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BF-PSO: a review of the hybrid bacterial foraging and particle swarm optimization algorithm, its mechanisms, applications, and research challenges

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ABSTRACT

Bacterial foraging–particle swarm optimization (BF-PSO) is a hybrid metaheuristic that combines the social learning and rapid directional updates of PSO with the chemotactic exploration and population-renewal mechanisms of bacterial foraging optimization (BFO). The hybrid is intended to address weaknesses that can arise when either method is used independently, including premature convergence in PSO and slow, weakly guided search in conventional BFO. This review examines the conceptual foundations, principal hybrid architectures, parameter interactions, objective-function design, and engineering applications of BF-PSO reported up to 2022. Particular attention is given to controller tuning, motor-drive regulation, power-system stability, economic dispatch, process control, and classification tasks. The literature shows that the term BF-PSO does not describe one universally standardized implementation: some studies use PSO information to guide bacterial chemotaxis, whereas others inject particle velocity into several bacterial life-cycle stages. Reported improvements are therefore application- and configuration-dependent rather than proof of universal superiority. The review identifies key requirements for reliable evaluation, including fair baseline comparisons, repeated stochastic trials, computational-cost reporting, constraint handling, and reproducible parameter settings. Future work should emphasize adaptive hybridization, multi-objective search, and real-time validation.

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1. INTRODUCTION

Optimization problems in engineering frequently involve nonlinear objective functions, interacting variables, constraints, and complex search landscapes. Conventional deterministic methods can become difficult to apply when the objective function is discontinuous, non-differentiable, or characterized by multiple local optima. Metaheuristic algorithms provide an alternative by exploring candidate solutions through population-based search strategies. Among these approaches, particle swarm optimization (PSO) and bacterial foraging optimization (BFO) have attracted attention because they use different mechanisms to balance exploration and exploitation [1]–[5].

PSO models collective movement and information sharing among particles, allowing candidate solutions to learn from individual and population experience. Its relatively simple structure and ability to search continuous parameter spaces have supported applications in controller design, engineering optimization, and computational intelligence [1], [5], [6]. However, PSO may lose population diversity and converge prematurely when particles become concentrated around a suboptimal region. This limitation has encouraged the development of hybrid methods that introduce additional search mechanisms to maintain diversity and improve local refinement [5], [6].

BFO is inspired by bacterial foraging behavior, particularly the movement and survival strategies of microorganisms searching for favorable environments. Its principal mechanisms include chemotaxis,

swarming, reproduction, and elimination-dispersal, which collectively support local exploration and population renewal [2], [3]. Nevertheless, conventional BFO may require many objective-function evaluations and can exhibit slow convergence because its search directions are not always guided by accumulated population knowledge. Combining BFO with PSO is therefore attractive because the two algorithms offer complementary search characteristics [3], [4], [7].

The hybrid approach is commonly called BF-PSO, BFO-PSO, or bacterial swarm optimization (BSO), depending on the authors and implementation. These names do not necessarily identify an identical algorithm because researchers integrate particle information into different stages of bacterial search. For example, some methods use PSO-based directional information during bacterial chemotaxis, while others incorporate particle velocity into chemotaxis, swarming, or reproduction [7]–[12]. This review examines these variations, evaluates their reported applications, and identifies methodological issues that must be addressed before performance claims can be generalized.

2. FUNDAMENTAL PRINCIPLES OF PSO AND BFO

PSO is a population-based optimization method in which each particle represents a candidate solution in the search space. Each particle updates its movement using information about its own best-known solution and the best-known solution identified by the population. This interaction encourages particles to explore promising regions while retaining information from previous search experiences. The method is computationally straightforward, although its behavior depends on parameters such as inertia weight, acceleration coefficients, population size, and velocity limits [1], [5], [6], [13].

BFO follows a different search philosophy based on the foraging behavior of bacteria. During chemotaxis, a bacterium alternates between tumbling and swimming to explore its surrounding search region. Swarming represents collective behavior in which bacterial individuals influence one another, while reproduction allows healthier individuals to contribute to subsequent populations. Elimination and dispersal introduce additional diversity by relocating selected bacteria, potentially helping the algorithm escape unproductive search regions [2], [3], [4].

The main difference between the two methods concerns how candidate solutions obtain and use search information. PSO explicitly shares individual and global best positions, which can accelerate movement toward promising solutions. BFO emphasizes repeated local exploration and population renewal, which can help preserve search diversity but may increase computational effort. Their combination is intended to use PSO information to guide bacterial movement while retaining bacterial mechanisms for local exploration and diversification [7]–[12].

3. BF-PSO HYBRIDIZATION MECHANISMS

BF-PSO integrates the two algorithms by allowing particle-based information to influence bacterial search. A common strategy is to use personal-best and global-best information to orient bacterial chemotaxis rather than relying entirely on random tumbling directions. This modification provides bacteria with a more informed search direction while preserving the possibility of local exploration. Korani *et al.* [7] applied this principle to PID controller tuning, illustrating the use of bacterial foraging guided by PSO information in a control-engineering problem.

A second strategy introduces particle velocity into bacterial movement and population operations. In this architecture, the directional information obtained from PSO can influence chemotaxis, swarming, or reproduction, depending on the selected design. Jayabarathi *et al*. [10] proposed a hybrid BFA-PSO approach for economic dispatch by incorporating PSO-based biased velocity into bacterial operations. Their study illustrates how particle information can reduce the randomness of bacterial movement and improve the search process for a nonlinear optimization problem.

A third strategy uses PSO to improve selected stages of an enhanced BFO algorithm. Ye *et al*. [14] incorporated PSO into bacterial chemotaxis and also modified reproduction and elimination-dispersal mechanisms for imbalanced-data classification. Their approach demonstrates that hybridization can extend beyond simply combining two movement equations, since population diversity and selection procedures can also be redesigned. These variations indicate that BF-PSO should be understood as a design framework with multiple possible architectures rather than as a single fixed computational procedure.

The general hybrid workflow begins by initializing a population of candidate solutions and evaluating their objective-function values. PSO information is then used to guide bacterial movement, after which bacterial operations update candidate solutions and population diversity. The resulting solutions are evaluated again, and the best candidates are retained until a stopping condition is reached. The exact sequence and frequency of these operations depend on the particular BF-PSO implementation and should therefore be reported explicitly in research publications.

4. APPLICATIONS OF BF-PSO AND RELATED HYBRID METHODS

Controller tuning is one of the important application areas for BF-PSO because controller performance often depends on several interacting parameters. Korani *et al*. [7] investigated BF-PSO for PID tuning, while Cheng *et al*. [8] applied a bacteria-particle swarm hybrid to a double-loop speed-control system. Rezgui *et al*. [9] subsequently applied a hybrid algorithm explicitly named BF-PSO to determine PI controller parameters for the speed loop of an induction motor using direct torque control. Their study used MATLAB/Simulink simulations and reported improved control performance compared with conventional calculated PI parameters.

Power-system applications provide another example of the hybrid algorithm's potential. Abd-Elazim and Ali developed a bacterial-swarm approach combining PSO and BFO to optimize a static var compensator damping controller in a multimachine power system. Their work considered power-system oscillation damping and evaluated controller performance under different operating conditions [11]. Abdelkarim *et al*. [12] also used a BFOA-PSO hybrid for decoupling and robust control of a coupled distillation-column process, illustrating its relevance to multivariable process optimization.

BF-PSO-related methods have also been investigated in economic dispatch and classification. Jayabarathi *et al*. [10] used a hybrid BFA-PSO strategy to solve economic dispatch problems involving valve-point effects, while Ye et al. [14] integrated PSO into improved BFO for classifying imbalanced datasets. Kora and Kalva [15] applied hybrid bacterial foraging and PSO to the detection of bundle branch block using electrocardiogram features. These studies demonstrate the flexibility of hybrid search, although their different objective functions and application domains prevent direct comparison of numerical performance.

Table 1 summarizes representative BF-PSO and related hybrid studies published no later than 2022. The table distinguishes studies that explicitly identify their approach as BF-PSO or BFOA-PSO from studies that use closely related bacterial-swarm hybridization. This distinction is important because not every BFO-PSO variant uses the same movement update or population-management strategy. The comparison also shows that applications range from controller tuning to energy systems, process control, and data classification.

Table 1. Representative BF-PSO and related bacterial-foraging–PSO hybrid applications

Study	Hybrid approach or designation	Application	Main research emphasis
Korani *et al*. [7]	Bacterial foraging oriented by PSO	PID tuning	PSO-guided bacterial search
Cheng *et al*. [8]	BF-PSO	Double-loop speed control	PID parameter optimization
Rezgui *et al*. [9]	BF-PSO	Induction motor DTC	PI speed-loop tuning
Jayabarathi *et al*. [10]	BFA-PSO	Economic dispatch	Nonlinear cost optimization
Abd-Elazim and Ali [11]	BSO	Power-system stability	SVC damping-controller design
Abdelkarim *et al*. [12]	BFOA-PSO / BSO	Distillation-column process	Decoupling and robust control
Ye *et al*. [14]	PSO-enhanced BFO	Imbalanced-data classification	Search and population improvement
Kora and Kalva [15]	BFPSO	ECG classification	Bundle branch block detection
Ibrahim *et al*. [16]	PSO and BF comparison	BLDC motor control	PID speed-control optimization

The studies in Table 1 indicate that BF-PSO-related algorithms have been explored in several engineering and computational domains. The motor-control studies are particularly relevant because they demonstrate the use of hybrid optimization to tune PI or PID parameters for dynamic systems [7]–[9], [15]. Power-system and process-control studies extend the approach to problems involving multiple variables and operating constraints [11], [12]. However, the reported results should not be interpreted as a universal ranking because the studies use different models, objective functions, algorithm configurations, and evaluation conditions.

5. PERFORMANCE ASSESSMENT AND ALGORITHMIC LIMITATIONS

The performance of BF-PSO depends strongly on how its objective function is formulated. Engineering studies commonly evaluate candidate solutions using measures such as tracking error, convergence quality, operating cost, stability, or classification accuracy. A single objective may be sufficient for a narrowly defined problem, but many practical applications require simultaneous consideration of several competing criteria. Multi-objective BFO research provides useful background for developing hybrid methods that preserve solution diversity while considering multiple performance requirements [17]–[19].

A major challenge is balancing exploration and exploitation during the search process. Excessive PSO influence can cause bacteria to follow the same promising region and reduce population diversity.

Conversely, excessive random bacterial movement can weaken directional guidance and increase the number of iterations required to obtain a satisfactory solution. Adaptive velocity limits, chemotactic step sizes, and population-diversity mechanisms are therefore important design considerations [4], [20], [21].

Computational cost is another important limitation because hybrid algorithms generally require additional operations compared with their individual components. Each iteration may involve particle updates, bacterial movement, objective-function evaluations, and population-management operations. This additional work can become significant when the objective function requires detailed simulations or when the search space contains many variables. Researchers should therefore report computational time and objective-function evaluation counts alongside solution quality [4], [5], [15].

A further concern is the reproducibility of stochastic optimization results. Different initial populations and random-number sequences may produce different final solutions, even when the algorithm settings remain unchanged. A single successful run is therefore insufficient to demonstrate consistent superiority over standard PSO or BFO. Repeated trials, statistical summaries, common benchmark problems, and transparent parameter settings are necessary for meaningful comparisons [5], [6], [15].

6. RESEARCH GAPS AND FUTURE DIRECTIONS

Although BF-PSO has been applied to several engineering problems, the literature still lacks a universally accepted hybrid architecture and standardized evaluation framework. Researchers use different names, update sequences, population structures, and parameter settings, which complicates comparisons across publications. A more systematic description should identify precisely where particle swarm optimization is integrated into bacterial search and which bacterial operations remain unchanged. Such reporting would make it easier to reproduce the algorithms and determine which hybridization mechanisms provide measurable benefits [4], [7]–[12], [14].

Future research should investigate adaptive hybridization in which the influence of PSO and bacterial foraging changes according to population diversity and search progress. This strategy could reduce unnecessary particle guidance when local exploration is already effective and strengthen bacterial diversification when premature convergence is detected. Multi-objective BF-PSO is also a promising direction for applications that require simultaneous optimization of response time, stability, energy consumption, or operating cost. The development of benchmark suites and standardized experimental protocols would further improve the reliability of published comparisons [5], [17], [18].

Real-time implementation represents an additional research opportunity, particularly for motor drives and industrial control systems. An algorithm that performs well in offline simulation may not be suitable for online tuning if its computational requirements exceed the available processing capacity. Future studies should evaluate implementation on embedded controllers and industrial processors while considering sampling time, measurement noise, actuator constraints, and parameter uncertainty. These investigations would help establish whether BF-PSO can provide practical benefits beyond numerical optimization.

7. CONCLUSION

BF-PSO combines the information-sharing mechanism of PSO with the chemotactic exploration and population-renewal characteristics of BFO. The hybrid is intended to improve search direction, maintain population diversity, and reduce weaknesses associated with using either method independently. Research published through 2022 demonstrates its use in PID tuning, motor-drive control, power-system stability, economic dispatch, process control, and classification. However, the term BF-PSO covers several algorithmic configurations, and their performance cannot be assumed to be equivalent. The effectiveness of a BF-PSO implementation depends on its hybridization architecture, parameter settings, objective function, and application constraints. Reliable evaluation therefore requires comparisons with standard PSO and BFO under consistent experimental conditions, together with repeated stochastic trials and computational-cost reporting. Adaptive search coordination, multi-objective optimization, and real-time implementation are important directions for further investigation. With clearer algorithm descriptions and more reproducible benchmarking, BF-PSO can be assessed more rigorously as a practical hybrid optimization method.

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