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Review Article

Application of bio-inspired optimization algorithms in food processing

Tanmay Sarkar [a,**], Molla Salauddin [b], Alok Mukherjee [c], Mohammad Ali Shariati [d], Maksim Rebezov [d,e,f], Lyudmila Tretyak [g], Mirian Pateiro [h,*], José M. Lorenzo [h,i]

[a] Department of Food Processing Technology, Malda Polytechnic, West Bengal State Council of Technical Education, Malda, 732102, West Bengal, India
[b] Department of Food Processing Technology, Mir Madan Mohanlal Govt. Polytechnic, West Bengal State Council of Technical Education, Nadia 741156, West Bengal, India
[c] Government College of Engineering and Ceramic Technology, Kolkata, India
[d] Department of Scientific Research, K.G. Razumovsky Moscow State University of Technologies and Management (The First Cossack University), 109004, Moscow, Russian Federation
[e] Biophotonics Center, Prokhorov General Physics Institute of the Russian Academy of Science, 119991, Moscow, Russian Federation
[f] Department of Scientific Research, V. M. Gorbatov Federal Research Center for Food Systems, 109316, Moscow, Russian Federation
[g] Department of Metrology, Standardization and Certification, Orenburg State University, 460018, Orenburg, Russian Federation
[h] Centro Tecnológico de La Carne de Galicia, Rúa Galicia Nº 4, Parque Tecnológico de Galicia, San Cibrao das Viñas, 32900, Ourense, Spain
[i] Universidade de Vigo, Área de Tecnoloxía dos Alimentos, Facultade de Ciencias, 32004 Ourense, Spain

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ABSTRACT

Bio-inspired optimization techniques (BOT) are part of intelligent computing techniques. There are several BOTs available and many new BOTs are evolving in this era of industrial revolution 4.0. Genetic algorithm, particle swarm optimization, artificial bee colony, and grey wolf optimization are the techniques explored by researchers in the field of food processing technology. Although, there are other potential methods that may efficiently solve the optimum related problem in food industries. In this review, the mathematical background of the techniques, their application and the potential microbial-based optimization methods with higher precision has been surveyed for a complete and comprehensive understanding of BOTs along with their mechanism of functioning. These techniques can simulate the process efficiently and able to find the near-to-optimal value expeditiously.

1. Introduction

In recent times, a remarkable innovation has been seen in the field of computational science and technology specifically in the field of application of computer-aided technology development in process design segment both in industrial and laboratory scale (Corradini, 2020; Peleg et al., 2007; Peña-Delgado et al., 2020). Ease of processing with cost optimization, maximum productivity and optimum quality – these are the major area of concern in today's industry arena (Lahiri et al., 2021; Lahiri et al., 2021a; Sarkar et al., 2021). To cope up with all these major concerns, the maximum focus has been given to the product development part where process optimization is the prime factor.

Conventionally process has been optimized by using different statistical techniques like response surface methodology, which is widely used in both industry and laboratory. But in the case of the too high volume of complex process parameters, difficulty arises in using such a conventional optimization method. In the last decade after the popularization of computer technology for different purposes both in industrial and lab process operation, based on artificial intelligence and machine learning several new optimization techniques are coming out as a need of time and within a very short span of time, these computer-based optimization techniques have become very popular for their excellent performance in process optimization.

All induction algorithms execute identically across a symmetrical allocation of inductive problems (learning or search problems), according to the No Free Lunch (NFL) theorems (Wolpert and Macready, 1997). In other words, all quasi optimization strategies work similarly and/or substantially when applied to all optimization tasks (McDermott, 2020). Therefore from the NFL, it is obvious that no such OA is there that can perform well for all types of problems, this is the reason for development of new metaheuristic algorithms. By the virtue of the NFL, not only the explicit dynamics of an optimization algorithm (OA) can be

* Corresponding author.
** Corresponding author.
E-mail addresses: tanmays468@gmail.com (T. Sarkar), mirianpateiro@ceteca.net (M. Pateiro).

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understood, the way these dynamics are related to the OA can also be traced (Joyce and Herrmann, 2018).

Like other industries, the food industry also replaced the conventional optimization techniques with newly developed different computer technology-based optimization techniques. Among the different computer-based optimization techniques in the last decade, bio-inspired algorithms have been coming out as one of the best promising optimization techniques in the agri-food sector. Bio-inspired computing optimization algorithms is an emerging approach that is based on the principles and inspiration of the biological evolution of nature to develop new and robust competing techniques (TalbiEl-Ghazali, 2021). Depending on the behaviour of a group of animals or insects or birds or fishes, computer technology scientists are developing different types of bio-inspired optimization tools. There are several types of bio-inspired algorithms such as Genetic Bee Colony (GBC) Algorithm (Alshamlan et al., 2015), Fish Swarm Algorithm (FSA) (Xiao, 2002), Cat Swarm Optimization (CSO) (Chu et al., 2006), Whale Optimization Algorithm (WOA) (Mirjalili and Lewis, 2016), Artificial Algae Algorithm (AAA) (Uymaz et al., 2015), Elephant Search Algorithm (ESA) (Deb et al., 2015), Chicken Swarm Optimization Algorithm (CSOA) (Meng et al., 2014), Moth flame optimization (MFO) (Mirjalili, 2015), and Grey Wolf Optimization (GWO) algorithm (Mirjalili et al., 2014), Particle swarm optimization (PSO) (Kennedy and Eberhart, 1995). These evolutionary algorithms are widely used in single and multi-objective optimization in food processing process design. Banga, Balsa-Canto, Moles and Alonso (2003) reported a summary of Evolutionary Computation methods for the different food processing engineering operations such as thermal, drying, contact cooking, microwave heating and other processing technologies (Banga et al., 2003). Researchers have reported the use of Tabu Search and Genetic Algorithm (GA) for optimization in different food engineering areas such as thermal processing, vehicle routing and heat exchangers design (Wari and Zhu, 2016). The food processing industries have used Evolutionary Algorithms (GA, Differential Evolution (DE) and their hybrids with other techniques) in thermal processing, food quality, process design, drying, fermentation and hydrogenation processes and they found the extensive application of GA and DE in most of the cases and also reported that about the other algorithms which have proven to be quite as effective and in some cases better in terms of the best result attained and run time required (Nayak et al., 2020).

In this study, we have reviewed the research work based on the application of different bio-inspired algorithms (BOT) in different food processing and related operations, the basic mathematical operations and the algorithms associated with these algorithms are also studied aiming the food industry experts who need ways to solve their problems and the readers looking for different optimization tools. The potential microorganism-based optimization algorithms for food process design has also be addressed.

2. Mathematical models used in the food industry

The real system may be represented with the help of a mathematical model that may build with a set of preferred features and properties of the system. Modern system and process engineering (control, optimization, and simulation) driven food industries are very much dependent on these models (Banga et al., 2003). The models are classified as white, grey and black box models in a broader view (Fig. 1). The software available in food process modelling is presented in Table 1.

The white box models generally consider the microscopic and/or macroscopic features of the system properties like momentum, energy and mass along with further interconnections with other physicochemical properties and kinetics behavior. Due to the presence of empirical relationships in a system the white-box model is relatively rare. Though this particular type of model is desired most due to the ease of scaling and extrapolation related benefits. The complex food process modelling is generally resources consuming and complicated task. Thus, the grey box and the black box modelling approach are the better possible choice as well as the more popular option for the industry application.

Food process industries generally deal with dynamic (more often) and static (less frequent instances) variables (Peleg et al., 2009; Sendín et al., 2010). The mathematical approaches to an optimization problem in the area of food processing is mainly concerned with process designing, optimization of operational policy, and model calibration.

Process designing: in food production units both static and dynamic parameters need to be modelled simultaneously. Number of the units, their sizes are the examples of static variables while most of the other variables are dynamic in nature e.g. flow variables (velocity, viscosity), issues related directly to the process design (controller) (Meneghetti and Monti, 2015; Perrot et al., 2011). The operational and capital investment need to be minimized with simultaneous optimization of process dynamics (Jagtap et al., 2021).

Optimization of operational policy: the open loop or dynamic optimization is one of the most popular field in food process optimization. Here, the optimum operational condition need to be computed for a dynamic model with specific parameters by which performance can be maximised (Banga et al., 2003; He et al., 2018).

Model calibration: it is the most practiced field in food processing optimization. Here, the parameters need to be searched for a nonlinear

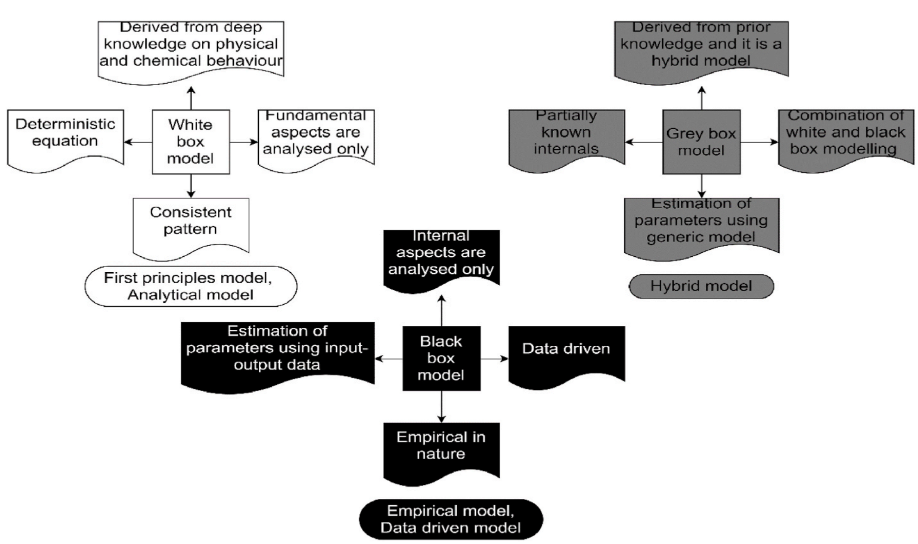

Fig. 1. The white, grey and black box models used in the food processing industry.

Table 1
Software available in the field of optimization.

Name of software	Open source (OS) /licensed software (LS)	Country of origin/Developer	Operating system	URL
Advanced Simulation Library (ASL)	OS	Avtech Scientific	Mac, Linux, Windows, FreeBSD	http://asl.org.il/
APMonitor	OS	APMonitor	Linux, Windows	http://apmonitor.com/
Aspen HYSYS	LS	Aspen Technology	Windows	https://www.aspentech.com/en/products/engineering/aspen-hysys
Aspen Plus	LS	Aspen Technology	Windows	https://www.aspentech.com/products/engineering/aspen-plus
BatchColumn	LS	ProSim	Windows	https://www.prosim.net/en/product/batch-column-simulation-and-optimization-of-batch-distillation-columns/
ChromWorks	LS	YPSO-FACTO	Windows	http://www.ypso-facto.com/
Cycle-Tempo	LS	Asimptote	Windows	http://www.asimptote.nl/software/cycle-tempo/
DynoChem	LS	Scale-up Systems	Windows	https://www.scale-up.com/Dynochem
OptiRamp	LS	Statistics & Control, Inc.	Windows	https://web.archive.org/web/20170919004510/http://www.stctrl.com/
Prode Process Interface	LS	Prode Software	Windows	https://www.prode.com/en/opcgashydrocarbon.htm
ProSimPlus	LS	ProSim	Windows	https://www.prosim.net/en/product/prosimplus-steady-state-simulation-and-optimization-of-processes/
ROMeo	LS	AVEVA	Windows	https://www.aveva.com/en/products/process-optimization/
Reaction Lab	LS	Scale-up Systems	Windows	https://www.scale-up.com/ReactionLab
AIMMS	OS	AIMMS	Windows	https://www.aimms.com/
AMPL	OS	*ALGLIB Project*	Windows POSIX, Linux	http://www.alglib.net/
ASTOS	OS	Astos Solutions	Mac, Linux, Windows, FreeBSD	http://www.astos.de/products/astos
CPLEX	OS	IBM	Linux macOS Windows AIX	https://www.ibm.com/products/ilog-cplex-optimization-studio
Couenne	OS	COIN-OR	Linux Windows	https://github.com/coin-or/Couenne
FICO Xpress	OS	FICO (NYSE: FICO)	Linux macOS Windows	https://www.fico.com/en/products/fico-xpress-optimization
GEKKO Python	OS	GEKKO	Linux Windows	http://gekko.readthedocs.io/en/latest/
Gurobi	OS	Gurobi Optimization	Linux MAC OSX Windows	http://gurobi.com/
LIONsolver	OS	LIONLAB	Linux macOS Windows	http://lionoso.com/
MIDACO-Solver	OS	MIDACO-SOLVER	Linux Windows	http://www.midaco-solver.com/
MINTO	OS	CORAL	Linux macOS Windows	https://coral.ise.lehigh.edu/~minto/
MOSEK	OS	MOSEK ApS	Linux Mac Windows	https://www.mosek.com/
PottersWheel	OS	PottersWheel	Linux Macintosh Windows	http://www.potterswheel.de/
SCIP	OS	Zuse Institute Berlin (ZIB)	Linux MacOS Windows Raspberry	http://scip.zib.de/
WORHP	OS	WORHP	Linux	http://www.worhp.de/
ALGLIB	LS	ALGLIB Project	Windows POSIX, Linux	http://www.alglib.net/
Altair HyperStudy	LS	Altair Engineering, Inc.	Linux Mac Windows	https://www.altair.com/
Artelys Kniutro	LS	ARTELYS	Linux Mac Windows	https://www.artelys.com/en/optimization-tools/knitro
BARON	LS	The Optimization Firm	Mac Windows	http://minlp.com/
COMSOL Multiphysics	LS	COMSOL	Linux macOS Windows	http://www.comsol.com/
FEATool Multiphysics	LS	Precise Simulation	Mac Windows	http://www.featool.com/

(*continued on next page*)

Table 1 (*continued*)

Name of software	Open source (OS) /licensed software (LS)	Country of origin/Developer	Operating system	URL
FICO Xpress	LS	FICO (NYSE: FICO)	Linux macOS Windows	https://www.fico.com/en/products/fico-xpress-optimization
FortMP	LS	OptiRisk Systems	Linux macOS Windows	http://www.optirisk-systems.com/products_fortmp.asp
GAMS	LS	GAMS Development Corp.	Linux Mac OSX Windows	https://www.gams.com/
HEEDS MDO	LS	Siemens Digital Industries Software Inc	Linux macOS Windows	http://www.redcedartech.com/
IMSL Numerical Libraries	LS	Perforce Software	Windows	https://www.imsl.com/
IOSO	LS	Sigma Technology	macOS Windows	https://www.iosotech.com/
Kimeme	LS	Cyberdynesoft	Windows	http://www.cyberdynesoft.it/
LINDO	LS	LINDO Systems, Inc.	Linux Windows	http://www.lindo.com/
modeFRONTIER	LS	ESTECO SpA	Windows	http://www.esteco.com/
Maple	LS	Waterloo Maple Inc.	Linux Windows	https://www.maplesoft.com/products/Maple/
MATLAB	LS	The MathWorks	Linux macOS Windows	https://www.mathworks.com/products/matlab.html
Mathematica	LS	Wolfram	Linux Windows	https://www.wolfram.com/mathematica/
ModelCenter	LS	Phoenix Integration	Linux macOS Windows	http://www.phoenix-int.com/software/phx_modelcenter_10.php
NAG	LS	Numerical Algorithms Group Ltd	Linux	https://www.nag.com/content/nag-library
NMath	LS	CenterSpace Software	Windows	http://www.centerspace.net/
Optimus platform	LS	Noesis Solutions	Linux Windows	http://www.noesissolutions.com/
optiSLang	LS	ANSYS, Inc	Linux macOS Windows	http://www.dynardo.de/en/software/optislang.html
OptiY	LS	OptiY GmbH	Windows	http://www.optiy.eu/
pSeven	LS	DATADVANCE	Windows	http://www.datadvance.net/
SAS	LS	SAS Institute Inc.	Linux macOS Windows	https://www.sas.com/en_us/home.html
SmartDO	LS	FEA-Opt Technology Co. Ltd.	Windows	http://www.smartdo.co/
SNOPT	LS	Centre for Computational Mathematics. University of California, San Diego	Linux Windows	http://ccom.ucsd.edu/~optimizers
TOMLAB	LS	TOMLAB	Windows (32/64-bit) Linux/OS X 64-bit	http://tomopt.com/tomlab/

dynamic model that provide the best fit to the dataset derived experimentally (Shoaib et al., 2021; Yousefi-Darani et al., 2020).

For all the three optimization problems namely process designing, optimization of operational policy, and model calibration the search space is significantly large and most of the time it is exponential or infinite as a result classical search algorithms become intractable. As a result metaheuristics is used.

3. Complexities in food process optimization

In food process industries batch process is the predominant one, which is a dynamic process and possible to described with partial differential and/or ordinary algebraic mathematical function (Banga et al., 2003). Though the models are simple (for empirical kinetics) (Sarkar et al., 2021) or maybe complex (for processing stages coupled with heat and mass transfer phenomena in a dynamic system, and for processing stages with complex chemical reactions) (Abakarov and Nuñez, 2013; Vilas et al., 2004). The challenges that exist in food process optimization may be listed as follows: (1) Processing related constraint-the existence of non-linearity in the dynamic models along with the mode of the process (continuous, semi-batch or batch) (Georgiadis et al., 2019), (2) Transportation and distribution-related constraint-the large numbers of process variables with complex interconnections (Wari and Zhu, 2019), (3) Food safety and quality-related constraint-nonlinear, complicated and dependent on various external factors (Enitan and Adeyemo, 2011; Roy et al., 2020).

4. Classification of bio-inspired optimization

The BOT techniques are artificial intelligent techniques and are still in the developing stage, thus there is no such unambiguous classification exist. In total 257 BOTs are available till now (Molina et al., 2020), which can be categorized into four main classes: 1. Evolution based (27), 2. Social human behavior based (43), 3. Plant based (17), and 4. Swarm intelligence based (170); human and math based algorithms are two other classes of metaheuristic techniques worth mentioning (Shastri et al., 2021) (Table 2). In this review, the latest BOTs (developed in the latter half of the last decade) are listed only. For Swarm

Table 2
Classification of Bio-inspired optimization techniques (Developed onwards from the year of 2016).

Class	Optimization algorithm	Year	Abbreviated form	Reference
Evolution based	Artificial Infections Disease	2016	AIDO	Huang (2016)
	Earthworm Optimization	2018	EOA	(G. . Wang et al., 2018)
	Improved Genetic Immune	2017	IGIA	Benbouzid-Si Tayeb et al. (2017)
	Virulence Optimization	2016	VOA	Jaderyan & Khotanlou (2016)
Plants based	Artificial Flora Optimization	2018	AFO	Cheng et al. (2018)
	Natural Forest Regeneration	2016	NFR	Moez et al. (2016)
	Root Tree Optimization	2016	RTOA	Labbi et al. (2016)
	Tree Growth	2018	TGA	Cheraghalipour et al. (2018)
	Tree Physiology Optimization	2018	TPO	Halim & Ismail (2018)
Social Human Behavior based	Adolescent Identity Search	2020	AISA	Bogar & Beyhan (2020)
	Cognitive Behavior Optimization	2016	COA	(M. Li et al., 2016)
Swarm intelligence based	Andean Condor	2019	ACA	Almonacid & Soto (2019)
	Bald Eagle Search	2020	BES	Alsattar et al. (2020)
	Bison Behavior	2019	BBA	Kazikova et al. (2019)
	Biology Migration	2019	BMA	Zhang et al. (2019)
	Binary Whale Optimization	2019	BWOA	(Reddy et al., 2019)
	Cultural Coyote Optimization	2019	CCOA	Pierezan et al. (2019)
	Dragonfly Swarm	2021	DSA	Bhardwaj & Kim (2021)
	Emperor Penguins Colony	2019	EPC	Harifi et al. (2019)
	Harry's Hawk Optimization	2019	HHO	Heidari et al. (2019)
	Naked Moled Rat	2019	NMR	Salgotra & Singh (2019)
	Nomadic People Optimizer	2020	NPO	Salih & Alsewari (2020)
	Regular Butterfly Optimization	2019	RBOA	Arora & Singh (2019)
	Squirrel Search	2019	SSA	Jain et al. (2019)
	Golden eagle optimizer	2021	GEO	Mohammadi-Balani et al. (2021)
	COOT bird optimization	2021	COOT	Naruei & Keynia (2021)
	Dingo Optimization	2021	DOA	(Peraza-Vázquez et al., 2021)
Human-Based Algorithms	Harmony Search	2001 (modified HS have been developed during 2016–2020)	HS	(Dubey et al., 2021; Geem et al., 2001)
	Ali Baba and the forty thieves algorithm	2021	AFT	Braik et al. (2021)
	Firework Algorithm	2010 (Different variants are evolved during 2010–2019)	FWA	(J. Li and Tan, 2019; Tan and Zhu, 2010)
	Soccer Inspired (In total 8 types of SI are available)	2009–2021	SI	Osaba & Yang (2021)
Math's Based Algorithms	Sine Cosine Algorithm	2016	SCA	Mirjalili (2016)
	Chaos Game Optimization	2021	CGO	Talatahari & Azizi (2021)
	Stochastic Fractal Search	2015–2021	SFS	(ElKomy, 2021; Salimi, 2015)
	Hyper-Spherical Search algorithm	2014	HSS	Karami et al. (2014)

intelligence-based methods only 2019–2021 has been covered.

5. Challenges in food process optimization

The differential, ordinary and/or partial differential equations and the models are error-prone and resource consuming. This may be one of the main barriers to the restricted use of the food industry. Plant scale simulation is one of the main challenges with this kind of modelling (Banga et al., 2003). The absence of an efficient and robust optimization solver in complex food processing problems is another challenge encountered by food industries (Table 2) (Banga et al., 2003; Wari and Zhu, 2016). The knowledge about the complexity of the process and lack of technical human resources are the third major challenge in food industries process optimization. The requirement of custom-fit software, unavailability of libraries in synchronisation with the dynamic models are the fourth key challenge faced by food industries.

These limitations of the traditional optimization processes may be conquered by the BOT methods. These intelligent computing methods comprise of some features, of which the most important one is the behaviour of the working mechanisms that resemble either a troop of living organisms or an individual. Compared to the traditional artificial intelligent method (e.g. fuzzy logic, and expert system) these methods are more efficient (Binitha and Sathya, 2012; Jianjun Ni et al., 2016). These special methods are different from the traditional methods in terms of self-organisation, nondeterminism, flexibility, robustness, emergence and simplicity (J Ni and Yang, 2011; Jianjun Ni et al., 2016). These BOTs are more likely to be used now because of their simplicity, higher performance in solving complex optimization problems, scalability, and flexibility. Though very few numbers of BOTs have been implemented in the food process industries. The applications of BOT methods in food processing are described in Table 3.

6. Critical features of BOT that make it suitable for food process industries

The computation and strategic nitty-gritty are simple for most of the algorithms, though the techniques are effective thus becoming an emerging field in artificial intelligence mediated food production. The working principles resemble ecological and/or biological systems, which provide the access to deal with real-world problems. The self-organizing or self-learning nature of these techniques can enhance the versatility, flexibility and efficient evolution of the BOTs. Non-determinism, robustness, precision, and parallelism are the other advantageous feature of these algorithms. These algorithms have resilient potency against the alteration in input parameters, responses and operational environments.

Modelling biological applications as computing or real-world processes is challenging. Researchers in the domains of biology, neuroscience, and computer science are still unable to characterise in sufficient depth both the process and architecture that constitute biological things, as well as the level of abstraction required to model them (Akerkar and Sajja, 2009). Finding an appropriate fitness function that leads to improved solutions is equally challenging. The other challenges are to find a suitable technique and conception of new BOT (Akerkar and Sajja, 2009). The performances of the BOTs depend on the setting parameters, and tweaking these parameters is critical and depends on the nature of

Table 3
Different bio-inspired (metaheuristic) techniques in food process optimization.

Optimization algorithm	Food product	Processing method	Aim of the optimization	Parameters considered	Metrics to determine aptness of the optimization technique	Optimized condition	Reference
ANN-PSO	Rasgulla (Sweetened cheese ball)	Hot air drying	Maximize the total colour value	Drying temperature, cooking time, pineapple amount	R^2 (0.934)	Drying temperature = 80 °C, pineapple amount = 35%, Cooking time = 5 min	Sarkar et al. (2020)
		Microwave drying	Maximize the total colour value	Power level, cooking time, pineapple amount	R^2 (0.97814)	Power level = , cooking time = , pineapple amount =	
		Freeze drying	Maximize the total colour value	cooking time, pineapple amount	R^2 (0.9789)	cooking time, pineapple amount	
		microwave convective drying	Maximize the total colour value	Drying temperature, cooking time, pineapple amount	R^2 (0.99021)	Drying temperature, cooking time, pineapple amount	
GA-SVM PSO-SVM GS-SVM	pork meat	GC-MS analysis of bacteria-infested meat followed by e-nose detection	Quantification of bacterial load	Produced volatile compounds	R^2 (0.986), RMSE (0.1370 R^2 (0.989), RMSE (0.145) R^2 (0.966), RMSE (0.148)	–	Bonah et al. (2020)
PSO SVM GA SVM GS SVM	*Escherichia coli, Listeria monocytogenes, Salmonella typhimurium, Salmonella enteritidis*	E-nose sensor-based data acquisition	Quantification of bacterial load	Produced volatile compounds	Prediction accuracy = 98.5% Prediction accuracy = 96.87% Prediction accuracy = 94.79%	–	Bonah et al. (2019)
Hybrid GA	Anthocyanin from purple sweet potato	–	Maximization the anthocyanin production	liquid-to-solid ratio (mL/g), ethanol concentration (w/w, %), ammonium sulphate concentration (w/w, %), and pH value	0.95	40:1 liquid-to-solid ratio, 23% ethanol concentration, 22% ammonium sulphate concentration, and a pH of 3.2407	Tumuluru & McCulloch (2016)
ANN-GA	Puffed rice	microwave puffing of preconditioned rice	To predict the values of expansion ratio and puffing percentage of puffed rice	microwave power, puffing time, butter level, and sodium bicarbonate level	R^2 (0.99)	850 W of microwave power, 35 s of puffing time,5.26% of butter, and 1.46% of sodium bicarbonate	(K. K. Dash and Das, 2021)
PSO GA	drying of sliced pineapple	Heating of pineapple slices	To find out the better performance and better range of the temperature and moisture content	ventilation rate and heater	Integral square error, Overshoot (%), Settling time (sec)	–	Manonmani et al. (2017)
Artificial bee colony (ABC) algorithm	production of succinate and lactate in *Escherichia coli*	–	To predict an near-to-optimal set of solutions in order to optimize the production rate of succinate and lactate	Numbers of gene knockout	–	Numbers of gene knockout = 3	Tang et al. (2015)
ANN-GA	Beef, pig liver, lamb, cod, shark, apple, Tylose, Mashed potatoes	Freezing and thawing	Prediction of foods freezing and thawing times	shape factor, characteristic dimension, Biot number, thermal diffusivity, initial, ambient and final temperatures	Average absolute relative error (8.52%), average relative error (0.44%)	–	Goñi et al. (2008)
GA	fish oil microencapsulation	to study the influence of emulsion	to optimize the emulsion preparation	Aqueous phase content, oil proportion in	R^2 (0.9973)	Aqueous phase content = 27.12%, oil	Aghbashlo et al. (2012)

(continued on next page)

Table 3 (*continued*)

Optimization algorithm	Food product	Processing method	Aim of the optimization	Parameters considered	Metrics to determine aptness of the optimization technique	Optimized condition	Reference
		characteristics on energy efficiency and quality of fish oil microencapsulated within skim milk powder (SMP) by spray drying.	procedure for the production of fish oil microcapsule in terms of maximum encapsulation efficiency	total solids, and emulsification time.		proportion in total solids = 10.82%, and emulsification time = 13.23 min.	
Multi-objective particle swarm optimization (MOPSO)	ostrich meat	deep-fat frying in microwave	Optimization of shrinkage, moisture content, and fat content	microwave power, temperature and frying time	mean absolute error (0.009–1.704); mean-squared error (0.032–0.198); normalized mean-squared error (0.017–1.2)	–	Amiryousefi et al. (2014)
GA	olive oil	ultrasound-assisted bleaching	optimization of ultrasound-assisted bleaching of olive oil to maximize the Lovibond red colour and minimize peroxide value	ultrasonic power, bleaching clay dosage, process temperature and time	R^2 (0.9228), MSE (0.0248)	ultrasonic power = 30%, bleaching clay dosage = 1.21%; bleaching time = 13 min; temperature = 65 °C	Asgari et al. (2017)
PSO and GA	tapioca	Fluidized Bed Drying	Error minimization in three-phase differential model	temperatures of the solid; gas at the dryer exit			Vitor & Gomes (2011)
GA	cooking of a fish and rice flour blend	Extrusion	Maximumisation of expansion ratio, water solubility index and minimum hardness, bulk density	barrel temperature (C), screw speed (rpm), fish content (%) and feed moisture content (%)	Percentage error (6.4–22.7%)	fish content = 41–45%; feed moisture contents = 40%	Shankar & Bandyopadhyay (2004)
GA-ANN	Pretreated Fried Mushroom	Frying	Modeling of Moisture and Oil Content of Pretreated Fried Mushroom	osmotic condition (dimensionless), gum coating conditions (dimensionless), frying temperature (°C), and time (minute)	R^2 for moisture content = 0.93 R^2 for oil content = 0.96	–	Mohebbi et al. (2011)
GA	Potatoes/French fries	Microwave treated frying operation	Optimization of moisture content, oil content, texture and color parameters	microwave power microwave time, frying temperature, frying time	R^2 (0.9946–0.9686)	400–500 W for 3–4 min and frying at 180 °C for 6–6.5 min	Hashemi Shahraki et al. (2014)
GA	fish and rice flour	extrusion process	effects of the process variables for minimization of moisture and fat and maximization of the protein content of the extrudates	barrel temperature, screw speed, fish content of the feed, feed moisture content	R^2 (0.94–0.99)	–	Tumuluru et al. (2013)
GA	Broken rice	extrusion process	Maximumisation of expansion ratio, water solubility index and minimum hardness, bulk density	Screw speed, die temperature, feed moisture content	–	Screw speed = 500 rpm, die temperature = 110 °C, feed moisture content = 12%	(Sm- et al., n.d.)
GA	Rice based snack	extrusion process	Optimization of water solubility index, water absorption index	feed moisture, screw speed, barrel temperature	R^2 (0.788–0.894)	feed moisture = 44.59%, screw speed = 323 rpm, barrel temperature = 65.82 °C	Das & Srivastav (2013)
ANN-GA	vegetable oil	hydrogenation process	total trans isomer minimization; maximization of cis-oleic acid formation	Temperature, H_2 pressure, catalyst condition, mixing time	R^2 (0.9627), MSE (0.016)	Temperature = 159.4 °C, H_2 pressure = 351.6 kPa, catalyst (Ni) condition =	Izadifar & Jahromi (2007)

(*continued on next page*)

Table 3 (*continued*)

Optimization algorithm	Food product	Processing method	Aim of the optimization	Parameters considered	Metrics to determine aptness of the optimization technique	Optimized condition	Reference
GA	Cocoa butter	enzymatic interesterification	Cocoa butter analog development	pressure, temperature, tristearin/camel hump fat ratio, water content, and incubation time	R^2 (0.932–0.991)	0.091%, mixing time = 11.67 s Pressure = 10 MPa; temperature = 40 °C; tristearin/ camel hump fat ratio ratio = 0.6:1; water content = 13% (w/w); incubation time = 4.5 h	Shekarchizadeh et al. (2014)
Grey Wolf optimization	Tea leaves	Microwave heating, drying, grinding	Optimization of NIR spectra wavelength for polyphenols, window gap	Wavelength	Accuracy (92.5%), R^2 (0.91), root mean square error (0.32)	–	Chanda et al. (2018)
Parallel Multi-Swarm Particle Swarm Optimization (PMSPSO)	Grass Carp Carp Silver Common carp Carp Big-head	Fish supply chain	Coordination mechanism designing between the supply chain management stakeholders to minimize the wholesale price	Amount of Fish supply, inventory policy	R^2 (0.868) for Grass Carp R^2 (0.983) for Carp Silver R^2 (0.799) for Common carp R^2 (0.978) for Carp Big-head	–	Tabrizi et al. (2018)
Simulated Annealing; GA	European food dishes	Salting of food materials in the production unit	Minimizing the amount of setup processes; Minimization of production volume peaks for cost-saving	Initial temperature, frozen temperature, iteration	–	Iteration: 100–200 Initial temperature: 0.0005 Frozen temperature: 0.000005	Kamhuber et al. (2020)
Artificial Fish Swarm	Soybean oil	Electronic Tongue measurement	Classification between the different blends of oil	Volta metric sensor-generated parameters	–	–	Men et al. (2013)

the problem. There is no simple way to properly tweak an algorithm (Darwish, 2018). The performance and the quality of a bio-inspired solution depend on the number of search agents and the stop condition of the algorithm, commonly determined by the number of iterations. These constraints may be overcome with the updated supporting architecture and algorithm.

7. BOTs in the food processing

Numbers of BOTs are there and number is growing day by day. With the industrial revolution 4.0, the rise in artificial intelligence in industries take place. Thus, the process optimization gets immense importance. In the latter half of the last decade (2015–2020) 23.33% of total BOTs (257) have been developed. Though in food industries, a few numbers of BOTs are in practice. The general structure of any bio-inspired algorithm is presented in Fig. 2. The BOTs in-practice are shown below (Table 4).

7.1. Fish Swarm Algorithm (FSA)

As the name suggests this algorithm utilizes the nature of fish. Among various algorithm techniques, it has been considered as an efficient and smart method due to its high convergence speed, effective searching ability. Like as an individual fish finds its resources using various ways this method also mimics this phenomenon. Another important characteristic of this method is each fish establishes communication with others in order to find the global optimization (Darwish, 2018).

To understand the details of this algorithm a problem is considered here in which it is assumed that it has D-dimension and also a swarm with N- artificial fish is taken. Considering A be the variable that represents the positions of the artificial fish. Hence $A = (a_1, a_2, \ldots, a_n)$. Now the food source is assumed as fitness function (B) of the algorithm, therefore it can be written as $B = f(A_i)$. Another four parameters are there in the algorithm. The distance between A_i and A_j is written as $p_{ij} = ||A_j\text{-}A_i||$. The next one is visual which is associated with the distance of each artificial fish. The movement size of the artificial fish is represented by step, and the last one is the crowd factor (α) of artificial fish. Swarming, following, foraging, and random behaviours are the characteristic behaviour of this algorithm (Fig. S1) (Darwish, 2018; Neshat et al., 2014).

7.1.1. Phase-1: preying behaviour

Suppose the current position of an artificial fish is represented by A_i, and A_j being the distance of that particular fish, there will be two cases. In the first case, suppose $f(A_j) < f(A_i)$ then the travel path of the artificial fish will be A_i to A_j or we can say in direction of $(A_j\text{-}A_i)$. The other case would be like another the artificial fish will follow a random state A_j. The preying step can be represented as:

$$\vec{A_i} = \begin{cases} A_i + step\, x\dfrac{A_j - A_i}{p_{ij}}\, a\ rand & if\ \left(B_j\right) < \left(B_i\right) \\ random\ behaviour & otherwise \end{cases}$$

$\vec{A_i}$ is the new position of fish. In the interval of [0,1] and is a random value.

7.1.2. Phase-2: the swarm behaviour

An artificial fish, suppose A_i, will search for its central position $(A_{c\text{-}p})$

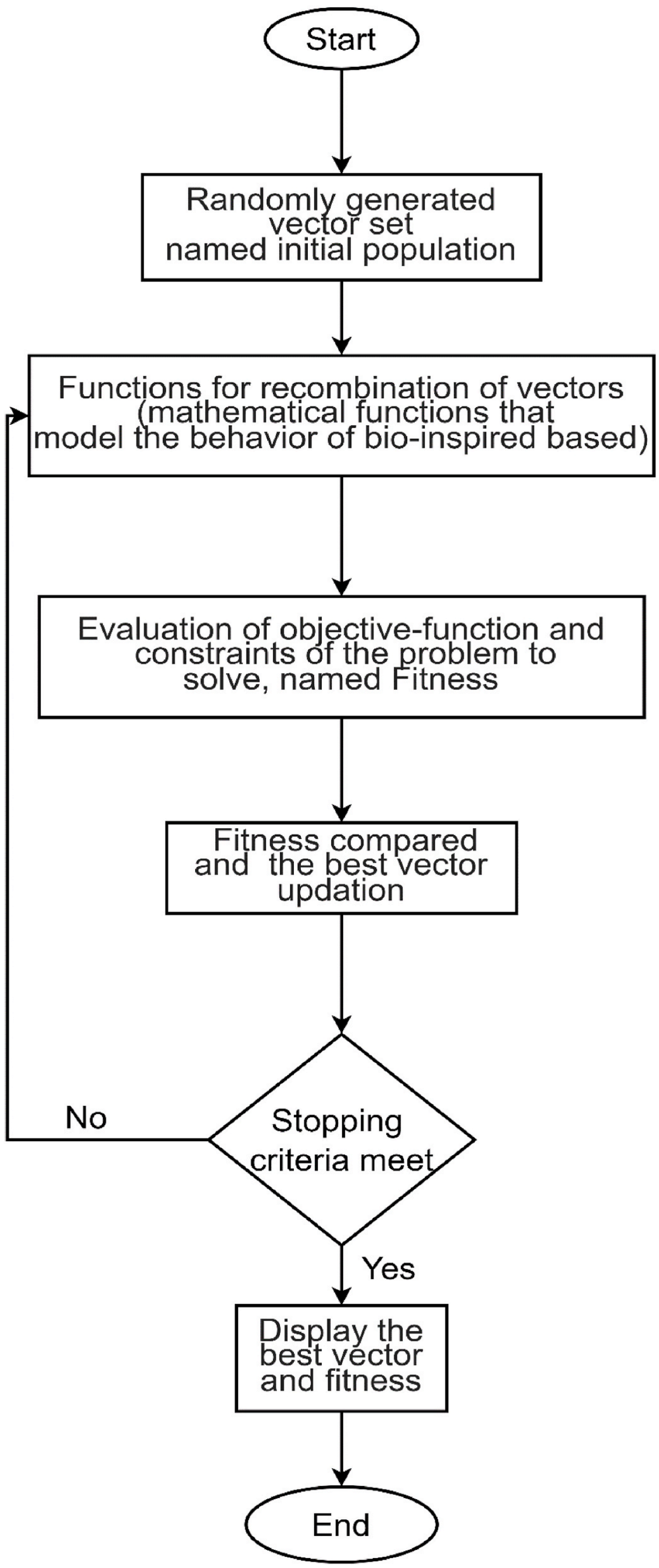

Fig. 2. The general structure of any bio-inspired algorithm.

Table 4
Codes for Bio-inspired optimization techniques freely available in MATLAB.

Bio-inspired optimization techniques	URL	References
Fish Swarm algorithm	https://www.mathworks.com/matlabcentral/fileexchange/32022-swarmfish-the-artificial-fish-swarm-algorithm	Chen (2022)
Whale optimization algorithm	https://www.mathworks.com/matlabcentral/fileexchange/55667-the-whale-optimization-algorithm?s_tid=srchtitle	Mirjalili (2022c)
Elephant Search Algorithm	https://www.mathworks.com/matlabcentral/fileexchange/53486-elephant-herding-optimization-eho	(G.-G. Wang, 2022)
Grey Wolf Optimization	https://www.mathworks.com/matlabcentral/fileexchange/44974-grey-wolf-optimizer-gwo	Mirjalili (2022a)
Ant colony optimization	https://www.mathworks.com/matlabcentral/fileexchange/52859-ant-colony-optimization-aco	Yarpiz (2022a)
Particle swarm optimization	https://www.mathworks.com/matlabcentral/fileexchange/67804-particle-swarm-optimization-pso-matlab-code-explanation	Raza (2022)
Genetic algorithms	https://in.mathworks.com/matlabcentral/fileexchange/67435-the-genetic-algorithm-ga-selection-crossover-mutation-elitism	Mirjalili (2022b)
Artificial Bee Colony Algorithm	https://in.mathworks.com/matlabcentral/fileexchange/52966-artificial-bee-colony-abc-in-matlab	Yarpiz (2022b)
Bacteria Foraging Optimization	https://in.mathworks.com/matlabcentral/fileexchange/45774-bacteria-foraging-optimization-bfo	(B. Dash, 2022)
Slime Mould Algorithm	https://in.mathworks.com/matlabcentral/fileexchange/76619-slime-mould-algorithm-sma-a-method-for-optimization	(S. Li et al., 2020)
Virus optimization	https://in.mathworks.com/matlabcentral/fileexchange/85710-coronavirus-herd-immunity-optimizer-chio	(Al-Betar et al., 2021; Alyasseri, 2022)
Black-widow optimization	https://www.mathworks.com/matlabcentral/fileexchange/94080-black-widow-optimization-algorithm	Peña-Delgado et al. (2020)
Golden Eagle Optimizer	https://www.mathworks.com/matlabcentral/fileexchange/84430-golden-eagle-optimizer-toolbox?s_tid=srchtitle	Mohammadi-Balani et al. (2021)
Dingo Optimization	https://www.mathworks.com/matlabcentral/fileexchange/98124-dingo-optimization-algorithm-doa?s_tid=srchtitle	(Peraza-Vázquez et al., 2021)
COOT optimization algorithm	https://www.mathworks.com/matlabcentral/fileexchange/89102-coot-optimization-algorithm?s_tid=srchtitle	(Naruei, 2022; Naruei and Keynia, 2021)
Chaos Game Optimization	https://www.mathworks.com/matlabcentral/fileexchange/83938-chaos-game-optimization-cgo?s_tid=srchtitle	(Talatahari and Azizi, 2020, 2021)

and the close one to it is c_f. The movement of the fish will be in the direction of Ac-p, if $B_{c-p}/c_f > \alpha B_i$ .The mathematical form of this phase is as follows:

$$\overrightarrow{A_i} = \begin{cases} A_i + step\, x \dfrac{A_{c-p} - A_i}{d_{ic-p}} & if\ (B_{c-p}|c_f < \alpha a B_i) \\ preying\ behaviour & otherwise \end{cases}$$

where $\alpha \in [0,1]$ represents the concentration of food sources.

7.1.3. Phase-3: following behaviour

Suppose Ai be the artificial fish and its current position local best neighbourhood be A_{bn}. Then the movement of the artificial fish will be towards A_{bn}-A_i. It can be mathematically represented as:

$$\overrightarrow{A_i} = \begin{cases} A_i + step\, x \dfrac{A_{bn} - A_i}{d_{i,bn}} & if\ (B_{bn}|c_f < \propto a B_i) \\ preying\ behaviour & otherwise \end{cases}$$

7.1.4. Phase-4: random behaviour

In the entire visual range, an artificial fish can randomly find a position and thereafter will step forward to it.

7.1.5. Phase-5: best behaviour

After all these four phases are done, the best behaviour will decide the present state of the artificial fish.

7.2. Whale Optimization Algorithm

Among all mammals, whales are found to be the biggest. Based on their characteristics this algorithm has been developed. Differences in specific characteristics have been observed for different types of whales namely humpback, finback, killer, and blue. The common phenomenon of all varieties of whales is due to breathing purposes most of the time they do not fall asleep. To understand this algorithm the following steps are required to discuss (Fig. S2) (Mirjalili and Lewis, 2016):

7.2.1. Encircle the prey

The optimal candidate solution is assumed to be the objective prey. Prey encircling by the whey can be expressed as-

$$D = \left| P\overrightarrow{A^*}(t) - A(t) \right|$$

$$A(t+1) = \overrightarrow{A^*}(t) - \overrightarrow{E}.\overrightarrow{D}$$

Whale's present position iteration is represented by t. $\overrightarrow{E}$, P both are the coefficient vectors. The position vector of the present near-to-optimal solution is presented by $\overrightarrow{A^*}$. $\overrightarrow{A}$ is represented as the position vector. || value gives the absolute value. Using the following equation $\overrightarrow{E}$ and $\overrightarrow{D}$ vectors can be evaluated.

$$\overrightarrow{E} = 2\overrightarrow{e}.\overrightarrow{m} - \overrightarrow{e}$$

$$\overrightarrow{P} = 2.\overrightarrow{m}$$

During the iterations the value of $\overrightarrow{e}$ can be selected between 2 and 0. $\overrightarrow{m}$ is said to be the random vector in the range of [0,1]. The bubble net method is adapted by humpback whales to attack the prey.

7.2.2. Bubble-net attacking phase

Two methods are there which elaborate the mathematical form of the bubble-net stage of humpback whales.

a. Method 1- shrinkage of encircle:

If the value of $\overrightarrow{e}$ is decreased then the value of $\overrightarrow{E}$ will be considered as a random value in [-e, e] interval in a way during the iterations the value of e may be decreased from 2 to 0. Also random values of $\overrightarrow{E}$ is considered in the interval of [−1,1].

b. Method 2- The spiral updating position method:

To determine the position of whale and prey a spiral equation can be generated as follows:

$$\overrightarrow{A}(t+1) = \overrightarrow{D'}.e^{fi}\cos(2\pi n) + \overrightarrow{A}^*$$

The distance between the ith whale and the prey is represented by $\overrightarrow{D'} = \left| \overrightarrow{A}^*(t) - \overrightarrow{A}(t) \right|$. N is considered as a random number in [−1,1] interval. f being the constant.

In this phase, the prey is encircled by the humpback whales and there is a 0.5% probability that either it will select a spiral model so that the position of the whales can be updated or it will choose the shrinking circling method. The behaviour can be expressed as:

$$\overrightarrow{A}(t+1) = \begin{cases} \overrightarrow{A}^*(t) - \overrightarrow{E}.\overrightarrow{D} & if\ r < 0.5 \\ \overrightarrow{D'}.e^{fi}\cos(2\pi n) + \overrightarrow{A}^*(t) & if\ r \geq 0.5 \end{cases}$$

where r is a random value in the interval [0,1].

7.2.3. Search for prey phase

The values of $\overrightarrow{E}$ is considered as random values between −1 and 1. Here it is considered that $\overrightarrow{E} > 1$ so that the algorithm is enabled to do a global search. The following equation will describe this-

$$\overrightarrow{D} = \left| \overrightarrow{P}.Ar - \overrightarrow{A} \right.$$

$$\overrightarrow{A}(t+1) = \overrightarrow{A}\overrightarrow{r} - \overrightarrow{E}.\overrightarrow{D}$$

where Ar is called the random position vector. Depending on the randomly selected solutions this algorithm proceeds for searching.

7.3. Elephant Search Algorithm (ESA)

This algorithm has been formed based on the behavioural characteristics of elephants. It uses the ideas of the dual search method. One group of the elephant may be partitioned into other clans. Each clan has one leader who is the oldest of the group. The characteristics of these clans are adapted to form this algorithm. One of the basic characteristics of the elephant group is female ones forms a family group whereas male ones keep themselves isolated from others. This algorithm possesses three main characteristics namely refining of solution in different iteration to find out the near-to-optimal solution, local searches are done mostly by the main female elephants thus the probability of finding the best solution increases, male elephants find out the local optima (Deb et al., 2015; Panda, 2020). ESA is formulated based on the characteristics of elephants and discussed below (Fig. S3) -

The group or clan of elephants is represented by Aclan. Now considering elephant m in the clan. This can be written as-

$$P_{new,clan,m} = P_{clan,m} + c.\left(P_{best,clan} - P_{clan,m}\right).d$$

In the above equation, $P_{new,clan,m}$ is the new position of the elephant m in the group, whereas $P_{clan,m}$ is the old position for the same elephant. The extent of influence of clan on $P_{clan,m}$ is determined by a factor, $c \in [0,1]$. $P_{best,clan}$ depicts the clan, $c \in [0,1]$. If $P_{clan,m} = P_{best,clan}$ then the below-mentioned expression can be used to describe the fittest elephant-

$$P_{new,clan,m} = \propto .P_{centre,clan}$$

The influence of $P_{centre,clan}$ on $P_{new,clan,m}$ is determined by $\propto \in [0,1]$. The below mentioned mathematical form represent the c-th dimension of $P_{new,clan,m}$.

$$P_{centre,clan,c} = \frac{1}{k_{clan}} \sum_{m=1}^{k_{clan}} P_{clan,m,c}$$

$1 \le c \le C$ indicates c-th dimension and C being the total dimension. k_{clan} is the total number of elephants in the clan. $P_{clan,m,c}$ is the c-th of the elephant $P_{clan,m}$.

Male adult elephants live in isolation. It is like solving a complex problem separating the operator. It is assumed that the least fit elephant will act as the separating operator. It can be expressed as:

$$P_{l,clan=}P_{min} + (P_{max} - P_{min} + 1).Rand$$

where P_{max} being the upper bound position of elephant, and P_{min} being the lower bound position of the elephant. The least fit elephant is represented by $P_{l,clan}$. $Rand \in [0, 1]$ represents the stochastic distribution.

7.4. Grey Wolf Optimization (GWO) algorithm

7.4.1. Inspiration analysis

This algorithm is developed recently as and it is s meta-heuristic type. Taking inspiration from the grey wolf characteristics like hunting as well as social leadership this algorithm is has been formed. In a group of grey wolves, there is a leader (α) in the group who makes several decisions like hunting and place of sleeping. There is another wolf (β) who supports the leader to make decisions. There is another wolf (ω) who communicates with other wolves to pass on the decisions made. All the other wolves in the group are represented by (δ) (Mirjalili et al., 2014). There are several phases of this algorithm (Fig. S4) which are:

a. Tracking, chasing and approaching the prey
b. Pursuing, encircling and harassing the prey
c. Attacking the prey

α is the fittest solution of the algorithm. Similarly, β, δ being the second, third-best solution respectively. The other candidate solutions are ω.

7.4.2. The mathematical model of GWO

In search of the near-to-optimal solution, the social characteristics of the grey wolf have been adapted.

7.4.3. Encircling prey

The following equations describe the mathematical modelling of the encircling character.

$$D = \left|P.A_{pr}(t) - A(t)\right|$$

$$A(t+1) = A_{pr}(t) - M.D$$

where t is the current iteration. M and P are the coefficient vectors. A_{pr} is the position vector of the prey. The position vector of the grey wolf is represented by A.

7.4.4. Exploration phase: searching for the prey

Identification of the position of i, j, l wolf is the key factor of this algorithm. To model the divergence, let us suppose, the random values of M greater than 1 or less than −1. Another component of this algorithm is P, the value of the P vector is random and in the interval [0,2]. P vector helps in getting the local optima in final iterations.

7.4.5. Attacking prey

To design this model mathematically, there should be a linear increase of value m, M has the random value in [-m,m] if | $(|M| < 1)$ 1, then in this algorithm the wolves will be able to attack the prey.

7.4.6. Hunting

The mathematical model of the hunting character of the grey wolf can be described as keeping the first three best solutions and therefore updating their position in respect to the position of best search agent. The mathematical expression is written below-

$$D_\alpha = |P_1.A_\alpha - A|,\ D_\beta = \left|P_2.A_\beta - A\right|,\ D_\delta = |P_3.A_\delta - A|$$

$$A_1 = A_\alpha - A_1.D_\alpha,\ A_2 = A_\beta - A_2.D_\beta,\ A_3 = A_\delta - A_3.D_\delta$$

$$A(t+1) = \frac{A_1 + A_2 + A_3}{3}$$

So, to design this algorithm, at first the population of grey wolves needs to be created. Alpha, beta, and delta wolves can find the prey position with iterations. After that candidate solutions make their position in respect to prey. If $|P| \ge 1$, then the candidate solution diverges from the prey. If $(|M| < 1)$, then the solution converges to the prey. The last step of this algorithm is to find the near-to-optimal solution.

7.5. Ant colony optimization

The capability of ants to obtain the shortest route of the nest to the source is the basis of this algorithm. Pheromone is a chemical compound secreted from ant to trace the path. Each arc (k,l) of the graph D = (Q, X) having associated variable γk,l is the pheromone trail. The pheromone intensity reflects arc utility to get a better solution. At any random node, ant takes a stochastic decision to select the next node (Fig. S5) (Zhao et al., 2021). All arcs are subjected to a constant amount of pheromone ($\gamma_{kl} = 1,\ \pounds\ (k,l) = X$) initially. The probability of the m-th ant at node k choosing node j using pheromone trail γk,l-

$$d_{ij}(m) = \begin{cases} \dfrac{\gamma_{ij}^{\beta}}{\sum_{p \in Q_l^m} \gamma_{ij}^{\beta}} & if\ l = Q_k^m \\ 0 & if\ l \ne Q_k^m \end{cases}$$

Q_k^m is the neighbour of the m ant when its position is at k-th node. All nodes are connected to the neighbour of m-th node except the predecessor node. This in turn informs the unidirectional path of the ants. For the destination node it is different, where Q_k^m is null the predecessor of node m is included. With each iteration, the pheromone level is updated by-

$$\gamma_{kl}(m+1) = \theta\gamma_{kl}(m) + \mu\gamma_{kl}(m)$$

$0 \le \theta < 1$ and 1-θ is the pheromone evaporation rate, $\mu\gamma_{kl}$ is the performance of each ant.

In an experiment with flowering tea, it has been observed by researchers that to determine the appropriate wavelength near-infrared spectroscopy measurement of anthocyanin for the said sample (Xiaowei et al., 2014), ACO is the best choice algorithm. Scholars have studied that to get the maximum yield ACO can be utilized, this algorithm will help to select the optimal gene knockout option (Tang et al., 2015). Alteration of microorganism genes will generate chemicals, this the methodology of gene knockout. Lactate and succinate are the chemicals generated in this study. To get the maximum yield, it is important to study the number of the gene which have been altered. This algorithm will help in finding the best gene knockout level. Researchers have used this algorithm in the optimization of the production planning of the bakery industry. The aim is to design a no wait hybrid flow shop model (Swangnop et al., 2019). With the help of this model, the idle time of the machines can be reduced. According to this model, the completion time is calculated as the initiation time and processing time for each product in each processing stage.

7.6. Differential evolution

Similar to the genetic algorithm differential evolution also uses the operators-crossover, mutation, selection. The significant difference between these two algorithms is DE is based on mutation operation whereas genetic algorithm is based on crossover (Deng et al., 2021). The DE process (Fig. S6) comprises of the following steps: (1) initialize population, (2) evaluation, (3) repeat, (4) mutation, (5) recombination, (6) evaluation, (7) selection, (8) until requirements are met. In mutation, each M parameter vector is subjected to mutation. The following equation represents the solution vector $\overrightarrow{a_i}$.

$$\overrightarrow{a_i} = a_{r1} + D(a_{r3} - a_{r2})$$

The scaling factor D has values in the range [0,1]. The randomly chosen solution vectors are a_{r1}, a_{r2}, a_{r3}. The following condition is to be satisfied-

$$a_{r1},\ a_{r2},\ a_{r3} \mid r1 \neq r2 \neq r3 \neq i$$

i being the current index solution.

In crossover, a trial vector is produced following the below-mentioned equation by mixing the parent vector with the mutated vector.

$$b_k^i = \begin{cases} \overrightarrow{a_k^i} & M_k \leq Ck \\ a_k^i & \end{cases}$$

Ck being the crossover constant. M_k is a random real number in the range [0,1]. k is the k-th component of the corresponding array.

The solutions can be selected as parents. After mutation and crossover, the child produced is evaluated. Comparing parent and child vectors it is decided which one is better.

In lipase and laccase production, researchers have used this optimization technique for the optimization of the production parameters (Bhattacharya et al., 2011; Roy et al., 2020). 48 has developed a model for the independent variables. Similarly for the independent variables are in experiments using RSM (Bhattacharya et al., 2011). Using DE the models are optimized hence the near-to-optimal production variables are received. Optimization of a feeding trajectory problem was done by scholars using multiple population-based algorithms (Sonego et al., 2017). In a fed-batch reactor, this was used to find out the near-to-optimal feed rate profile. In this problem, process variables are defined by using multiple dynamic mathematical functions. In order to maximize the final product yield PSO, DE, an evolutionary algorithm was used to find out the feed rate. To compare the results of the algorithms a pre-defined performance index function was used. To optimize the temperature profile of beer production by fed-batch fermentation method researchers has used DE (Oonsivilai and Oonsivilai, 2010). They have estimated the effect of temperature profiles in the fermentation process with help of a kinetic model on the basis of experimental data obtained.

7.7. Genetic algorithm

If in an optimization problem, there are some fixed inputs and for that task needs to have a function value of h. each population m is a set of inputs, with a function value of hi. GA is designed in such a way that it will get an input sets, the value of which is closer to desirable value h. The error in the value of h and hi is required to be minimized (Chai et al., 2021; Shrestha and Mahmood, 2019). For the i-th individual, the fitness value is-

$$fit_i = \frac{1}{1 + |h - h_i|}$$

Based on the fitness score the individuals are selected, and this process is called reproduction. It may also be represented as 'roulette wheel selection' for each individual piece of the wheel is selected according to the fitness value. The high fitness value function is in a position to be selected first if from a point the rotation of the wheel is observed.

The selected individuals are combined together with the help of genetic operators like mutation and crossover. The crossover probability having a range of 0.6–0.8.

With each generation that is algorithmically equivalent to iterations, the algorithm will give better solutions (Fig. S7).

The controlling factors of the termination of programs are either any termination criterion or the maximum number of generations. If the average fitness to maximum fitness ratio in a generation exceeds the threshold, then it may be considered as a realistic termination criterion. The solution for the optimization problem achieved from encoded variables of the final generation.

In an experiment of pre-treatment of French fries with microwave drying the RSM, a model has been developed with the experimental data therefore GA was used to optimize it. Researchers have utilized this algorithm in RSM modelling of extrusion of fish and rice flour for the optimization of process variables (Al-Obaidi et al., 2017; Dokeroglu et al., 2019; Tumuluru et al., 2013). Researchers have utilized this method to resolve the time management issue of a single machine resource utilization constraint as multi-objective optimization (Tumuluru and McCulloch, 2016). Freshness, make span, distribution discount costs are the objectives. The problem may be stated as the encoding of schedule into gene and for each population, multiple solution schedule has been observed. Scholars have used this algorithm in addition to the local search approach in pharmaceutical production where optimization of a scheduling problem in batch production is done (Costa, 2015). Optimization of the make span objective was done and the constraints were changed over time, processing intervals and other setup times. The algorithm helps to find out the appropriate schedules and iteration based local searches to get the schedule solutions. The researcher has shown that in hyperspectral imaging of food the application of the algorithm lowers the computational burden and improve the accuracy (Dai et al., 2015). Hyperspectral imaging is a combination of two methods namely spectroscopy and computer vision or imaging. This algorithm has an application in the dairy industry where the GA help in optimizing the multiobjective routing problem. The objectives are CO_2 emission and the total cost of transportation. The aim of using the algorithm is to find the best route which can meet customer demand. Modified GA was used by scholars to solve the multi-objective two layers sustainable distribution model (Validi et al., 2015). Inventory management problem of fresh food product in a supermarket and is solved by the application of the algorithm. They also used this algorithm for the prediction of food demand after a disaster. Optimization of the quality parameters in flatbread processing was done by (Castañeda-Valbuena et al., 2021). They also used this algorithm to optimize the total phenolics and anthocyanin yield in an extraction process of phenolics by ultrasound.

7.8. Particle swarm optimization

Social behaviour and characteristics of birds, insects fish influence the PSO. For survival purposes, these animals need to optimize their adaption. In any situation, they can optimize to any random environment (Cao et al., 2019; Sarkar et al., 2021). This is the basis of PSO (Fig. S8).

Each no of agents are assigned to a particle number I and their position may be located in the coordinates in n-dimension. The imaginary velocity of these particles is considered as their position to the optimal position. For a number of iterations, it is considered that particle velocity is u and position p. After each iteration velocity and position are updated as follows:

$$p_i(a+1) = p_i(a) + u_i(a+1)$$

$u_i(a+1)=e_iu_i(a)+c_{g1}r_1(u_{i-best}-u_i(a))+c_{g2}r_2($

where, e_i is the inertia possessed by each particle

u_{i-best} is the best location the particle
$u_{g_{-best}}$ is the best location amongst the particles of a whole swarm
c_{g_1} is the cognitive weight that represents the individual thinking of the particle
c_{g2} is the social weight for the swarm $u_{g_{-best}}$, it represents the collaboration among particles.
r_1, r_2 are the random values in the range [0,1]

In protein extraction of enzymatically pre-treated oat bran, PSO has been utilized to determine the near-to-optimal solution with respect to enzyme factors. To determine the factors from the experimental data a mathematical model was prepared using RSM and the optimization is done through PSO (Liu et al., 2008). To optimize the parameters of a mathematical model used in the determination of the weight of wheat dough during proofing (Zettel et al., 2016). Researchers have used this algorithm along with GA in an experiment of fluidized bed drying to determine the heat and mass transfer coefficient (Vitor and Gomes, 2011). To minimize the error in the experimental data and the data obtained from the three-phase drying differential model. To determine the near-to-optimal solution quality factor in deep fat frying process control of ostrich meat (Amiryousefi et al., 2014). To optimize the planning as well as distribution of perishable products PSO was used by (He et al., 2018). For the planning, part LINGO software was used. PSO was used for the distribution part. Researchers also used the LINGO + PSO model to optimize the production and transport cost of the agri-food supply chain network (Esteso et al., 2018). To optimize the multi-objective routing problem PSO has been used. PSO, Variable neighbour search optimization with mathematical programming was used for this problem (Zhalechian et al., 2016).

7.9. The artificial bee colony algorithm

There are three types of bees seen in the artificial bee colony. The employed bees have a food source. Onlooker bees are those observe the dance of employed bee to find a food source. The last ones are scout bees who search for food sources randomly. Scout bees initially search the sources of food. After that employed bees and onlooker bees exhaust the nectar of food source in due course. After the food source is totally exhausted the employed bees turn to scout bees to find another food source. In this algorithm, the possible solution to a particular problem is the food source. The quality or fitness of the solution is the nectar amount present in the food. Each employed bee is assigned to only one food source. Hence the number of employed bees represents the number of food sources or solutions (Fig. S9) (Hussain et al., 2018).

7.9.1. Initialization phase

The vectors of the population food sources are represented by $\underset{a_p}{\rightarrow}$ are started by scout bees and other control parameters. In the optimization problem, the solution vector is $\underset{a_p}{\rightarrow}$. Each $\underset{a_p}{\rightarrow}$ vector having m variables that required to be optimized. This can be represented as:

$$a_{pi}=l_{bi}+rand(0,1)*(u_{bi}-l_{bi})$$

u_{bi} is the upper bound limit of the parameter a_{pi} and l_{bi} is the lower bound limit of parameter a_{pi}.

7.9.2. Employed bees phase

In the close proximity of food source $\underset{a_p}{\rightarrow}$ employed bees will search for another food source $\overrightarrow{b_p}$. After finding the new source the fitness is evaluated. Determination of the new food source can be obtained from the following equation-

$$b_{pi}=a_{pi}+\varnothing_{pi}(a_{pi}-a_{ki})$$

$\overrightarrow{a_k}$ is any food source selected randomly. i is a parameter index chosen randomly. The random number $\varnothing_{pi}$ has a range of … the fitness is calculated after the new source of food $\overrightarrow{b_p}$ is produced, in between the two food sources namely, $\overrightarrow{b_p}$, $\overrightarrow{a_p}$ a greedy selection applied.

From the below-mentioned formula the fitness value of the solution $fitn_p(\overrightarrow{a_p})$ can be evaluated.

$$fitn_p(\overrightarrow{a_p})=\begin{cases}\dfrac{1}{1+f_a(\overrightarrow{a_p})} & if\ f_a(\overrightarrow{a_p})\geq 0\\ 1+absl(f_a(\overrightarrow{a_p})) & if\ f_a(\overrightarrow{a_p})<0\end{cases}$$

$f_a(\overrightarrow{a_p})$ represents the objective function value of the solution $\overrightarrow{a_p}$.

7.9.3. Onlooker bees phase

Unemployed bees are of two types: onlooker bees and scout bees. Based on the information provided by employed bees the onlooker bees try to find the food sources. In this algorithm, based on the probable values calculated from the fitness value of the employed bees, onlooker bees find a new food source. The roulette wheel selection method can be employed in such cases.

The following expression is used to calculate the probability value $prob_p$.

$$prob_p=\frac{fitn_p(\overrightarrow{a_p})}{\sum_{a=1}^{SN}fitn_p(\overrightarrow{a_p})}$$

The fitness value of neighbourhood source $\overrightarrow{b_p}$ is determined when the onlooker bees find the food source $\overrightarrow{a_p}$. More onlooker bees are engaged to richer sources as the greedy selection is done between $\overrightarrow{b_p}$, $\overrightarrow{a_p}$. Thus, there is a positive feedback behaviour.

7.9.4. Scout bees phase

Employed bees turn to scout bees in the specific situation. When the solutions of employed bees are not in a state to improve them with some predefined number of trials then they are called “abandonment criteria” or “limit”. Eventually, they are called scout bees. After the employed bees turn to scout bees they find new solutions randomly. The exploited sources are abandoned and positive feedback is balanced by arising negative feedback behaviour.

7.10. Microorganism based potential algorithms may useful in food processing industries

7.10.1. Artificial Algae Algorithm (AA)

The algae growth generally follows the direction of light, they can adapt to the changes in the environmental conditions, and follows a helical movement pattern. The AA mimics these three basic characteristics of algae and the algorithm is segmented into three parts namely evolutionary phase, environmental adaptation and helical migration (Uymaz et al., 2015). The protocol is represented in Fig. 3. It is an algorithm with balanced search characteristics. Due to the mix up of evolutionary and adaptation processes the algorithm is capable of avoiding the local minima problem. The algorithm is thus helpful in food processing optimization problems as it uses the helical movement to find a new solution for a given problem with the aid of a) diversity increase by tournament method, b) changes in size that may provide an increase in sensitivity, c) greedy selection based local optima searching.

7.10.2. Bacterial foraging optimization

The bacteria always try to approach the highest nutrient source by chemotaxis (tumbling and swimming) movement and the reproductive

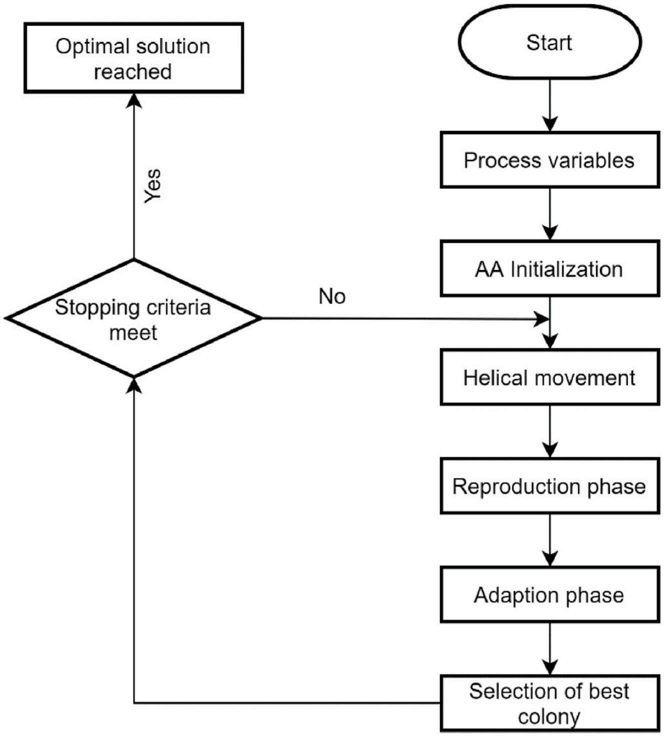

Fig. 3. Flowchart for the artificial algae optimization algorithm.

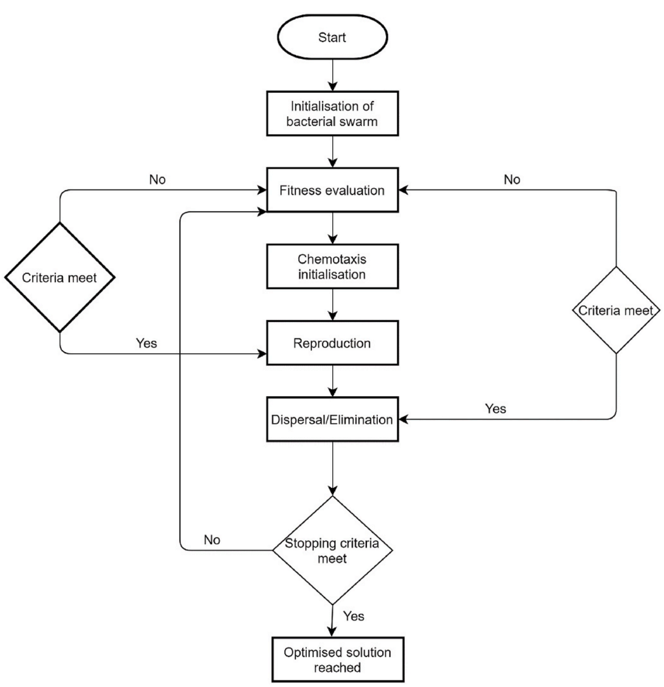

Fig. 4. Flowchart for the bacterial foraging optimization algorithm.

phase is initiated followed by the final dispersal or elimination phase (Ganguli et al., 2021). The protocol is represented in Fig. 4.

7.10.3. Bacterial-GA foraging

The bacterial forage system and genetic algorithm are amalgamated in this algorithm to find the best optimum value (Chen et al., 2007). The flowchart for the algorithm is as follows (Fig. 5).

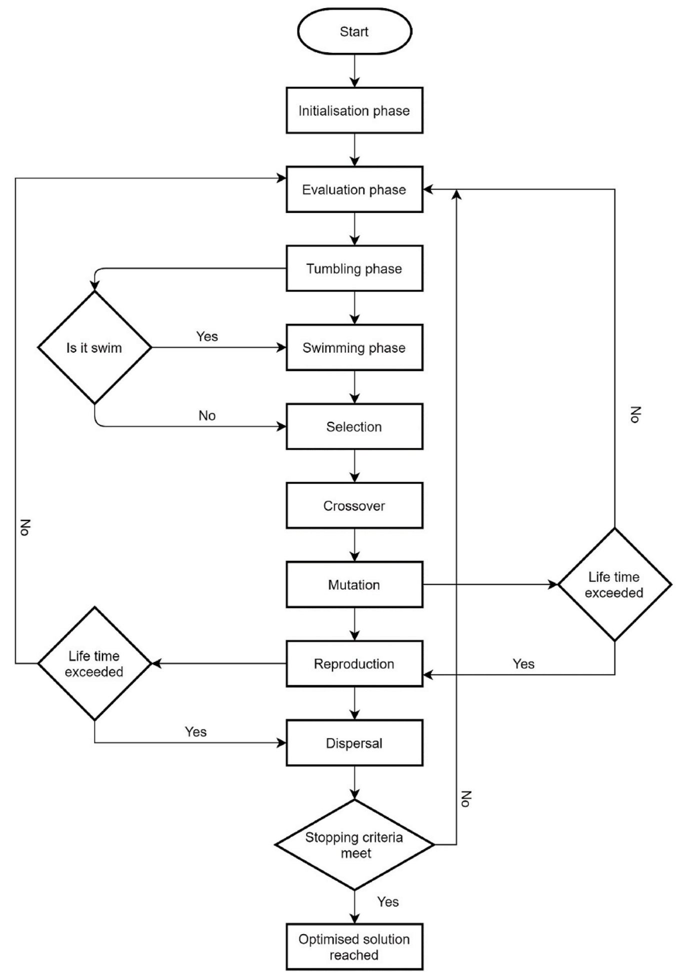

Fig. 5. Flowchart for the bacterial-GA foraging optimization algorithm.

7.10.4. Slime mould algorithm (SM)

Slime mould (Physarum polycephalum) extends their front ends in search of food. They also can divide themselves in search of diversified food sources. According to the nutrient requirement, they can adapt themselves to a region-limited exploration mechanism. The SM is segregated into three distinct phases namely approach food, wrap food and oscillation phase (S. Li et al., 2020). The flowchart (Fig. 6) for operational steps of SM is as follows.

7.10.5. Virus optimization (VO) algorithm

It is a population-based technique, where the process of infection through the virus attack is mimicked. The replication process of the viruses is dynamic in nature while the host cell is protected by an antivirus mechanism. When the maximum virus replication is achieved or when the cell is dead then the near-to-optimal solution is reached (Liang and Cuevas Juarez, 2016). The process flowchart (Fig. 7) is represented as follows. Table 5 represents the key features and the setting parameters for the BOTs discussed.

Apart from these techniques some more microorganism based optimization techniques are explored by researchers like fast bacterial swarming (Molina et al., 2020), magnetotactic bacteria (Dokeroglu et al., 2019), viral systems (Ezugwu et al., 2021) and coronavirus optimization algorithm (Martínez-Álvarez et al., 2020).

8. Statistical indexes for performance analysis

From the perspective of a food industry expert the performance of the BOTs are important, as the near-to-optimal solutions will be

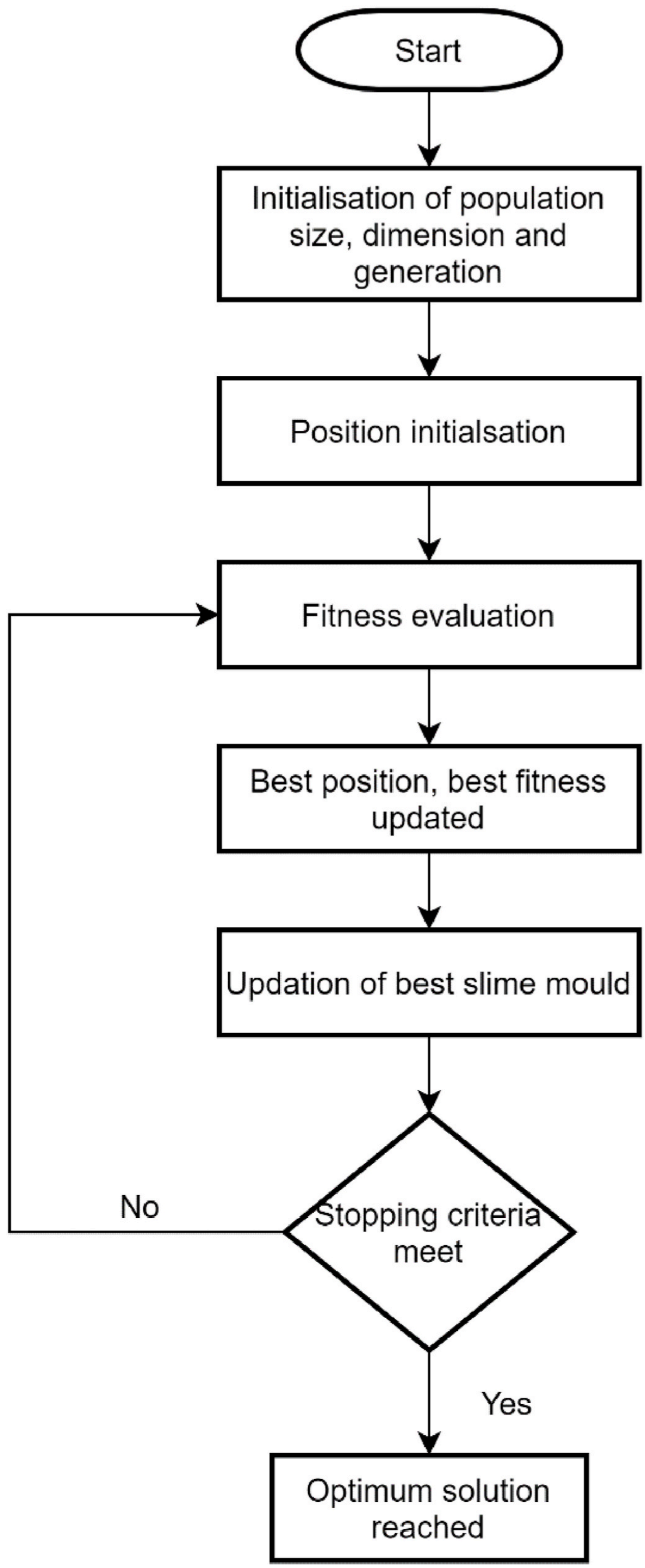

Fig. 6. Flowchart for the slime mould optimization algorithm.

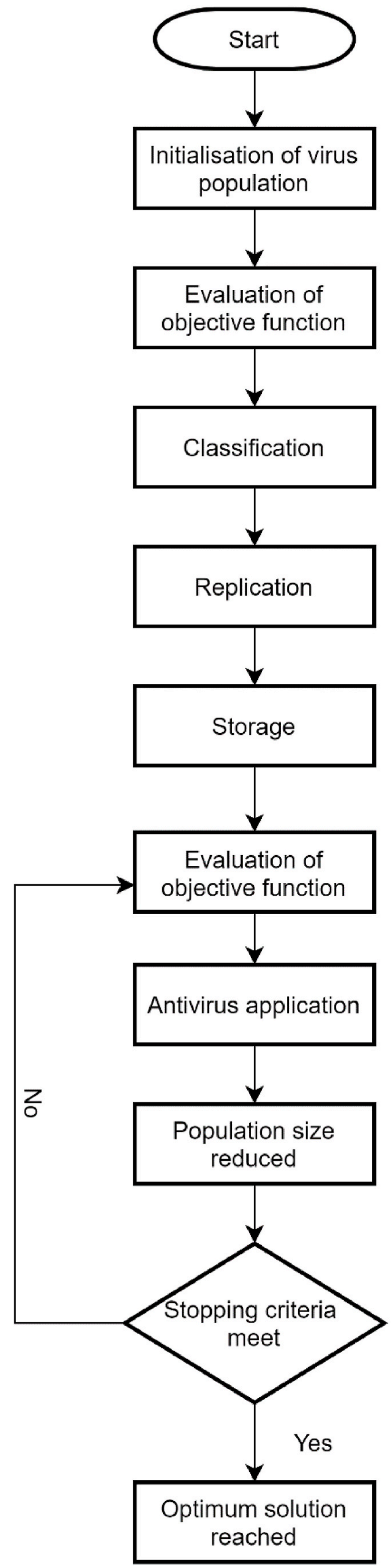

Fig. 7. Flowchart for the virus optimization algorithm.

considered for the process design, operational policy determination or model prediction. Thus, they need to run experiments with the near-to-optimal solution obtained from the optimizer. Therefore, several statistical indexes should be used to analyse or compare different BOTs.

Table 5
Setting parameters and the key features of the bio-inspired optimization techniques.

Bio-inspired optimization techniques	Setting parameters	Key Features
Fish Swarm algorithm	Crowd factor Distance Step length	Higher accuracy, higher fault tolerability, and flexible; Time complexity is higher, Inconsistency in local and global search
Whale optimization algorithm	Population size Iterations	It has the potential to achieve a global optimal solution while avoiding local optima. An ideal technique for tackling many unconstrained and/or constrained optimization problems without requiring fundamental reconstruction. Premature convergence
Elephant Search Algorithm	Population size Iterations Generation number	Semi-swarm type of algorithm
Grey Wolf Optimization	Population size Iterations Problem dimension Position	Simple structure and simple to implement, lower computing requirements and storage. sluggish rate of convergence, poor capability of local search
Ant colony optimization	Population size rate of pheromone evaporation reinforcement amount	Inherent parallelism, suitable for dynamic applications. Iteration affects the probability distribution.
Particle swarm optimization	Particle number Iterations Learning factor Inertial weight	No calculation related with mutation and overlapping. The approach is incapable of resolving non-coordinate system.
Genetic algorithms	Population size Chromosome length Number of generation Probability of cross over and mutation	Easy to understand, suitable for multi-objective problem. Time consuming and difficult to attain the objective function.
Artificial Bee Colony Algorithm	Number of onlooker bees Number of maximum cycle	Ability to explore adequately and simple Inappropriate exploitation in the solution of complex problems
Artificial Algae Algorithm	Population size Adaptation parameters Energy loss Shear force	Semi-random selection has been considered while selecting the light source in order to avoid local minima. It has been tested for real-world problem and achieved good results.
Bacteria Foraging	Population size Iterations chemotactic steps Search space dimension Reproduction number	Suitable for continuous optimization Constant step size, there is a chance to end up at the local optimal rather than the global optimum.
Bacterial-GA Foraging	Elimination Times Mutation rate Swim length Elimination rate	It has been tested for real-world problem and achieved good results.
Slime Mould Algorithm	Population size Iterations Position	Promising method to achieve the optimal solution efficiently. Convergence speed is inconsistent, search accuracy is imprecise
Virus optimization	Population size Iterations Disease statistics	The input parameters have already been defined, prohibiting researchers from entering random values. The approach can stop after a certain number of iterations.

8.1. Basic descriptive analysis

Quantile analysis, central tendency, Harrell-Davis quantile estimator, median absolute deviation, outlier detection, Wilcoxon tests (Saha et al., 2017; Shabani et al., 2019), Friedman's test (Peng et al., 2017) (non-parametric hypothesis testing) are few techniques used extensively.

8.2. Prediction error analysis

Mean absolute error, mean standard error, root mean squared error, coefficient of determination, and adjusted R^2 are used most frequently to evaluate the prediction error of the models (Dehghani et al., 2021; Maiti and Bidinger, 1981).

9. Conclusions

Optimization in food processing is generally carried out with statistical approaches, but efficient BOTs are gradually increasing their share in solving process optimization problems. These robust, efficient and adaptive algorithms are capable enough to find the optimum process condition or output response. Researchers adopted different approaches to find the near-optimum solutions which is summarised along with the supporting statistical indices such as error percentage, MSE, MAE, R^2, and RMSE to validate the model performance; from their observations, it is obvious that these techniques may simulate the process efficiently to find the near-to-optimal value. Stochastics searching is the basis for most of these algorithms, the initial set of vectors are randomly generated (initial population). The difference between them lies in the fact that the vector recombination function (mathematical model on which the bio-inspired is based e.g. Elephant, Whale, Wolf, Microorganisms, etc). And the balance that the algorithm design has between exploration and exploitation in the solution search space. There is no generic meta-heuristic algorithm that will perform well for each food process optimization problem. That is the main driving force behind the continuous development of new metaheuristic algorithms.

CRediT authorship contribution statement

Tanmay Sarkar: Data curation, Resources, Writing – original draft. **Molla Salauddin:** Data curation, Methodology, Writing – original draft. **Alok Mukherjee:** Writing – review & editing. **Mohammad Ali Shariati:** Conceptualization, Supervision, Writing – review & editing. **Maksim Rebezov:** Conceptualization, Supervision, Writing – review & editing. **Lyudmila Tretyak:** Writing – review & editing. **Mirian Pateiro:** Writing – review & editing. **José M. Lorenzo:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crfs.2022.02.006.

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