

Towards an Improved Particle Swarm Optimization for Feature Selection: A Survey

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Abstract

Over the years, scientists have used natural discoveries such as evolution to solve real-world problems. Addressing the challenges that arise when dealing with high-dimensional data is one such problem. These challenges include difficulties in analyzing, visualizing, and modelling these high-dimensional data. As a result, the Swarm Intelligence (SI) technique was developed, which was inspired by natural swarm foraging behaviors. Particle swarm optimization (PSO) is a well-known SI algorithm for addressing a wide range of optimization problems. As a result, it has been used to solve a variety of optimization problems in fields as diverse as genomic analysis and intrusion detection systems. One of the most successful areas of PSO application is feature selection, which entails using computational techniques to select a reduced subset of features that have a sufficient relationship with their corresponding class labels. This, in turn, addresses the mentioned challenges. Nonetheless, progressive research has revealed several problems with PSO, including problems with diversity, and premature convergence among others. As a result, several improvements and extensions were made to various aspects of the algorithm since its inception to make it efficient. This paper organizes and summarizes current research on improvements to the PSO algorithm for solving the feature selection problem. Consequently, it presents current trends and directions for scholars in the field, as well as open challenges and literature gaps to investigate.

Keywords: *Swarm Intelligence, Particle Swarm Optimization, Feature Selection, Dimensionality Reduction*

1. Introduction

Data pre-processing is unquestionably an important step in any machine-learning task. To gain insights into the massive amounts of data generated, such as in social media, adequate pre-processing is required (Houssein et al., 2021). The majority of these data not only have high dimensions but also have redundant and irrelevant features, which are referred to as noise (Hassan et al., 2023; Isuwa et al., 2022). The presence of these noisy features, combined with the high dimension of the data, deteriorates the performance of machine learning algorithms, resulting in poor performance (Adamu et al., 2021; Isuwa et al., 2022). To address these issues, the dimensionality reduction (DR) technique of data pre-processing is used to remove redundant and irrelevant features, which reduces the dimension and computational cost of learning, among other things (Song, Zhang, Gong, & Gao, 2021).

The wrapper method of feature selection (FS) can be applied either heuristically or using special techniques known as metaheuristics (Karimi-mamaghan et al., 2021). Heuristic methods are problem-specific and include techniques such as sequential forward and sequential backward search (Hu et al., 2023; Karimi-mamaghan et al., 2021). Although these techniques have proven effective in unusual circumstances, they cannot be generalized or guarantee optimality (Almazrue & Alshamlan, 2022; Mohd Ali et al., 2022). This resulted in the development of problem-independent Metaheuristic Algorithms (MAs), which are designed to mimic natural life behaviours. So far, this class of algorithms has been classified into various categories based on their source of inspiration, with the Swarm

Intelligence (SI) paradigm being the most popular (Almazruea & Alshamlan, 2022). The PSO, in particular, has gotten a lot of attention and acceptance as the most promising SI paradigm for dealing with the FS optimization problem and beyond (Sharma et al., 2021; Tadist et al., 2021). It has undoubtedly achieved enormous success in solving a wide range of complex FS problems in diverse fields such as genetics (Agustin, 2021; Tadist et al., 2021), speech-emotions recognition (Manohar & Logashanmugam, 2022), and intrusion detection (Donkol et al., 2023), to name a few.

Despite its widespread recognition and acceptance, the PSO suffers from issues such as poor or insufficient exploitation, a lack of diversity, high computational demands, and premature convergence to suboptimal solutions (Song, Zhang, Gong, & Gao, 2021; Song et al., 2022). The primary concept underlying PSO's operating principle is to maintain an appropriate balance between its exploration and exploitation phases during the search process (Sharma et al., 2021). However, several factors, including insufficient particle initialization, selecting appropriate coefficient values, and regulating particle velocity during the search, among others, may cause the particles to become trapped in a suboptimal solution, resulting in poor performance (Isuwa et al., 2022; Nabi & Ramya Laxmi, 2021). As a result, several researchers in the field have conducted in-depth studies of the algorithm over the years, presenting various improvements, extensions, and variants. Some notable enhancements include parallelizing to reduce computation costs and hybridizing with either the filter counterparts, other MAs, local search methods, or other special methods to compensate for the algorithm's shortcomings (Almazruea & Alshamlan, 2022; Hassan et al., 2023).

This paper, therefore, focuses on organizing and summarizing state-of-the-art research works in the literature that present information on the improvement of the PSO algorithm for solving the FS optimization problem from 2019 to present. Although Table 1 presents recent related survey works on the topic of this study, none of them captured its exact context and period. We have, in fact, rigorously captured the improvement strategy, area of improvement, and specific goal of improvement of each work and created a classification as a result. This, in turn, will provide contemporary scholars in the field with the necessary information on current advancement trends in PSO for FS, open challenges, and potential literature gaps to capitalize on. The following are the main contributions of this work:

- i. Create a classification for a survey of research works that improve the PSO to solve the feature selection problem in various domains.
- ii. Identify research trends in the field, analyse literature findings, and identify potential literature gaps

The rest of this paper is structured as follows: Section 2 provides a brief overview of the theoretical and mathematical concepts of PSO and FS. Section 3 describes the survey method used in this study. This includes the developed classification for the organization and summarization of literary works. Section 4 presents a detailed discussion of our findings, open challenges, and potential gaps in the literature. Section 5 presents the limitations and future works. Finally, section 6 brings the work to a conclusion.

Table 1. Related survey studies on PSO for feature selection

| Reference | Context(s) | Year |
|--------------------------------|---|------|
| (Jeremiah et al., 2022) | PSO with local search methods for FS | 2022 |
| (Karimi-mamaghan et al., 2021) | Machine learning with metaheuristic algorithms for combinatorial optimization | 2021 |
| (Houssein et al., 2021) | PSO Advances: Theory, Analysis, and Application | 2021 |
| (Lalwani et al., 2019) | Parallel PSO: A Survey | 2019 |
| (Nayar et al., 2019) | Swarm Intelligence for FS | 2019 |

2. Preliminaries

The goal of this study is to present a classification for state-of-the-art improvements to the PSO algorithm for optimizing the FS process from 2019 to present. After a rigorous and comprehensive search of related research works on major digital databases including Google Scholar, over 300 scholarly publications were collected. Afterward, a pre-screening was performed, which included removing redundant papers collected from more than one library and papers

not in the period specified. However, considering the keywords and period, only 74 publications were identified as relevant for inclusion in our literature and used for the subsequent study. Fig 1 depicts the number of papers published in each of the years under consideration.

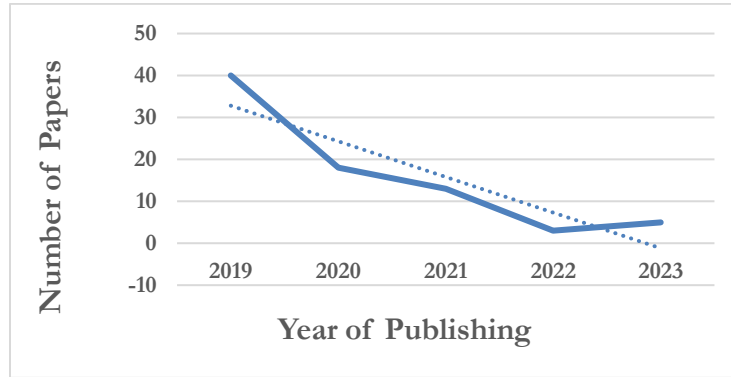


Figure 1. Number of papers published in each of the years under consideration

2.1 Particle Swarm Optimization (PSO)

The optimization process in PSO is iteratively performed by a collection of randomly initialized particles in a search space that reaches the optimum over time through communication and learning. The position of each particle is influenced by its own learning experience as well as the experience of the best particle. The major equations in PSO are the velocity, Eq. (1): responsible for each particle's speed and direction, and the position, Eq. (2): which represents a potential solution to the optimization problem.

$$V_{id}^{k+1} = \Omega V_{id}^k + C_1 r_1^k (pbest_{id}^k - x_{id}^k) + C_2 r_2^k (gbest_d^k - x_{id}^k) \tag{1}$$

$$X_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \tag{2}$$

where $pbest_{id}^k$ and $gbest_d^k$ represents the particle's personal best position in the D-dimension, as well as the swarm's best position in k^{th} generation respectively. " Ω " is the inertia weight. The " C_1 ", " C_2 " and the " r_1 " And " r_2 " are the acceleration constants and random numbers in the range [0,1] respectively.

2.2 Feature Selection (FS)

The FS problem entails choosing the most relevant features from a collection of available features. This collection of features primarily constitutes relevant, irrelevant, and redundant features, and it is expected that features should affect the class label. Mathematically put, Consider a dataset with feature set $F = f_1, f_2, f_3, \dots, F_m$ and class label set $C = c_1, c_2, c_3, \dots, c_k$. Select a feature subset F_s from F with a feature set $F_s = f_{s1}, f_{s2}, f_{s3}, \dots, F_{sn}$, where each feature in F_s correlates with the class label and, $n < m$.

The solution in FS optimization is the output of the optimization problem, and it can take diverse forms i.e., single, multi, or many objectives. In a single-objective problem, only the best solution is returned as the final result; however, in a multi- or many-objective problem, all objectives must be examined simultaneously, so no single solution is regarded as the best (Abdollahzadeh & Gharehchopogh, 2021; Han et al., 2021). Multi-objective or many-objective optimizations, which necessitate the minimization or maximization of multiple conflicting objective functions, are formally represented in Eq. (3) and (4):

$$Z(x_1, x_2, \dots, x_n) = [Z_1(x_1, x_2, \dots, x_n), Z_2(x_1, x_2, \dots, x_n), \dots, Z_P(x_1, x_2, \dots, x_n)] \tag{3}$$

$$X = \{(x_1, \dots, x_n | x_j \in \mathbb{R}; j = 1, 2, \dots, n; \} \tag{4}$$

where n stands for decision variables (X) and p for objectives.

3. Proposed Survey Method

The classification for organizing and summarizing the improvements to PSO for FS is divided into three parts i.e.,

- i. Improvement strategy
- ii. Area of improvement, and
- iii. Aim of improvement

3.1 Improvement Strategy

This subsection is further subdivided into the improvement by *hybridization strategy* and improvement by *other strategies*. The former is again split into hybridization by filter methods, other MAs, and Local Search. Most often, hybridization with filter methods occurs during the initialization stage to help eliminate the noisy features before advancing to PSO, resulting in reduced search complexity, computational cost, and improved diversity i.e., (A. Li et al., 2021; Song, Zhang, Gong, & Gao, 2021; Wang et al., 2020; Zhou et al., 2020). It could also be used to improve PSO's internal searching mechanism, as in Song, Zhang, Gong, & Sun, (2021). PSO is also hybridized with other MAs such as the Grey Wolf Optimization (GWO) and the Crow Search Algorithm (CSA), among others, to compensate for the algorithms' shortcomings in adequate exploitation (Adamu et al., 2021; El-hasnony et al., 2020; El-Kenawy & Eid, 2020). Furthermore, various local search algorithms, such as the one-way and two-way presented by Isuwa et al., (2022), are as well hybridized with the PSO to compensate for the shortcomings of the algorithm. Examples of hybridization with the one-way local search i.e., sequential-one-point-flipping can be seen in Ghosh et al., (2020). Isuwa et al., (2022) and the two-way such as adaptive Local Search and simulated annealing can be seen in Alzaqebah et al., (2021), Mirsadeghi & Khodayifar, (2020).

Concerning improvements by other strategies, any other methods that do not fall under the classes discussed above are classified here. This includes areas such as the acceleration coefficient (Donkol et al., 2023), the use of chaotic maps and opposition-based learning (El-hasnony et al., 2020), update mechanism (Isuwa et al., 2022), use of clustering (Song et al., 2022), use of multi-swarm (Qiu, 2019, 2020), use of fuzzy cost (Hu et al., 2020), inertia weight (Nagra, Han, & Ling, 2019; Pan, 2020; Too, Abdullah, & Saad, 2019a), parallelization (Tadist et al., 2021), and using unaltered PSO with different classifiers (Dulhare, 2019). It should be noted that some works, such as Ghosh et al., (2020) choose to combine two or more of the aforementioned improvement strategies for even better performance.

3.2 Area of Improvement

This subsection is divided into three major areas that received the most attention for improvement. These are the:

- i. Initialization
- ii. Fitness evaluation, and
- iii. Search procedure

Figure 2 depicts how much attention was paid to each of these three areas during the period. This is statistically represented by the number of papers included in our literature that worked to improve each specific area. The search procedure received the most attention, followed by initialization and then fitness evaluation.

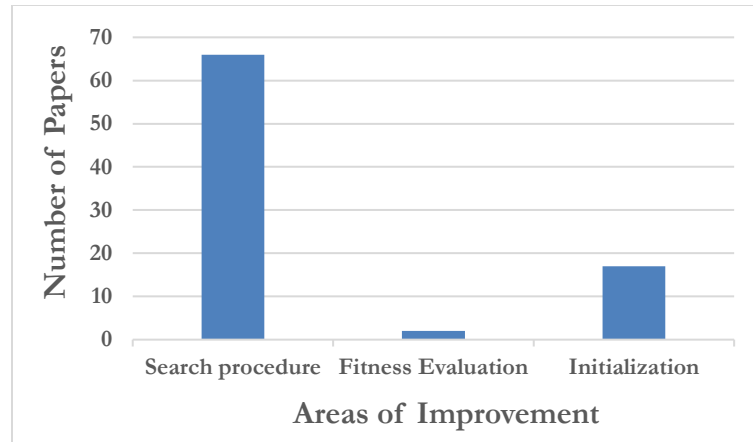


Figure 2. The amount of attention received by each of the three areas of improvement during the period

3.2.1 Initialization

Starting the PSO with bad guesses may prevent it from finding the global optimum (Huda & Banka, 2020). Thus, different approaches have been investigated in improving the classical random initialization strategy in PSO. As discussed in subsection A, these strategies can either be hybridization with filter methods, such as in (Song, Zhang, Gong, & Gao, 2021), or using other strategies i.e., the chaotic maps (Adamu et al., 2021), multi swarm (Qiu, 2019), clustering (Song et al., 2022), and other novel methods such as in (Huda & Banka, 2020).

3.2.2 Fitness Evaluation

A machine learning algorithm is used to test the goodness of selected feature subsets in a wrapper method of FS. However, because of the multiple evaluations over generations, this may incur additional computational costs among others. As a result, research work has been carried out in developing special methods to directly reduce the computational cost as in Moslehi & Haeri, (2019a), or indirectly by selecting a reduced and optimal feature subset as in Nguyen et al., (2018).

3.2.3 Search Procedure

Maintaining a balance between the exploration (global search) and exploitation (local search) search phases of PSO is vital for its success. Failure might lead to premature convergence to a sub-optimal position. PSO has the problem of weak exploitation as reported in several works such as Ghosh et al., (2020), Huda & Banka, (2020), Isuwa et al., (2022). Thus, as discussed in section A and shown in Fig 2, most research works have been to improve the search procedure using either hybridization with other MAs, using specialized local search methods, or developing other novel methods.

Figures 3-5 depict the relationships between the improvement strategies discussed in subsection A and each area of improvement discussed in subsection B, graphically explaining the amount of attention paid to each combination. Where F, MA, LS, and O represent filter, metaheuristic algorithms, local search, and others respectively as the improvement strategies. Whereas FE, I, and SP represent fitness function, initialization, and search procedure respectively as the areas of improvement.

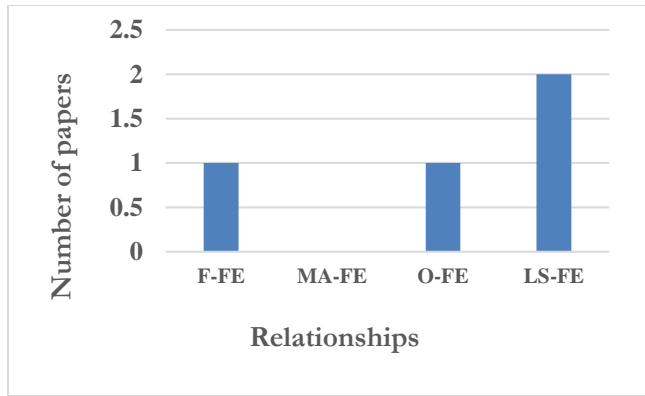


Figure 3. Relationship between Improvement Strategies and Fitness Evaluation

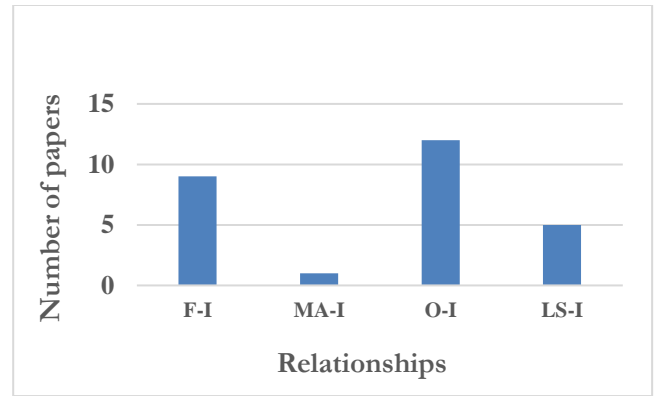


Figure 4. Relationship between Improvement Strategies and Initialization

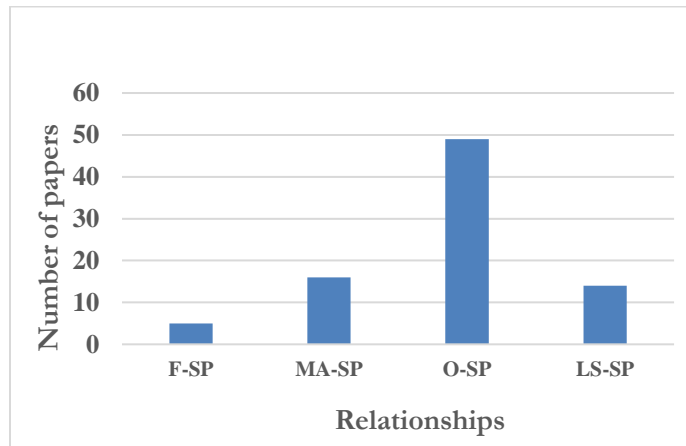


Figure 5. Relationship between Improvement Strategies and Search Procedure

In Figure 3, for example, the use of other strategies for improving fitness evaluation received the most attention, followed by using local search and then the filter methods. Although generally, there have been a limited number of works in improving the fitness evaluation aspect of PSO. Again, note that Figures 3-5 are statistically represented by the number of papers included in our literature that worked on each combination.

3.3 Aim of Improvement

In addition to achieving the FS goal of minimizing features and maximizing accuracy, several authors have focused on more specific objectives that can be considered a subset of the overall goal. As a result, we grouped them into five categories:

- i. Exploration
- ii. Exploitation
- iii. Balance Exploration-Exploitation
- iv. Computational cost, and
- v. Overall Improvement

3.3.1 Exploration

The PSO is expected to conduct a diversified search in previously unexplored areas of the search space to find potential solutions, followed by a more focused search in previously explored areas. However, the success of the operation may be influenced among other things, by the initialization strategy of the search agents. As a result, several

works employing various strategies have been carried out to achieve a diverse search that, in turn, provides an optimal solution(s). An example is using the filter method (Wang et al., 2020), the use of LS methods (Song, Zhang, Gong, & Sun, 2021), and other novel methods (Song et al., 2020; XueYu et al., 2019).

3.3.2 Exploitation

The PSO's ability to perform a more refined search in previously visited areas of the search space has been deemed insufficient. As a result, the algorithm became trapped in a suboptimal position. As a result, various efforts have been made to improve the exploitation or local search capability of PSO. This includes hybridization with LS methods (Ghosh et al., 2020; Isuwa et al., 2022), other MAs with strength in exploitation (Adamu et al., 2021; Mirsadeghi & Khodayifar, 2020), filter methods (Wu et al., 2019), and other methods such as in (Nagra, Han, & Ling, 2019; Qiu, 2019).

3.3.3 Balance Exploration-Exploitation

A successful PSO search for optimality balances the exploration and exploitation phases. This can be accomplished in a variety of ways. i.e., Hybridizing with filter methods (Sahu, 2019), other MAs (Kumar & Kumari, 2019), and a combination of one or more other methods (Nagra, Han, Ling, et al., 2019; Nguyen et al., 2019)

3.3.4 Computational Cost

The PSO search process is complex, especially when a high number of features and instances are involved. This complexity results in a higher computational cost. As a result, different methods have been developed to mitigate this issue. Such as parallelization (Cao et al., 2020) and several other methods such as in (K. Chen et al., 2020; Song et al., 2022; Tadist et al., 2021).

3.3.5 Overall Improvement

This category includes works that used PSO without any modifications and that we chose to include in the scope of this work. Examples include Li et al., (2021), where no improvement in the PSO was recorded. Fig 6 depicts the amount of attention each of the five aims of PSO improvements received during the period. This is also statistically represented by the number of papers included in our literature that worked toward achieving any of the discussed aims of improvement.

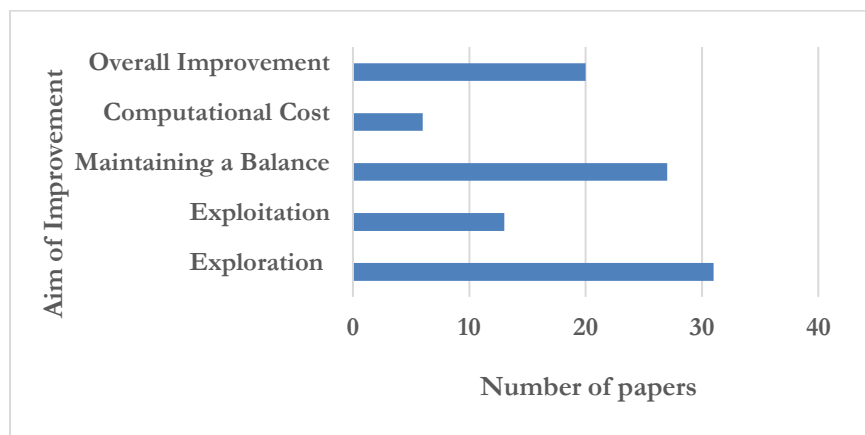


Figure 6. The amount of attention given to each of the five aims of improvement during the period

Improving the exploration phase of PSO received the most attention, followed by maintaining a balance between the two phases. Table 2 presents a summary of the works in our literature based on the classification structure described above. Each instance is explained in terms of the improvement strategy, area of improvement, and the aim(s) of improvement. It should be noted that the scope of this study only covers a detailed categorization of hybridization strategies. Techniques under ‘other’ strategies are grouped altogether.

Table 2. Summary of the works in our literature based on the classification structure discussed

| Reference | Improvement strategy | | | Area(s) of Improvement | | | Aim(s) of Improvement | | | | | |
|----------------------------------|----------------------|-----|----|------------------------|---------------|-------|-----------------------|---------|----------|----------------------|--------|----------------|
| | Hybrid. | | | Others | Fitness Eval. | Init. | Search proce. | Explor. | Exploit. | Bal. Explor-Exploit. | C cost | Overall improv |
| | Fil. | MAs | LS | | | | | | | | | |
| (Sun et al., 2023) | ✓ | | | | | | ✓ | ✓ | | | | |
| (Y. Chen et al., 2023) | | | ✓ | ✓ | | | ✓ | ✓ | ✓ | | | |
| (T. C. Chen et al., 2023) | | | | ✓ | | | ✓ | | ✓ | | | ✓ |
| (Rafiei et al., 2023) | | | ✓ | | | | ✓ | | | | | |
| (Hu et al., 2023) | | | | ✓ | | | ✓ | | | ✓ | | |
| (Song et al., 2022) | | | | ✓ | | | ✓ | | | | ✓ | |
| (Alrefai & Ibrahim, 2022) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Isuwa et al., 2022) | | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | | |
| (Tadist et al., 2021) | | | | ✓ | | | ✓ | | | | ✓ | |
| (Song, Zhang, Gong, & Sun, 2021) | | | ✓ | | | ✓ | | ✓ | ✓ | | | |
| (Han et al., 2021) | | | | ✓ | | | ✓ | ✓ | | | | |
| (Song, Zhang, Gong, & Gao, 2021) | ✓ | | | | | ✓ | | | | | ✓ | |
| (Adamu et al., 2021) | | ✓ | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ | | |
| (A. Li et al., 2021) | ✓ | | | ✓ | | | ✓ | | | | | ✓ |
| (Alzaqebah et al., 2021) | | | ✓ | | | | ✓ | | ✓ | | | |
| (X. Li et al., 2021) | | ✓ | | | | | ✓ | | | | | ✓ |
| (Agustin, 2021) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Kılıç et al., 2021) | | | | ✓ | | ✓ | | ✓ | | | | |
| (Sharma et al., 2021) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Qiu & Liu, 2021) | | | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | | |
| (Nabi & Ramya Laxmi, 2021) | | ✓ | | | | | ✓ | | | ✓ | | |
| (Qi et al., 2020) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Kunhare et al., 2020) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Sundaramurthy & Jayavel, 2020) | | | | ✓ | | | ✓ | | | | | ✓ |
| (K. Chen et al., 2020) | | | | ✓ | | | ✓ | ✓ | | | ✓ | |
| (Huda & Banka, 2020) | | | | ✓ | | ✓ | ✓ | ✓ | | | | |
| (Zhou et al., 2020) | ✓ | | | ✓ | | ✓ | ✓ | ✓ | | | | |
| (Pan, 2020) | | | | ✓ | | | ✓ | | | ✓ | | |
| (Wang et al., 2020) | ✓ | | | | | ✓ | | ✓ | | | | |
| (Hu et al., 2020) | | | | ✓ | | | ✓ | ✓ | | | | |
| (Qiu, 2020) | | | ✓ | ✓ | | | ✓ | ✓ | ✓ | | | |
| (Mirsadeghi & Khodayifar, 2020) | | ✓ | ✓ | | | | ✓ | ✓ | ✓ | | | |
| (Song et al., 2020) | | | | ✓ | | | ✓ | ✓ | | | ✓ | ✓ |
| (El-Kenawy & Eid, 2020) | | ✓ | | | | | ✓ | | | ✓ | | |
| (Ji et al., 2020) | | | | ✓ | | | ✓ | ✓ | | | | |
| (Rahmi et al., 2020) | | | | ✓ | | | ✓ | | | | | ✓ |
| (El-hasnony et al., 2020) | | ✓ | | ✓ | | ✓ | ✓ | ✓ | | ✓ | | |
| (Xue et al., 2020) | | | | ✓ | | | ✓ | | | ✓ | | |
| (Ghosh et al., 2020) | | ✓ | ✓ | | | | ✓ | | ✓ | ✓ | | |
| (XueYu et al., 2019) | | | | ✓ | | | ✓ | ✓ | | | | |
| (Zhang et al., 2019) | | | ✓ | ✓ | ✓ | | ✓ | | ✓ | | ✓ | |
| (Moslehi & Haeri, 2019a) | | ✓ | | | | | ✓ | | | ✓ | | |

| Reference | Improvement strategy | | | | Area(s) of Improvement | | | Aim(s) of Improvement | | | | |
|-------------------------------------|----------------------|-----|----|--------|------------------------|-------|---------------|-----------------------|----------|----------------------|--------|----------------|
| | Hybrid. | | | Others | Fitness Eval. | Init. | Search proce. | Explor. | Exploit. | Bal. Explor-Exploit. | C cost | Overall improv |
| | Fil. | MAs | LS | | | | | | | | | |
| (Too, Abdullah, & Saad, 2019a) | | | | ✓ | | | ✓ | ✓ | | ✓ | | |
| (Too, Abdullah, Saad, et al., 2019) | | | | ✓ | | | ✓ | ✓ | | ✓ | | |
| (Dulhare, 2019) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Xue et al., 2019) | | | | ✓ | | | ✓ | | | ✓ | | |
| (Khourdifi & Bahaj, 2019) | | ✓ | | | | | ✓ | | | ✓ | | |
| (Nguyen et al., 2019) | | | | ✓ | | | ✓ | | | ✓ | | |
| (Al-tashi et al., 2019) | | ✓ | | | | | ✓ | | | ✓ | | |
| (Yan et al., 2019) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Sarkar et al., 2019) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Engelbrecht et al., 2019) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Tawhid & Dsouza, 2019) | | ✓ | | | | | ✓ | | | ✓ | | |
| (Nagra, Han, Ling, et al., 2019) | | | ✓ | ✓ | | | ✓ | | ✓ | ✓ | | |
| (Lee et al., 2019) | ✓ | | | | | | ✓ | | | | | ✓ |
| (Dhrif et al., 2019) | | | ✓ | ✓ | | | ✓ | ✓ | | ✓ | | |
| (Moslehi & Haeri, 2019b) | | ✓ | | | | | ✓ | | | ✓ | | |
| (Narasimhan & Malathi, 2019) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Mahsa et al., 2019) | | ✓ | | | | | ✓ | | | ✓ | | |
| (Yan et al., 2019) | | | | ✓ | | ✓ | ✓ | ✓ | | ✓ | | |
| (Rodrigues et al., 2019) | | ✓ | | | | | ✓ | | | ✓ | | |
| (Too, Abdullah, & Saad, 2019b) | | ✓ | | | | | ✓ | | | ✓ | | |
| (Abdollahi et al., 2019) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Huang et al., 2019) | ✓ | | | ✓ | | ✓ | ✓ | ✓ | | | | |
| (Aldasht, 2019) | ✓ | | | | | ✓ | ✓ | ✓ | | | | |
| (Sahu, 2019) | ✓ | | | ✓ | | ✓ | ✓ | | | ✓ | | |
| (Daneshfar & Kabudian, 2019) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Ansari et al., 2019) | ✓ | | | | | ✓ | | ✓ | | | | |
| (Rustam & Kintandani, 2019) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Wang & Song, 2019) | | | | ✓ | | | ✓ | ✓ | | | | |
| (Nemet et al., 2019) | | | | ✓ | | | ✓ | | | | | ✓ |
| (Nagra, Han, & Ling, 2019) | | | ✓ | ✓ | | | ✓ | | ✓ | ✓ | | |
| (Hafiz et al., 2019) | | | ✓ | | | | ✓ | ✓ | | | | |
| (Wei et al., 2019) | | | | ✓ | | | ✓ | ✓ | | ✓ | | |
| (Wu et al., 2019) | ✓ | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| (Qiu, 2019) | | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | | |
| (K. Chen et al., 2019) | | | ✓ | ✓ | | | ✓ | ✓ | ✓ | | | |
| (Kumar & Kumari, 2019) | | ✓ | | | | | ✓ | | | ✓ | | |
| (Xiong et al., 2019) | | | | ✓ | | ✓ | | ✓ | | | | |

Abbreviations: Filter (Fil.), Metaheuristic Algorithms (MAs), Local Search (LS), Fitness Evaluation (Fitness Eval.), Initialization (Init.), Search Procedure (Search Proce.), Exploration (Explor.), Exploitation (Exploit.), Balance Exploration-Exploitation (Bal Explor-Exploit.), Computational Cost (C cost), Overall Improvement (Overall improve.)

4. Discussions of Literary Findings and Open Challenges

From Fig. 1, it is depicted that research on the topic was at a peak in 2019 and declined significantly afterward. The rapid decline could be attributed to less attention being paid to the field of FS in recent years, or to other MAs being investigated for the purpose. In future work, we expect to conduct a thorough general investigation into the trending MAs used in addressing the FS problem. Nonetheless, the PSO's potential cannot be exhausted. As a result, the FS research community should investigate this further, developing new methods and strategies or improving existing ones. In terms of improvement strategies, it was discovered that employing other strategies was more profound than performing hybridization. Other strategies, such as improving the inertia weight and using multi-swarm to balance the exploration-exploitation phases, received more attention. Although others such as improving update mechanisms have been thoroughly researched, the scope of this paper did not explicitly cover and explain this. In our future work, we hope to provide an explicit investigation into other strategies.

Furthermore, it was discovered that most of the research work that performed a hybridization of the filter methods was to improve on the PSO initialization strategy. This is done to increase diversity, decrease search complexity, and lower computational costs. Our findings also revealed that one-way local search methods have received more attention for improving PSO exploitation capability than two-way local search methods. This is majorly due to the ability of one-way local search methods to perform a more refined search without incurring additional costs. More effort should be made in the future to investigate the effect of two-way LS methods, such as low-cost variants of the hill climbing algorithm, on improving the exploitation ability of PSO, as they have been reported in related fields to provide promising performance.

Among areas of improvement investigated, the search procedure received the most attention, followed by initialization. This is possible because an appropriate balance between the two search phases of PSO is strongly associated with its success. As a result, improving the search procedure is always critical. The initialization strategy, which is responsible for the diversity of search agents and thus reduces the possibility of premature convergence, was also thoroughly researched. The fitness function, which assesses the goodness of selected feature subsets, has received the least attention. The fact that a learning algorithm must be invoked at each generation of the search process, incurring significant computational cost is reason enough for the research community to invest more effort in developing cheap and effective fitness evaluation methods. Concerning hybridization, the use of MAs to improve the search procedure received the most attention, followed by the use of local search methods. The weakness of PSO is compensated for by the strength of the corresponding MA or local search methods. However, the use of other strategies is more profound and applied for this purpose in general, though the specific methods were not identified because it is not within the scope of this work.

The sole purpose of altering the PSO is to improve overall performance. However, to achieve overall improvement, specific areas of the algorithm must be improved. As shown in Fig 6, the most investigated topic was improving the exploration phase of PSO to reduce the risk of premature convergence to the sub-optimal position, followed by maintaining a balance between the two phases. This is because when the risk of premature convergence to sub-optimality is avoided, the possibility of achieving the desired optimum result becomes feasible. Although overall improvement follows on the chart, it is not taken into account. This is because we do not logically consider it an aim, but rather a category to accommodate works that used PSO without modification(s). Even though weak exploitation has been identified as an important area for PSO improvement over the years, it has received insufficient attention. This raises an open research question for us in the future. Furthermore, despite the computational cost of PSO as a result of the complexity of the search procedure, it nevertheless received the least attention. Perhaps, if an efficient and low-cost evaluation measure for selected features is developed as an alternative to the most common parallelization, the problem of computation cost in FS will be addressed to a great extent.

5. Limitations and Future Works

One of the major limitations of this work that we would like to investigate further is the lack of detailed and explicit explanation of 'other' improvement strategies. This is because there are numerous existing and novel PSO improvement strategies other than hybridization that may necessitate specialized in-depth study to enable the creation of a classification structure. Another limitation is the lack of a thorough examination of the number of objectives used in each of the works in the literature. Although the use of PSO for feature selection has traditionally been limited to a single objective in which only the best solution is returned as the final result, the use of multi-or many objectives PSO where no single solution is regarded as the best has recently been on the rise and necessitates extensive research.

Finally, in the future, we plan to investigate the specific machine-learning algorithms used in each paper, as well as the specific application area. This is because machine learning algorithms have a significant impact on the overall performance of MAs. Furthermore, the performance of optimization algorithms may be affected by the domain or area of application in question, i.e., the nature of the datasets. As a result, we will investigate the nature of the datasets used in each study in relation to the algorithm's performance. Other aspects to consider may include investigating the most notable filter methods combined with PSO for feature selection.

6. Conclusion

In this survey work, we developed a classification for organizing and summarizing recent works in the literature that present information on the improvement of the PSO algorithm for solving the FS optimization problem from 2019 to present. This classification includes the improvement strategy, area of improvement, and aim of improvement, with each having appropriate sub-classes. Some of our many findings reveal that employing other improvement strategies in PSO such as enhancing the inertia weight and update strategies among others was more profound than performing hybridization with either filter methods, other metaheuristic algorithms, or local search methods. Furthermore, combining PSO with filter methods at the initialization stage was tremendously investigated because of its major role in improving diversity, and reducing computational cost among other things. Other important findings were discussed, highlighting potential future research directions and open research questions.

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