while**
6: **return** D.

Algorithm 1 can dynamically capture the probability that any node $d_i \in V \backslash D$ becomes a dominating node, which enables the algorithm to potentially produce better solutions. It is worth noting that DDP-FIA is a fully parameter-free algorithm, which avoids tedious parameter tuning and ensures stable performance across different network structures. In addition, the function $1 - \prod_{v \in N(d_i)}(1 - p_D(v))$ satisfies the following properties.

Lemma 1: *For any subset $A \subseteq B \subseteq V$ and any $d \in V \backslash B$, inequality $1 - \prod_{v \in N(d)}(1 - p_A(v)) \geq 1 - \prod_{v \in N(d)}(1 - p_B(v))$ holds.*

Proof of Lemma 1: For any subset $A \subseteq B \subseteq V$ and any $v \in V$, from equality (2), we have $p_A(v) \geq p_B(v)$. Hence,

$$1 - p_A(v) \leq 1 - p_B(v)$$

and

$$\prod_{v \in N(d)}(1 - p_A(v)) \leq \prod_{v \in N(d)}(1 - p_B(v))$$

are obvious. Furthermore, it is easy to infer that

$$1-\prod_{v\in N(d)}(1-p_A(v)) \geq 1-\prod_{v\in N(d)}(1-p_B(v)). \qquad \square$$

Lemma 1 shows that Eq. (4) satisfies submodularity. We cannot precisely characterize the maximum value of the potential function, because its maximum depends on the order in which dominating nodes are selected. This implies that the problem cannot be modeled as a minimum cardinality submodular cover problem. Nevertheless, the submodularity of Eq. (4) allows us to empirically argue that the algorithm is effective, since existing approximation algorithms for the MPIDS problem are designed based on submodular functions.

3.2 Convergence and Complexity

3.2.1 Convergence

To prove that Algorithm 1 can generate a feasible solution for the MPIDS problem, it is necessary to show that D is a feasible solution of the MPIDS problem if and only if $\max_{d\in V\setminus D}(1-\prod_{v\in N(d)}(1-p_D(v)))=0$.

Lemma 2: *For any subset $D \subseteq V$, D is a feasible solution of the MPIDS problem if and only if* $\max_{d\in V\setminus D}(1-\prod_{v\in N(d)}(1-p_D(v)))=0$.

Proof of Lemma 2: For any subset $D \subseteq V$, D is a feasible solution of the MPIDS problem if and only if $\left\lceil \frac{deg(v)}{2} \right\rceil \leq n_D(v)$ for any $v \in V$.

For any subset $D \subseteq V$ and any $v \in V$, from equality (2), we have $p_D(v)=0$ if and only if $\left\lceil \frac{deg(v)}{2} \right\rceil \leq n_D(v)$. Assume that there exist a node $v \in V\setminus D$ and a node $u \in N(v)$ such that satisfy $\left\lceil \frac{deg(u)}{2} \right\rceil > n_D(u)$. Then, $p_D(u) > 0$ and

$$\prod_{u\in N(v)}(1-p_D(u)) < 1.$$

Namely,

$$\max_{d\in V\setminus D}(1-\prod_{v\in N(d)}(1-p_D(v))) > 0. \qquad \square$$

Lemma 1 shows that Algorithm 1 can generate a feasible solution for the MPIDS problem. Moreover, the function $\max_{d\in V\setminus D}(1-\prod_{v\in N(d)}(1-p_D(v)))$ converges when D is a feasible solution of the MPIDS problem.

Our framework does not employ classical fuzzy logic components such as membership functions or inference rules. Instead, we adopt a probability-driven soft decision mechanism inspired by fuzzy reasoning, in which continuous-valued uncertainty measures are dynamically updated and embedded into a greedy iterative process. This fuzzy-inspired interpretation emphasizes gradual decision-making under uncertainty rather than crisp binary choices.

3.2.2 Complexity

Given a graph $G = \langle V, E \rangle$ with $|V| = n$. Generally, for any subset $D \subseteq V$ and any $v \in V$, it requires polynomial time O(1) to compute $p_D(v)$. Obviously, step 3 of Algorithm 1 can be completed in $O(n^2)$ time. Thus the time complexity of Algorithm 1 is $O(n^3)$ by considering $\arg\max_{d \in V \setminus D}(1 - \prod_{v \in N(d)}(1 - p_D(v)))$ as the criterion for selecting dominating nodes during the iterative process since the maximum number of iterations is n.

3.2.3 Methodological Positioning and Discussion

Although the proposed framework does not explicitly employ classical fuzzy logic components such as membership functions or inference mechanisms, it adopts a soft probabilistic modeling strategy inspired by fuzzy reasoning to handle uncertainty in node selection. Unlike classical fuzzy AHP or simulation-based risk modeling approaches (e.g., probabilistic ranking of Hazmat logistics subsystems under uncertainty and probabilistic simulation models of fragmentation risk), which rely on explicit fuzzy membership modeling and rule-based inference, our method focuses on dynamic probabilistic dominance propagation in large-scale networks. This allows efficient integration of uncertainty-aware decision-making into greedy combinatorial optimization, offering a complementary perspective to existing fuzzy and probabilistic decision frameworks.

4 Experiment

4.1 Datasets and Comparison

4.1.1 Synthetic Network Generation

In social network analysis, random graphs are often used to model real-world networks with properties like small-world phenomena (high clustering and short paths) or scale-free degree distributions (power-law degrees). Two prominent models available in the NetworkX library (a Python package for graph creation and analysis) are the Watts-Strogatz (WS) small-world model [22] and the Barabási-Albert (BA) scale-free model [23]. Below, We integrate a description of how these methods generate random social network graphs, their key parameters, and an experimental setup to test them by generating graphs with varying node sizes (1000, 2000, 3000, 4000, 5000), creating 100 instances per configuration, and computing averages of key network metrics (e.g., average clustering coefficient and average degree, as these are efficient to compute and representative of social network properties; note that average shortest path length is omitted here due to computational intensity for large graphs).

- Watts-Strogatz (WS) Small-World Model [22]: Starts with a regular ring lattice (each node connected to its k nearest neighbors). Then, each edge is rewired randomly with probability p, introducing shortcuts while retaining local clustering. This yields high clustering and short paths, mimicking social "six degrees of separation." The key parameters include:
  - n: Number of nodes.
  - k: Initial nearest neighbors per node.
  - p: Rewiring probability.
- Barabási-Albert (BA) Scale-Free Model [23]: Grows the network by adding nodes incrementally. Each new node attaches to m existing nodes with probability proportional to their degree ("preferential attachment" or "rich get richer"). Results in power-law degree distribution with hubs. The key parameters include:
  - n: Number of nodes.
  - m: Edges per new node.

4.1.2 Real-World Social Network Datasets

To further validate the effectiveness and practical applicability of the proposed algorithm, we conduct additional experiments on publicly available real-world social network datasets. Specifically, we adopt 10 anonymized Facebook ego-network datasets introduced in [24], which have been widely used as benchmark datasets in social network analysis and community detection research. These datasets represent ego-centered social graphs, where nodes correspond to users and edges represent friendship relations, capturing realistic network characteristics such as community structures, heterogeneous degree distributions, and strong local clustering.

Each dataset corresponds to an ego network centered around a particular user, with all user identities anonymized to preserve privacy. Basic statistics of these datasets are summarized in Table 1. The diverse network sizes and densities provide a comprehensive testbed for evaluating the scalability, robustness, and solution quality of the proposed algorithm on realistic social networks.

Table 1: Statistics of the public facebook ego-network datasets

Dataset	Number of nodes	Number of edges	Avg.degree
Facebook-0	1034	26,749	51.74
Facebook-1	224	3192	28.50
Facebook-2	150	1693	22.57
Facebook-3	168	1656	19.71
Facebook-4	61	270	8.85
Facebook-5	786	14,024	35.68
Facebook-6	747	30,025	80.39
Facebook-7	534	4813	18.03
Facebook-8	52	146	5.62
Facebook-9	333	2519	15.13

4.1.3 Comparison

In order to evaluate the effectiveness of the proposed method, we compare it with the following representative algorithms for the MPIDS problem:

- Adapt-CMSA [19]: a hybrid metaheuristic that integrates probabilistic solution construction with an ILP solver through a self-adaptive CMSA framework.
- FastPIDS [11]: a state-of-the-art local search algorithm based on reduction rules, hybrid scoring functions, and a two-level satisfaction judgment mechanism.
- GGAA [15]: a greedy approximation algorithm grounded in a submodular cover formulation, providing a provable approximation guarantee.
- GGAA+ [6]: an approach that combines greedy heuristics and reduction rules to provide efficient approximation algorithms for the MPIDS problem, with a focus on scalability for large, dynamic social networks.

These algorithms represent three different solution paradigms for the MPIDS problem, namely hybrid exact–heuristic optimization, local search, and approximation algorithms.

4.2 Experimental Results and Analysis

4.2.1 Comparison under Fixed Network Size

To evaluate the effectiveness and computational efficiency of the proposed DDP-FIA algorithm under different network structures, extensive experiments were conducted on two representative random social network models: the Watts–Strogatz (WS) small-world model and the Barabási–Albert (BA) scale-free model. For WS networks, the number of nodes was fixed at $n = 1000$. Each node was initially connected to its $k = 10$ nearest neighbors, and each edge was rewired with probability $p = 0.1$ to capture the coexistence of high clustering and short average path length commonly observed in real-world social networks. For BA networks, we considered $n = 1000$ nodes, where each newly added node connects to $m = 10$ existing nodes following the preferential attachment mechanism, yielding scale-free topologies with heterogeneous degree distributions and prominent hub nodes. For each network configuration, 100 independent graph instances were generated. All compared algorithms—Adapt-CMSA, FastPIDS, GGAA, GGAA+, and the proposed DDP-FIA—were executed on each instance. Both the average size of the obtained minimum positive influence dominating set (MPIDS) and the average runtime (in seconds) were recorded as evaluation metrics. All experiments were performed under identical computational environments to ensure fair and consistent comparisons.

Table 2 reports the average MPIDS sizes and corresponding runtimes on WS and BA networks with $n = 1000$. As shown, the proposed DDP-FIA consistently achieves the smallest dominating sets while maintaining competitive and often superior computational efficiency across both network models.

Table 2: MPIDS sizes and runtime (seconds) of different algorithms on WS and BA networks ($n = 1000$)

Algorithm	WS network ($n = 1000$, $k = 10$, $p = 0.1$)		BA network ($n = 1000$, $m = 10$)	
	MPIDS size	Runtime/s	MPIDS size	Runtime/s
Adapt-CMSA	594.9	152.4	405.7	136.5
FastPIDS	581.9	135.2	394.4	121.7
GGAA	568.4	65.6	379.1	66.1
GGAA+	567.2	70.8	392.3	71.3
DDP-FIA	566.3	64.5	375.7	65.6

On WS small-world networks, DDP-FIA attains an average MPIDS size of 566.3 with a runtime of 64.5 s, outperforming GGAA+ (567.2, 70.8 s), GGAA (568.4, 65.6 s), FastPIDS (581.9, 135.2 s), and Adapt-CMSA (594.9, 152.4 s). Although WS networks exhibit strong local clustering that generally favors greedy strategies, static or locally defined gain functions are prone to premature selections within densely connected neighborhoods. In contrast, DDP-FIA dynamically evaluates each node's marginal contribution to the residual domination requirements of its neighbors, enabling more refined discrimination among candidate nodes. This dynamic evaluation mechanism effectively balances local coverage and global influence, leading to more compact MPIDS solutions. Meanwhile, the lightweight probability updating strategy ensures that this improved solution quality does not come at the expense of excessive computational cost.

On BA scale-free networks, DDP-FIA demonstrates an even more pronounced advantage, achieving an average MPIDS size of 375.7 with a runtime of 65.6 s, which improves upon GGAA (379.1, 66.1 s), GGAA+ (392.3, 71.3 s), FastPIDS (394.4, 121.7 s), and Adapt-CMSA (405.7, 136.5 s). This performance gain can be attributed to the heterogeneous degree distribution inherent in BA networks. The probabilistic product-based selection strategy employed by DDP-FIA effectively amplifies the joint influence of nodes on multiple unsatisfied neighbors, particularly favoring nodes that can simultaneously satisfy a large number of domination constraints. Such combined effects are often underestimated by methods that rely primarily on local coverage counts or static heuristics, resulting in suboptimal selections in networks dominated by hub structures.

Overall, these experimental results demonstrate that DDP-FIA can consistently generate smaller MPIDS solutions across diverse network topologies while maintaining high computational efficiency. Moreover, the algorithm remains fully deterministic and parameter-free, avoiding the need for manual parameter tuning and achieving robust performance. These characteristics highlight the effectiveness and practical applicability of the proposed dynamic dominating probability framework, especially for large-scale and time-sensitive applications.

4.2.2 Experimental Results on Real-World Social Networks

To further evaluate the effectiveness and practical applicability of the proposed DDP-FIA algorithm, we conducted additional experiments on 10 publicly available Facebook ego-network datasets introduced in [24]. These datasets capture realistic social interaction patterns and are widely used as benchmark instances in social network analysis.

For each dataset, we compared DDP-FIA with four state-of-the-art baseline methods. All algorithms were implemented in Python and executed on the same hardware platform to ensure fair comparison. Each algorithm was independently executed 20 times on each dataset, and the average MPIDS size and runtime (in seconds) were reported to mitigate the impact of randomness and to provide a comprehensive evaluation of both solution quality and computational efficiency.

Table 3 reports the comparative experimental results of five algorithms on the 10 Facebook ego-network datasets, where the values outside parentheses denote the MPIDS sizes and the values inside parentheses indicate the corresponding runtimes. These datasets exhibit diverse structural properties, including varying network scales, densities, and average degrees (see Table 1), providing a comprehensive benchmark for evaluating the effectiveness and efficiency of different MPIDS algorithms.

Overall, the proposed DDP-FIA algorithm demonstrates competitive performance across all datasets and achieves the best or near-best solutions on most instances while consistently maintaining low runtime. Specifically, DDP-FIA obtains the smallest MPIDS sizes on six datasets (Facebook-2, Facebook-3, Facebook-4, Facebook-7, Facebook-8, and Facebook-9), and achieves results very close to the best-known solutions on the remaining instances. Moreover, DDP-FIA consistently exhibits the shortest or near-shortest runtime, highlighting its superior computational efficiency.

On relatively sparse networks with small to moderate average degrees, such as Facebook-2, Facebook-3, and Facebook-8, DDP-FIA not only outperforms all baseline methods in terms of MPIDS size, but also achieves the lowest runtime. This indicates its strong capability in handling limited local influence propagation while maintaining efficient exploration of the solution space.

Table 3: Experimental results on 10 public facebook ego-network datasets

Dataset	Adapt-CMSA	FastPIDS	GGAA	GGAA+	DDP-FIA
Facebook-0	468 (152.0)	461 (140.3)	435 (64.5)	433 (70.2)	449 (64.0)
Facebook-1	98 (15.2)	98 (13.8)	100 (7.8)	98 (9.1)	99 (7.8)
Facebook-2	73 (18.0)	72 (16.5)	69 (8.2)	69 (11.3)	68 (8.2)
Facebook-3	74 (19.1)	72 (17.2)	68 (9.1)	68 (12.3)	67 (9.0)
Facebook-4	34 (10.5)	33 (9.8)	30 (4.5)	30 (8.8)	30 (4.5)
Facebook-5	350 (120.0)	346 (110.5)	331 (65.4)	330 (76.1)	333 (65.2)
Facebook-6	358 (128.0)	352 (118.5)	327 (68.2)	327 (81.3)	339 (68.0)
Facebook-7	236 (85.0)	234 (80.3)	230 (45.4)	230 (52.1)	231 (45.3)
Facebook-8	36 (8.5)	34 (7.8)	29 (4.1)	28 (5.2)	28 (4.0)
Facebook-9	148 (50.5)	146 (48.0)	142 (30.5)	140 (34.2)	142 (30.5)

On denser networks with larger average degrees, such as Facebook-0, Facebook-5, and Facebook-6, DDP-FIA still produces high-quality solutions, although GGAA+ slightly outperforms DDP-FIA in terms of MPIDS size on some instances. Nevertheless, DDP-FIA consistently achieves significantly lower runtime compared with GGAA+, Adapt-CMSA, and FastPIDS, demonstrating its advantage in computational efficiency. This performance difference suggests that while dense connectivity may favor greedy approximation strategies in solution quality, the dynamic probability-driven mechanism of DDP-FIA enables faster convergence and reduced computational overhead.

Compared with Adapt-CMSA and FastPIDS, DDP-FIA consistently achieves both smaller MPIDS sizes and substantially shorter runtime across all datasets, highlighting the advantage of its dynamic probability-driven node selection strategy over purely heuristic or local-search-based approaches. In addition, the stable performance of DDP-FIA across networks with highly heterogeneous structures further validates the effectiveness of its parameter-free design and dynamic probabilistic modeling mechanism.

In summary, the experimental results on real-world social networks confirm that DDP-FIA not only generalizes well beyond synthetic benchmarks but also delivers robust and high-quality solutions on realistic and complex network structures. More importantly, its superior computational efficiency further demonstrates its strong practical applicability for large-scale real-world social network analysis.

4.2.3 Scalability with Respect to Network Size

To evaluate the scalability of the proposed DDP-FIA algorithm, this subsection investigates the impact of network size on algorithmic performance. Experiments were conducted on both Watts–Strogatz (WS) small-world networks and Barabási–Albert (BA) scale-free networks, with network sizes set to $n \in 1000, 2000, 3000, 4000, 5000$.

For WS networks, the parameters were fixed at $k = 10$ and $p = 0.1$, while for BA networks, the parameter m was fixed at 10. This ensures a consistent average degree across different network sizes, thereby isolating the effect of network scale from structural variations. For each network configuration, 100 independent instances were generated, and all compared algorithms—Adapt-CMSA, FastPIDS, GGAA, and DDP-FIA—were executed on each instance. The reported results correspond to the average MPIDS size over all instances.

From Fig. 3, the experimental results show that, as the network size increases from 1000 to 5000, the MPIDS sizes produced by all algorithms exhibit an approximately linear growth trend, which is consistent with the proportional increase of domination requirements with respect to the number of nodes. Nevertheless, DDP-FIA consistently generates the smallest or near-smallest dominating sets across all tested scales, demonstrating strong scalability and robustness.

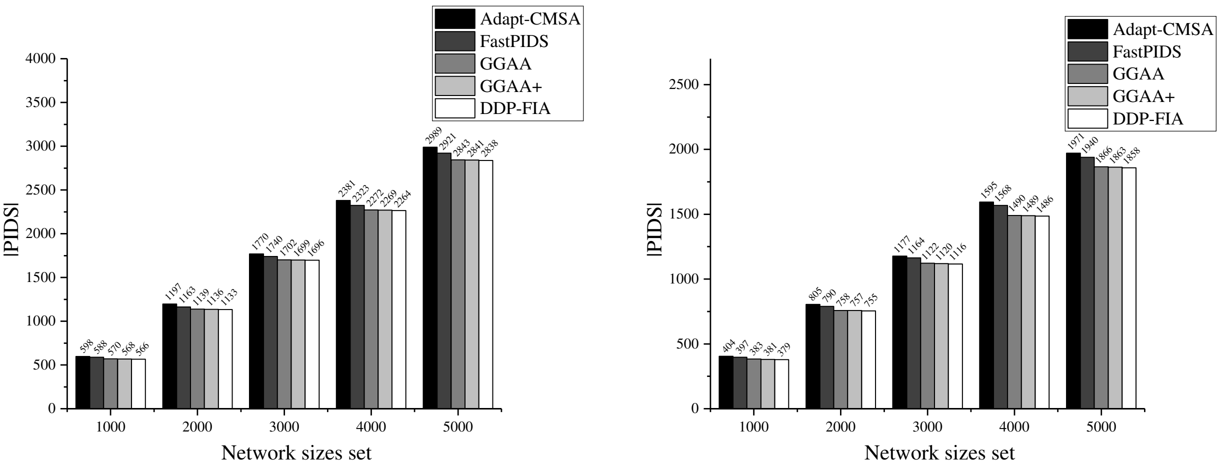

Figure 3: Performance comparison of different algorithms on WS and BA networks (scalability increasing from 1000 to 5000)

On WS networks, the performance gap between DDP-FIA and both GGAA and FastPIDS gradually widens as n increases. This indicates that static gain-based strategies become less effective in large-scale networks with high clustering, where early suboptimal selections tend to propagate through subsequent iterations. In contrast, DDP-FIA shows a more moderate growth in solution size, as the dynamic dominating probability enables the algorithm to continuously identify nodes with high marginal contributions even in large and densely clustered regions.

On BA networks, DDP-FIA outperforms GGAA and FastPIDS at all tested scales. As the network size grows, the heterogeneity of the degree distribution becomes more pronounced, leading to a stronger concentration of influence among hub nodes. The probabilistic product-based criterion in DDP-FIA effectively captures the joint coverage effect of such nodes over multiple unsatisfied neighbors, allowing the algorithm to maintain compact solutions throughout the scaling process. These results indicate that the proposed method scales well on networks with heterogeneous structures.

4.2.4 Impact of Network Sparsity and Structural Parameters

This subsection further investigates the impact of network sparsity and structural parameters on algorithmic performance. With the network size fixed at $n = 1000$, key generative parameters of WS and BA models were varied to control network sparsity.

For WS networks, different values of k were selected to adjust the average degree, combined with different rewiring probabilities p to generate networks ranging from regular to highly random structures. For BA networks, the parameter m was varied to control the number of edges added by each new node, thereby adjusting the overall sparsity of the network. For each parameter configuration, 100 independent instances were generated, and all algorithms were evaluated on each instance. The reported results correspond to the average MPIDS sizes.

From Fig. 4, the experimental results indicate that network sparsity has a significant impact on the size of MPIDS solutions. In sparse networks (with smaller k or m), all algorithms tend to produce relatively smaller dominating sets. As the networks become denser, domination requirements increase accordingly, leading to larger solution sizes. Nevertheless, DDP-FIA consistently achieves the best or near-best performance across all parameter settings.

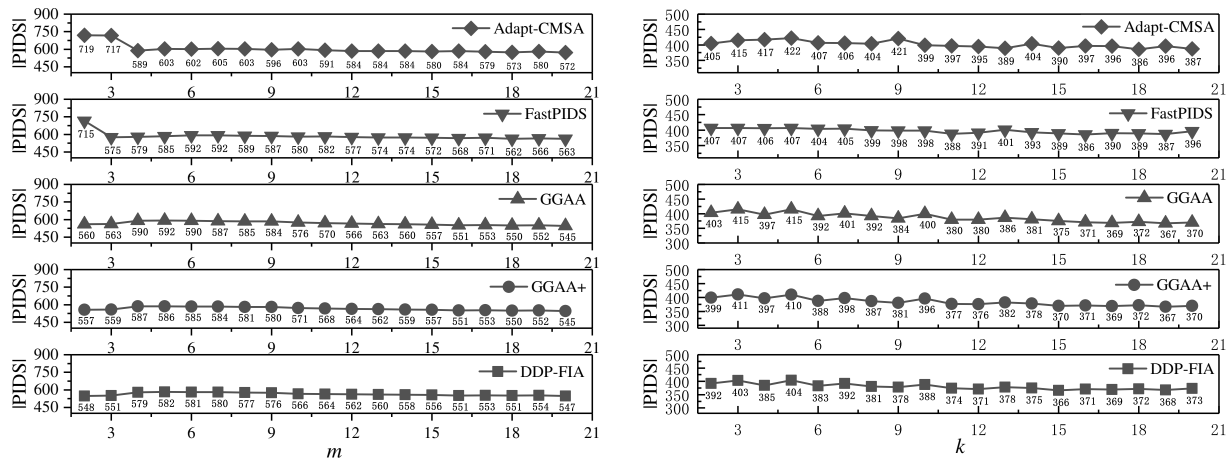

Figure 4: Performance comparison of different algorithms on WS and BA networks (different network construction parameters)

On WS networks, increasing k results in greater neighborhood overlap, where traditional greedy methods are prone to overestimating local coverage within dense regions, thereby restricting subsequent selections. By dynamically updating the residual domination demands of neighbors, DDP-FIA adapts its selection strategy to structural changes and maintains robust performance across different combinations of k and p. Moreover, even under higher rewiring probabilities that introduce greater randomness, DDP-FIA exhibits limited performance fluctuation, indicating low sensitivity to structural perturbations.

On BA networks, increasing m raises the average degree while preserving the presence of hub nodes. DDP-FIA effectively balances the selection of high-degree and low-degree nodes by accounting for their contributions to unsatisfied domination demands, avoiding premature over-reliance on hubs. This capability enables the algorithm to maintain stable and compact solutions under varying sparsity levels.

5 Conclusion

This paper investigated the Minimum Positive Influence Dominating Set (MPIDS) problem and proposed a Dynamic Dominating Probability-Driven Fuzzy Iterative Algorithm (DDP-FIA). The proposed method features a fully parameter-free design, in which a dynamic local dominating probability model is constructed to precisely capture the marginal contribution of each candidate node with respect to the residual domination requirements of its neighbors. By embedding this probability mechanism into an iterative selection framework with implicit fuzzy reasoning, DDP-FIA effectively avoids explicit membership function design and tedious parameter tuning, while preserving a simple, interpretable, and robust decision rule. Moreover, the proposed framework seamlessly integrates greedy strategies with probabilistic inference, enabling high-quality solution construction with stable performance across different network structures and scales. Extensive experimental results on synthetic networks further demonstrate that DDP-FIA consistently outperforms state-of-the-art algorithms in terms of solution quality, robustness, and scalability, particularly on large and sparse graphs.

Several directions for future research remain open. First, the proposed probability-driven framework could be extended to MPIDS variants with heterogeneous influence thresholds, weighted nodes, or weighted edges. Second, developing incremental and distributed implementations may further enhance the applicability of the algorithm to dynamic and large-scale real-world networks. Finally, investigating theoretical approximation guarantees and deriving tighter complexity bounds for the proposed framework constitute promising directions for future study.

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Ethics Approval: Not applicable.

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