Swarm Intelligence-Based Algorithms within IoT-Based Systems: a Review

Ouarda Zedadra

LabSTIC, 8 May 1945 University. P.O.Box 401, 24000 Guelma, Algeria
zedadra_nawel1@yahoo.fr

Antonio Guerrieri

CNR - National Research Council of Italy Institute for High Performance Computing and Networking (ICAR) Via P. Bucci 7-11C - 87036 Rende(CS) - Italy
antonio.guerrieri@icar.cnr.it

Nicolas Jouandeau

LIASD, Paris 8 University. Saint Denis 93526, France
n@ai.univ-paris8.fr

Giandomenico Spezzano

CNR - National Research Council of Italy Institute for High Performance Computing and Networking (ICAR) Via P. Bucci 7-11C - 87036 Rende(CS) - Italy
giandomenico.spezzano@icar.cnr.it

Hamid Seridi

LabSTIC, 8 May 1945 University. P.O.Box 401, 24000 Guelma, Algeria
seridihamid@yahoo.fr

Giancarlo Fortino

DIMES, Università della Calabria. Via P. Bucci, cubo 41c-87036. Rende, Italy
CNR - National Research Council of Italy Institute for High Performance Computing and Networking (ICAR) Via P. Bucci 7-11C - 87036 Rende(CS) - Italy
giancarlo.fortino@unical.it

Abstract

IoT-based systems are complex and dynamic aggregations of entities (Smart Objects) which usually lack decentralized control. Swarm Intelligence systems are decentralized, self-organized algorithms used to resolve complex problems with dynamic properties, incomplete information, and limited computation capabilities. This study provides an initial understanding of the technical aspects of swarm intelligence algorithms and their potential use in IoT-based applications. We present the existing swarm intelligence-based algorithms with their main applications, then we present existing IoT-based systems that use SI-based algorithms. Finally, we discuss trends to bring together swarm intelligence and IoT-based systems. This review will pave the path for future studies to easily choose the appropriate SI-based algorithm for IoT-based systems.

Keywords: Swarm Intelligence, SI-based Algorithms, Internet of Things, Application of SI-based Algorithms to IoT

---

1. Introduction

The fascinating behaviors observed in nature form an interesting source of inspiration for solving real-world problems. Swarm Intelligence (SI)-based computation is so important in bio-inspired computation which focuses on the collective behavior of decentralized, self-organized systems [1]. It is inspired by the behavior of some animals or insects such as ants, termites, birds, and fishes. It is characterized by its emergent behaviors resulted from the local interactions between individuals and produce intelligent behaviors at the group level [2]. Several SI-based algorithms were proposed and applied successfully in a vast range of problems. Newer ones have been proposed and still under study to prove their efficiency. Unlike the existing reviews on SI, this review paper gathers classic and new SI-based algorithms each with its scope of applications and reports them in a brief and concise way. This can help the readers to easily localize their research by providing them with direct access to the related literature. Also, this review might be used as an initial reading point to explore many SI-based algorithms and related IoT-based applications.

Internet of Things (IoT) [3] aims at promoting a paradigm according to which everything around us (e.g. traffic lights or water distribution pumps) is transformed into a smart thing with the ability of sensing, processing, communicating and/or actuating and is always connected. It is a research field in which both digital and physical entities (i.e. humans, objects, machines) are interconnected through Internet, thus enabling a whole new class of applications and services. To realize such applications and services, many significant challenges have to be overcome because IoT-based systems are complex and dynamic in nature. Robustness and flexibility make SI a successful design paradigm for algorithms that deal with increasingly complex problems such as IoT-based systems. Thus, SI constitutes a source of inspiration for IoT-based systems that can be modeled as a swarm of simpler devices or can integrate SI-based algorithms to achieve some global goals. In this way, starting from simple rules for individual behaviors and interactions among individuals, a global optimum can be achieved at system-level. This self-organization ability is needed to adapt systems to varying environmental conditions, to scale efficiently, and to provide resilient operation for the sustainability of the system.

This paper presents a review of the literature research works which use SI-based algorithms in IoT-based systems. It is conducted in three phases. In the first one, the objective is the identification of the algorithms and their usage in different problems and domains. Further, we categorize them according to maturity of theory. In the second phase, we present the application of SI-based algorithms to IoT-based systems and at an industry level. In the third phase, we highlight important features of SI which can take benefits if replicated in IoT-based systems and we present some suggestions to be addressed in future research works. A preliminary study has been already done in this context, where we proposed an architecture to integrate and use SI-based algorithms in IoT-based systems [4].

The rest of the paper is organized as follows: in Section 2, we propose two taxonomies: the first consists in the classification of SI-based algorithms based on their "source of inspiration" and the second includes their categorization with respect to the "maturity of theory". Then, we present an overview of existing SI-based algorithms and their scope of application. In Section 3, we present the existing SI-based IoT systems. We discuss, in Section 4, how SI-based algorithms could be applied to IoT-based systems. We conclude the paper in Section 5.

2. Swarm Intelligence Algorithms: an Overview

SI, which is an artificial intelligence discipline, is concerned with the design of intelligent Multi-Agent Systems that take inspiration from the collective behavior of social animals/insects. Even though the modeling of the single individuals of these colonies is non-sophisticated, they are able to achieve complex tasks in cooperation. The term SI was originally conceived as a *buzz word* by Beni in the 1980s, to denote a class of cellular robotic systems. Later, it was used to cover a wide range of studies from optimization to social insects [5].

2.1. Definitions

The origins of SI are embedded in the biological study of self-organized behaviors in social insects [6]. It is defined as any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social living beings, such as ants, termites, birds, and fishes. According to Collins Dictionary, SI is *"an artificial-intelligence approach to problem solving using algorithms based on the self-organized collective behavior of social insects"*. Research on SI can be classified according to different criteria [6]:

1. Nature of the analyzed systems: we distinguish natural SI area where biological systems are studied and artificial SI area where human artifacts are considered.
2. Goals pursued: we distinguish between (1) scientific swarm intelligence which focuses on the understanding of natural swarm systems, and (2) engineering swarm intelligence which focuses on the design and implementation of artificial swarm systems able to solve problems by exploiting conclusions from a scientific stream.

A social insect colony is rather like a decentralized system made of autonomous units that are distributed in the environment which follows simple probabilistic stimulus-response behaviors. The rules that govern interactions among insects are executed on the basis of local information without the need to know global patterns. Organization emerges at the colony level from the interactions that take place among individuals exhibiting these simple behaviors. Because of the simple interactions between individuals, social insects can solve a whole range of problems and respond to external challenges in a very flexible and robust way. Stigmergy is the first concept used to explain the organization of social insects behaviors by Pierre-Paul Grassè [7]. He showed that information coming from the local environment and the work in progress can guide individual activities. Self-organization is a set of dynamical mechanisms whereby structures appear at the global level of a system from interactions among its lower-level components, without being explicitly coded at the individual level.

2.2. Review of SI-Based Algorithms

Many algorithms have been developed depending on different intelligent behaviors of natural swarms such as birds, ants, bees, fireflies, bats and pigeons. In this Section, we classify and summarize the existing SI-based algorithms which include Firefly Optimization Algorithm (FFA) [8], Glow-worm Swarm Optimization Algorithm (GSO) [9], Ant Colony Optimization (ACO) [10], Artificial Bee Colony (ABC) [11], Honey Bee Mating Optimization (HBMO) [12], Roach Infestation Optimization (RIO) [13], Mosquito Host-Seeking Algorithm (MHSA) [14], Social Spider Optimization (SSO) [15], Bacterial Foraging Optimization Algorithm (BFOA) [16], Slime Mould Optimization Algorithm (SMOA) [17], Particle Swarm optimization (PSO) [18], Cuckoo Search Algorithm (CSA) [19], Pigeon Inspired Optimization (PIO) [20], Bat Algorithm (BA) [21], Shuffled Frog Leaping Algorithm (SFLA) [22], Frog Calling Algorithm (FCA) [23], Artificial Fish Swarm Algorithm (AFSA) [24] , Fish School Search (FSS) [25], Dolphin Echolocation Algorithm (DEA) [26], Grey Wolf Optimizer (GWO) [27], Lion-inspired algorithms: Lion's [28], Lion Pride Optimizer (LPO) [29], Lion Optimization Algorithm (LOA) [30], Monkey Algorithm (MA) [31], and Cat Swarm Optimization (CSO) [32]. The common characteristics of these algorithms is that they are all inspired from animals, population-based and iterative. However, they differ by their exploration and exploitation of work space.

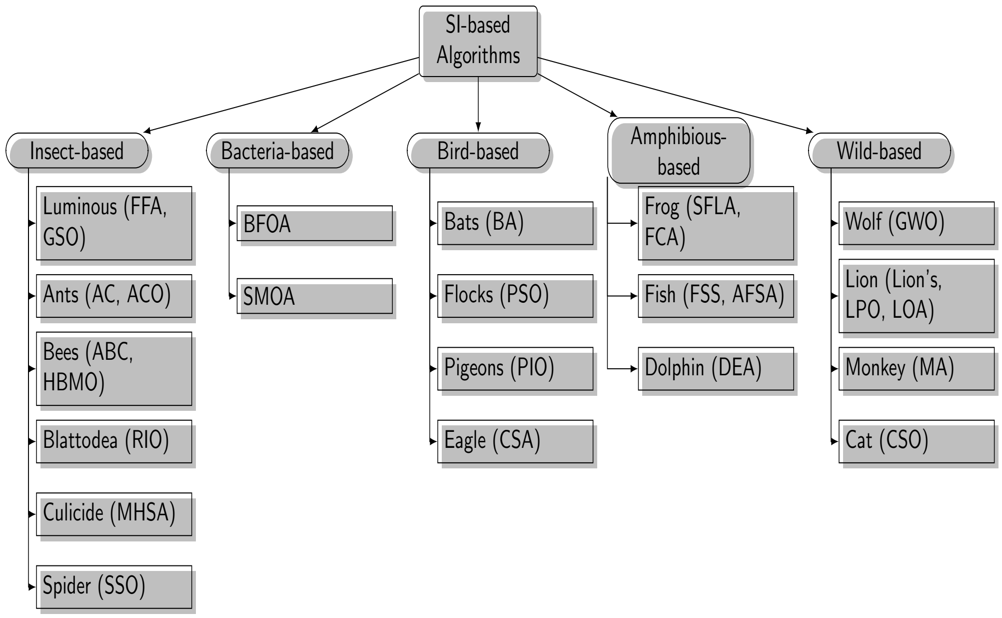

Figure 1: Taxonomy of SI-based Algorithms according to their source of inspiration.

Here, we present relevant applications of the algorithms based on published scientific literature. There exists Python implementations/frameworks of SI-based algorithms such as: EvoloPy [1], NiaPy [2], SwarmPackagePy [3].

In Table 1, we classify SI-based algorithms and present their scope of application according to a proposed taxonomy (see Figure 1).

Table 1 is composed of six column used to present: the category of source of inspiration (*A1*), the source of inspiration family (*A2*), name of the proposed algorithm (*Algorithm- Alg*), reference in which the algorithm first appeared (*Proposed-Pro*), specific behavior from which the algorithm is inspired (*Inspired*), and the different application domains of the algorithm (*Application Area*).

[1] `https://github.com/7ossam81/EvoloPy`
[2] `https://github.com/NiaOrg/NiaPy`
[3] `https://github.com/SISDevelop/SwarmPackagePy`

A1	A2	Alg	Pro	Inspired	Application Area
Insect-based	Luminous	FFA	[8]	Flashing behavior of fireflies.	Electrical load forecasting, estimation of water resources, heart disease prediction, image processing (segmentation of brain tissues, multilevel color image thresholding), clustering and classification (protein complex identification, hyperspectral image classification), Travel Salesman Problem (TSP), Job Scheduling Problem (JSP), vehicle routing, routing in Wireless Sensor Networks (WSNs), decomposition for RFID networking planning, big data optimization, optimize mobile robot navigation, learning parameters in deep belief network, train Artificial Neural Network (ANN), feature selection and fault detection, numerical optimization, Load Frequency Control (LFC).
		GSO	[9]	Foraging behavior of glowworm swarm.	TSP, forecasting daily global solar radiation, prediction of remaining useful life for lithium battery, image processing (multi-level thresholding, MRI brain lesion segmentation), vehicle routing, energy efficient sensor movement in WSNs, optimal power flow, Knapsack Problem (KP), clustering, multi-spectral satellite image classification, vibrant fault diagnosis for hydro-turbine generating unit, air pollution source identification, economic load dispatch problems (ELD).
	Ants	ACO	[10]	Foraging behavior of ants.	Intrusion detection, predictive control for nonlinear processes, anomaly detection, treating missing values in big data sets, resource discovery in peer to peer networks, dynamic routing (railway junction rescheduling, path discovery in WSNs, vehicle routing, train routing selection), 3D printing process, TSP, flexible JSP, indoor evacuation guidance, robotics (wall following, navigation in cluttered environment, path planning), medical image denoising, satellite image segmentation, water allocation, hyperspectral image classification, data transmission in WSNs, optimization for RFID reader deployment, node search for WSNs, auto-disturbance rejection control, solving Resource-Constrained Project Scheduling Problems (RCPSP), clustering for ego network analysis, solving constrained satisfaction problems (video games).
	Bees	ABC	[11]	Foraging behavior of honey bee.	Image watermarking optimization, gray image segmentation, JSP, economic dispatch problem, KP, optimizing network attacks, multiple sequence alignment, improving the convolutional ANN, training ANN, text clustering, forecasting displacement of hydro-power dam, 3D protein structure prediction, travel time estimation, prediction of water temperature in prawn cultures, route planning algorithm for use in pedestrian navigation at night, vehicle routing, route optimization, robot path planning, design of controller for robot manipulator, robot wall following, ground water management, modeling of a solar collector, damage detection, RFID tag design, feature selection, placement of relay nodes in WSNs, crowd evacuation in buildings, design water quality monitoring networks in river basins.
		HBMO	[12]	Marriage in real honey-bee.	Global unconstrained optimization, localization and sizing of flexible AC transmission system devices in power system, searching for common patterns on protein sequences, loss minimization in distribution systems, course timetabling problem, multi-machine power system stabilization, routing, characterization of a microwave transistor, design of water distribution networks, materialized view selection, design of side sway steel frames, feature selection, mining the induction rules, JSP, clustering in WSNs, hydro-power optimization problem.
	Blattodea	RIO	[13]	Communication behavior of cockroaches insects.	Benchmark mathematical functions optimization, constrained engineering optimization problems, improve swarm stability.
	Culicide	MHSA	[14]	Host-seeking behavior of mosquitoes.	TSP, Multi-Depot Vehicle Routing Problem, targeting a dual detector of skin.

	Spider	SSO	[15]	Foraging behavior of social spider.	Electromagnetic optimization, proportional integral derivative controller optimization, maximizing reliability of grid transaction processing system, home energy management system, multi-level thresholding segmentation, image fusion, clustering text documents, calibration of fractional fuzzy controllers, constrained optimization, solving minimum number attribute reduction problem, solving transmission expansion planning problem, multi-modal function, KP, solving conduction heat transfer problem, solving integer programming and minmax problems, economic load dispatch problem, sensor deployment in WSNs, community detection, web services selection.
Bacteria-based	Bacteria	BFOA	[16]	Foraging behavior of Escherichia coli bacteria.	Cellular manufacturing in supply chain, controller design for electro-hydraulic system, home energy management, power quality improvement in micro grid, optimal controller design for battery energy storage, collaborative mobile sensing in WSNs, heterogeneous network security enhancement, extraction of photovoltaic module parameters, protein structure prediction, learning of Bayesian networks, medical image registration, finding the optimal threshold values for edge detection, image compression, edge detection, vehicle routing, routing in WSNs, optimization of graph-based problem, dynamic facility layout problem, classification of plant leaf diseases, clustering-based heed protocol for WSNs, signal classification, dynamic economic dispatch, multiple sequence alignment, robot path planning, RFID network planning, nurse scheduling, hydro-thermal-wind generation system, face recognition, feature selection.
		SMOA	[17]	Foraging behavior of the amoeba dictyostelium discoideum.	Graph optimization problems, numerical optimization, shortest path problem, approximating highways, solving linear transportation problem, path planning, electronic circuit model for maze solving computations, transport networks and cellular automata.
Bird-based	Flocks	PSO	[18]	Movement of fish schools and bird flocks.	The quadratic assignment problem (QAP), data clustering, training ANN, time series prediction, image contrast enhancement, bilinear spectral unmixing of hyperspectral images, remote sensing image registration, split delivery vehicle routing, remote sensing of water quality, optimization of the building energy performance, modeling of super capacitors, design of a heat exchanger working with organic nanofluids, identification of groundwater contamination sources, charger deployment in wireless rechargeable sensor networks, photovoltaic systems, optimization of power allocation in wireless location network, node placement problem in Wireless Mesh Networks, optimization of water distribution networks, fault detection and isolation in GPS receiver autonomous integrity monitoring, navigation satellite selection, cancer classification, multi-robot path planning, rule mining, KP, primary user emulation attack detection, feature selection for high-dimensional classification, optimization driven urban traffic light scheduling model, modeling of ash agglomerating fluidized bed gasifier, solving the obnoxious p-median problem, solving data allocation problem, solving cell formation problem, solving multi-objective flexible JSP, solving the optimal power flow problem, effective cluster head selection in WSNs.
	Eagle	CSA	[19]	Breeding behavior of cuckoo bird.	Grayscale image enhancement, feature selection, data clustering, electrical energy output prediction, solving inverse geometry heat conduction problems, parameter estimation of activated sludge process, clustering protocol for WSNs, manufacturing cell formation problem, parallel batch processing machines, cost forecasting of substation projects, nonlinear friction and dynamical identification for a robot manipulator, color image multilevel thresholding [], optimization of colour image watermarking, multispectral satellite image denoising, time delays estimation of chaotic systems, optimal placement of actuators problem, ANN training, JSP, TSP.

	Pigeons	PIO	[20]	Homing behavior of pigeons.	Multidimensional KP, image matching, image restoration, image fusion, control parameters optimization in automatic carrier landing system, prediction control for unmanned air vehicles, explicit nonlinear model predictive controller for quadrotor, air robot path planning, detecting protein complexes from dynamic protein-protein interaction network, clustering analysis problems, flying vehicle longitudinal controller, design, energy management.
	Bats	BA	[21]	Echolocation characteristics of micro-bats.	Continuous optimization, combinatorial optimization and scheduling, classification, clustering, data mining, load frequency controller design for nonlinear interconnected power system, economic dispatch, training ANN for digital image compression, 2D tsallis entropy for image segmentation, clustering, reducing electrical power consumption of air conditioning systems, JSP, image thresholding, localization of WSNs, image compression, multi-step-ahead wind speed forecasting, solving a medical goods distribution problem with pharmacological waste collection, asymmetric TSP, KP, trajectory optimization for an autonomous mobile robot, capacitated vehicle routing problem.
Amphibious-based	Frog	SFLA	[22]	Leaping and shuffling behavior of frogs.	Design optimization of transverse flux linear motor, improve network life time in WSNs, load balancing of gateways for WSNs, loss minimization, short-term solar power prediction, rectangular packing problem, dynamic emergency vehicle dispatching, feature selection for biomedical data, JSP, design of Raman fibre amplifier, prediction of water quality parameters, regional air pollution control, Identification of noise in multi noise plant, cooperative spectrum sensing in 5G network, face recognition, spectrum aggregation and allocation for cognitive radio networks.
		FCA	[23]	Japanese tree frog calling behavior.	Solving connected dominating set, energy efficient control for WSNs.
	Fish	AFSA	[24]	Natural social behavior of fish schooling.	ANN training, data mining, image processing, optimization of ejector geometric parameters for PEM fuel cell, cutting stock problem, parameter estimation of a composite production function, allocation for cognitive radio networks, routing for WSNs, path planning of mobile robots, optimization of renewable energy sources in a microgrid, stroke detection, energy optimization in home energy management system, protein folding prediction, time series forecasting, solving a multi-objective fuzzy disassembly line balancing problem, optimal chiller loading for energy saving, power allocation algorithm for Multiple-Input and Multiple-Output-Orthogonal Frequency-Division Multiplexing (MIMO-OFDM) relay underwater acoustic communication, evacuation behaviors and link selection.
		FSS	[25]	Social behavior of biologic fish	Finite element model updating, feature selection, solving dynamic problems, solving assembly line balancing problems, lighting consumption optimization, image channel-optimized vector quantization, constrained optimization, data clustering task on graphics processing units.
	Dolphin	DEA	[26]	Biological characteristics of dolphin	Seismic layout optimization of steel braced frames, design of cantilever retaining walls, solving optimal reactive power dispatch problem, solving manufacturing cell design problems.
Wild-based	Wolf	GWO	[27]	hunting technique and the social hierarchy of grey wolves	Speed ripple reduction at low speed operation of Permanent Magnet Synchronous Machine (PMSM) drives, feature selection, clustering for vehicular ad-hoc networks, load frequency control of interconnected power system, community detection, economic dispatch problem, heat and power dispatch with cogeneration systems, satellite image segmentation, constrained optimization problems, distributed compressed sensing, iris recognition, human recognition, multi-criterion optimization, multilevel image thresholding, prediction of polyphenol content in inward tea leaves, economic load dispatch problems, node localization problem in WSNs, wide-area power system stabilizer design, wide-area power system stabilizer design, color difference classification.

	Lion	Lion's	[28]	Lion's behavior: territorial defense and territorial takeover.	Single variable and multi-variable cost function problems, large scale bilinear system identification.
		LPO	[29]	Lion pride behavior.	design of double-layer barrel vaults.
		LOA	[30]	Lion cooperation characteristics.	Community detection, data clustering, extracting liver from the abdominal CT images.
	Monkey	MA	[31]	Behavior of a monkey climbing trees.	Solving specific benchmarking functions, solving uncapacitated facility location problem, robot path planning and vehicle routing problems, global numerical optimization, calibration of an anisotropic continuum model, KP.
	Cat	CSO	[32]	Natural behavior of cats.	Array pattern optimization for steerable circular isotropic antenna array, optimized cluster head selection in WSNs, solving set covering problems, JSP, TSP, optimal infinite impulse response filter design, photovoltaic system, parameter identification and sensitivity analysis of solar cell models, noise removal from computed tomography images, feature selection for big data classification, groundwater management, fast convergence of multimodal functions, solving the high school timetabling problem, routing for vehicular ad-hoc networks, allocating the sink node in WSNs, facial emotion recognition, alcohol use disorder identification.

Table 1: Classification of SI-based literature works according to the taxonomy proposed in Figure 1.

From Table 1, we classify SI-based algorithms into three categories based on the maturity of the theory (see Figure 2):

1. **Category 1- Ready to Adopt**: envelops the old proposed algorithms, highly used and standardized by the scientific community, applied in several domains. These algorithms captured a great attention from the scientific community. The algorithms in the following belong to this category: ACO, PSO, ABC, and BFOA.
2. **Category 2- Under Exploitation**: includes the new generation of proposed algorithms which are mature in theory but rather applied to limited domains. These algorithms are already capturing attention from the scientific community but they still need to enlarge their scope of applications and explore other not yet explored applications. The algorithms concerned are FFA, HBMO, SSO, CSA, BA, PIO, SFLA, AFSA, GWO, and CSO.
3. **Category 3- Under Exploration**: This category includes the newer proposed algorithms which are not yet mature in theory. The algorithms in this category did not capture the attention of the scientific community but could be interesting. These algorithms need further understanding of

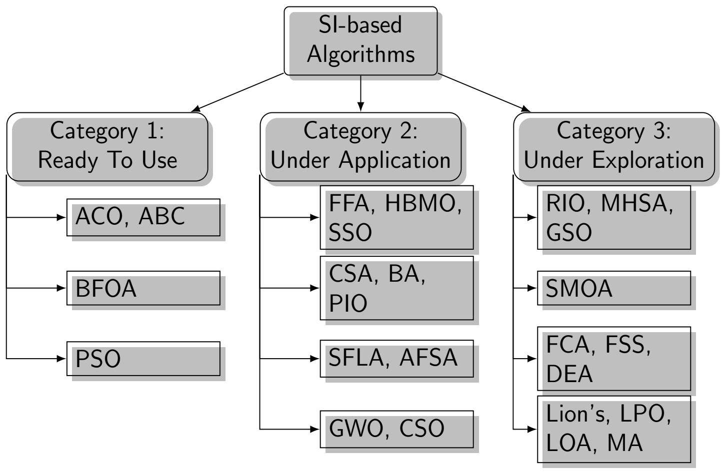

Figure 2: Categorization of SI-based Algorithms according to their maturity of theory.

their principles, reinforcing their theory. The algorithms included in this category are RIO, MHSA, GSO, SMOA, FCA, FSS, DEA, Lion's, LPO, LOA, and MA.

In order to show the significant and practical use of SI in real-world applications, we present some existing applications shown on professional websites [33]:

- The first practical application is the add of the so-called *car-to-x* services to cars in certain markets [4]. Vehicles equipped with *e-SIMs* can exchange relevant traffic information in real-time via the mobile-phone network.

- Continental adapted the vehicle-to-vehicle information system called *eHorizon* for automobiles and motorcycles, announcing a new version of the system designed specifically for two-wheelers [5]. The system gathers data

[4]https://www.whichcar.com.au/car-advice/swarm-intelligence-for-autonomous-cars-explained

[5]http://blog.motorcycle.com/2016/12/06/products/continental-bringing-ehorizon-swarm-intelligence-system-motorcycles/

from multiple vehicles into the cloud which sends the information back to individual vehicles.

- The Defense Advanced Research Agency (DARPA) is planning to overwhelm enemies with swarming drones [6]. It is developing a technology that allows drones to deploy hordes of other drones that perform a series of functions to destroy the target in unison.

Slowik [33] and Karkalos et al. [34] have discussed the main applications of SI-based algorithms in industry. Also, we made a selection from Table 1 of applications that we judge relevant for industry applications: optimization of the building energy performance, photovoltaic systems, optimization of water distribution networks, fault detection and isolation in GPS receiver, power flow problem, cellular manufacturing in supply chain [35], controller design for electro-hydraulic system, home energy management, power quality improvement in micro grid, optimal controller design for battery energy storage, ground water management, modeling of a solar collector, vibrant fault diagnosis for hydroturbine generating unit [36], load frequency control of interconnected power system, optimization of renewable energy sources in a microgrid [37], design optimization of transverse flux linear motor [38], reducing electrical power consumption of air conditioning systems, RCPSP problems [39].

3. SI-Based IoT applications: an Overview

In this Section we present researches related to the use of SI-based algorithms in IoT applications. Table 2 summarizes the reviewed works. It is composed of six columns used to show: the algorithm on which the specific work is based on (*Axis1*), aim of the research (*Aim*), name of the proposed algorithm (*Algorithm*), type of experimentations (*Experimentation*) and the main characteristics of each work (*Highlights*). In the following subsections, the reviewed IoT systems have been categorized with respect to the used SI algorithm.

[6]http://blogs.discovermagazine.com/drone360/2015/04/06/darpas-swarming-drones/

Axis1	Paper	Aim	Algorithm	Experimentation	Highlights
AC	[40]	Search route in routing processing of IoT	AC	Computer Simulation	Used to overcome the problems: (1) more network nodes, (2) more variable network structure, (3) reduce the broadcast storm effectively
	[41]	Gathering data from multiple sensors, automate the processing	H-ABC	3D printed environment	H-ABC realize the necessary data transformation based on ABC algorithm
	[42]	cluster sensors based on their context information	AntClust	Computer Simulation	The ant-based proposed algorithm aims at clustering sensors into specific classes based on their context information. A user query will be only forwarded to the most appropriate clusters
	[43]	Trustable object selection	Modified AC	Computer Simulation	Modified AC used to calculate the trust value
	[44]	Path routing problem	AC	None	AC is represented by a Multi-Agents System. Each artificial ant is represented by a vehicle and the urban traffic network by the graph-theoretic approach
	[45]	Tourist mobility	ANT	Computer Simulation	ANT is a route ranking mechanism. It uses a stigmergy-based routing which corroborates the benefits of stigmergy to detect live Points Of Interests (POIs)
ACO	[46]	Find a cycle route in an automatic way	MOACO	Computer Simulation	MOACO is used to resolve the model of the problem.
	[47]	Identify Sybil's in communities of SIoT	ACO	Computer Simulation	ACO is employed along with node attribute similarity to efficiently detect communities
	[48]	Routing in IoT	ACO	Computer Simulation	A Multi-Agent Systems architecture is used where local agents use ACO to find the optimal path in the local networks and global agents control the best ACO to use
	[49]	Identify disruption	IACO	Computer Simulation	ACO and some adjustments to pheromone trail, crossover and mutation to obtain new schedule quickly
	[50]	Predict the best route in VRP	–	Computer Simulation	ACO was used in one module of the system to solve the VRP.
	[51]	Optimize the resource indexing of IoT	–	Computer Simulation	After constructing structure model of cluster resource indexing nodes of IoT, the strong ability of global optimization of ACO os used to realize resource indexing optimization.
	[52]	Improve IoT routing algorithm	–	Computer Simulation	The proposed algorithm is used to enhance the packet delivery rate and avoid the overlapped intersections using the multi-agent technology
	[53]	Smart waste management system based-IoT	–	Real experiment	The ACO is used to decide the most efficient waste collection route to garbage container regarding their level.
	[54]	Optimization in routing protocol	–	Computer Simulation	Authors implemented ACO and provided a mechanism to change over the ailing link to another efficient link.

PSO	[55]	Physiological signal processing of multi-sensor android remote medical care system	IPSO	Real experiment	Used to increase the measurement radio effect precision for multi-physiological signals fusion in android medical care IoT system
	[56]	Platform information fusion in WSN	IPSO	Real experiment	They developed an experimental monitoring system using a variety of different sensors to construct IoT systems although integrating various sensors together to test signal processing and data fusion
	[57]	Data management and mining technologies to manage and analyze data	DMFSO	Computer Simulation	the sensing of agents is inspired by the ACO and PSO, agents act like swarm by sharing information and experience
	[58]	Fault tolerance routing problem	IEIFTA algorithm	Computer Simulation	They recover the routing for the path failure and achieve energy conservation by avoiding unnecessary retransmission
	[59]	Building energy management system	BEMS system	Computer Simulation	APSO optimizer is used to improve the MAS's capacity in exploiting the building's flexibility.
	[60]	Recovery of the end-of-use products	Novel PSO	Computer Simulation	Inertia weight method of PSO is used to evaluate revenue to find good solutions
	[61]	optimize the MEC calculation offloading decision	HQPSO	Computer Simulation	A computing resources allocation scheme based on Hybrid Quantum-behaved Particle Swarm Optimization is proposed.
	[62]	Find the best position and operating channel of SBSs	–	Computer Simulation	Find the optimal location and operating channel of SBSs of loT sensor networks to manage the interference and resource allocation.
	[63]	Maximizing the profit of the broker while minimizing the response time of the request and the energy consumption	MOPSO	Computer Simulation	A novel optimization problem is formulated to solve how to maximize the broker profit and to minimize the energy consumption of the system and response time of users. The MOPSO is used to solve the formulated problems.
	[64]	Tuning cascade control system in an IoT Environment	–	Real experiment	PSO is used to control the cascaded processes.
ABC	[65]	Radio frequency identification network planning problem	Bat-OM	Computer Simulation	Search function of Bat is improved by incorporating onlooker mechanism from ABC
	[66]	Optimization of service composition and selection	CMABC	Computer Simulation	Authors build a service model and use CMABC to accomplish its instantiation
	[67]	Solve distributed access problem for virtual data centers	MSACM	Real experiment	Designs an optimal scheduling algorithm of group migration based on the combination scheme between ABC and chaos searching theory
	[68]	Service optimization problem (SOPs)	S-ABC	Computer Simulation	Used to enhance the efficiency and effectiveness of solving SOPs

	[69]	Providing vertical handover management in heterogeneous WSNs	IABC	Computer Simulation	A handover triggering scheme is proposed based on the data rate required by the applications running on the mobile node device and IABC is used for selection
	[70]	Features selection in e-health Big Data IoT	HABC	Computer Simulation	ABC is used to select features and process large data sets.
	[71]	Resolve scheduling problem	HABCA-EST	Computer Simulation	HABCA-EST ensures rapid improvement in the fitness value of each food source due to efficient initialization, device scheduling of more critical objects, and full utilization of redundancy information using an EST of SDs.
	[72]	Cluster head selection	–	Computer Simulation	GSA algorithm updates the position and velocity of the agents until it reaches the stopping condition. Alternately, the proposed GSA algorithm applies the concept of update procedure of employed bee phase of ABC algorithm.
BFOA	[73]	Energy efficient routing protocol in IoT	IBFO	Computer Simulation	IBFO is responsible of the key selection.
	[74]	Demand side management in smart buildings	HBG	Computer Simulation	The BFA emphasizes on a local search whereas, the GA focuses on a global search.
BA	[75]	Mathematical analysis of BLDC motor parameter estimation	–	Computer Simulation	BAT optimization algorithm methods are implemented for the estimation of parameters of the BLDC motor using IoT.
	[76]	Big data sensing systems in IoT	–	Computer Simulation	BA variant is capable of not only enhancing the optimization performance and convergence speed but also enlarging the global search space.
AFSA	[77]	smart parking	-	Computer Simulation	AFSA is used to build the recommendation mechanism which helps drivers to find a parking space quickly.
HBMO	[78]	Cognitive radio frequency sensor networks routing	HBMO-based clustering	Computer Simulation	Decreases the probability of packet loss and preserves high link quality in harsh smart grid spectrum environments
Gossip	[79]	reduce sewer flooding and combined sewer overflows	DRTC	Computer Simulation	DRTC is a decentralized real-time control based on a Multi Agent paradigm and on a gossip-based algorithm. It was applied to the urban drainage system in the city of Cosenza, Italy.
PIO	[80]	Optimization and enhanced differential evolution in Smart Grid	–	Computer Simulation	PIO is used to deal with electric consumption, electric bill and peak-load-reduction.
GWO	[81]	Energy optimization in Smart Grid	–	Computer Simulation	GWO anf BFOA are used to optimize the HEMS.
CSA	[82]	Coverage optimization of VLC in Smart Homes	ICS	Computer Simulation	The proposed ICS algorithm employed chaos theory to optimize the structure of the initial solutions .

Table 2: SI-based IoT literature works summary

3.1. AC-based IoT systems

Lu and Hu [40] use Ant Colony (AC) algorithm to search for a specific route in routing processing of IoT. The algorithm helps in reducing: the number of used network nodes, the variability of network structure and the broadcast storm effectively.

Chamoso et al. [41] address the problem of gathering data from multiple sensors, automate the processing and generate useful information that can be used effectively in the automatic managing of traffic flow in large cities. Authors propose a new open platform, designed for the integration of heterogeneous sensors, using lightweight agents and intelligent management of automated environment using heavyweight agents. These latter ones are specialized in information fusion. Specialized agents use H-ABC (Hierarchical Ant-based Control) to apply the necessary data transformations.

Ebrahimi et al. [42] propose a new approach to improve the efficiency of context-aware sensor search in IoT. The aim is to cluster sensors with similar context information into Sensor Semantic Overlay Networks (SSONs). Authors proceed by grouping sensors based on their types to create SSONs. Then, they cluster sensors regarding their context information using an ant-based algorithm called AntClust. Finally, they use adjustments to reduce the cost of sensor search process.

A modified AC algorithm proposed by Suryani et al. in [43] is used to calculate the trust value in order to determine whether an object is trusted or not. Authors made modifications for the pheromone deposit as trust value increase and pheromone evaporation as trust value reduction.

To solve the routing problem of the urban traffic in an IoT system, AC is used by Sabbani et al. [44]. It is represented by a Multi-Agents System and each artificial ant by single computational Vehicle Agent, and the urban traffic network by the graph-theoretic approach.

López-Matencio et al. [45] propose ANT, a guiding system for tourists based on the foraging mechanism of ants. ANT enables unique features for tourist navigation by using an artificial stigmergy algorithm. It provides tourists with:

(1) the serendipitous discovery while providing the information to the rest of participants, and (2) route decisions using the data provided by the server.

3.2. ACO-based IoT systems

Cosido et al. propose in [46] a method to find a cycle route in an automatic way (area of Santander). The model uses a combination of soft computing and geographic information system techniques. The resulting multi-objective NP-hard problem is resolved with a population-based bio-inspired meta-heuristics (adaptation of the Ant Colony Optimization (ACO) and Multi Objective Ant Colony Optimization (MOACO) algorithms).

Social IoT (SIoT) is a new paradigm that integrates IoT and social networks. A major threat with social things is Sybil attacks. Kowshalya and Valarmathi [47] used ACO algorithm along with node attribute similarity to efficiently detect communities.

Said proposes in [48] a routing algorithm to optimize the selection of the best path for the transmitted data within IoT. Using different networks means that many ACO algorithms should be applied. Each network has its own ACO for regulating the routing process. Authors propose an algorithm to control the use of ACO algorithms and to determine a solution for overlapped areas.

Jiang et al. [49] design a real-time analyzer to identify the disruption and propose a recovery model to deal with it. Authors improved ACO (IACO) to obtain new schedule quickly. They use the classical ACO with some adjustments to pheromone trail, also crossover and mutation are adopted in IACO to avoid premature convergence.

Bellini et al. [50] develop an IoT-based and real-time waste monitoring system. The ACO was used to predict the best route that solves the Vehicle Routing Problem (VRP). The road network was described by a graph where the arcs are roads and vertices are junctions between roads.

Hong et al. [51] propose an algorithm for cluster resource indexing of IoT on improved ACO. The improved ACO is used to crawl and capture cluster information in IoT. According to the ant colony trajectory information, the velocity and position of the cluster resource indexing of IoT are updated, and the balanced ACO is used to carry out global search and local search for resources.

Mahalaxmi and Rajakumari [52] propose a routing algorithm within the IoT system. The proposed algorithm divides the IoT environment into different areas depending on the network type. Then, it selects the ACO algorithm that was suitable for each network. The proposed algorithm considers the routing problem in the overlapped areas that may arise in the IoT system. A dual agent has been developed to produce an optimized algorithm from different ACO algorithms.

Oralhan et al. [53] propose a smart waste management system based Internet of Things (IoT) technologies and apply it to waste collection management in a town in Kayseri, Turkey. Authors designed a garbage container integrated sensors for measuring the fill level of a container, temperature, and ratio of carbon dioxide inside the container. All collected data is transmitted to the waste management software. Then the ACO is used to decide the most efficient waste collection route to garbage container, which will be delivered to garbage truck drivers cellular smart tablet.

Thapar and Batra [54] propose an approach whereby ACO is used to optimize the path energy consumption, i.e., the sum of energy consumed by the transmitting node during transmission and energy consumed by listening node during listen process, over the expected transmission count metric-based objective function.

3.3. PSO-based IoT systems

Sung and Chiang [55] propose an Improved Particle Swarm Optimization algorithm (IPSO) to increase the measurement radio effect precision for multi-physiological (body weight, body fat, blood pressure, blood oxygen, heart rate) signals fusion in Android medical care IoT system computing. The developed system can be used in hospitals to collect personal data to monitor the physical healthcare information system.

Sung and Hsu [56] propose a non-linear weight with decreasing strategy to implement the IPSO. This latter is used to perform information fusion in a multi-sensor network. This study developed an experimental monitoring system using a variety of different sensors to construct IoT systems by integrating various sensors together to test signal processing and data fusion.

A discussion on how to apply data mining and computational intelligence to Future IoT (FIoT) is given in [57]. Authors propose an intelligent Data Management Framework based on Swarm Optimization (DMFSO), where each sensor is associated with a simple agent. The sensing of each agent is inspired by ACO and PSO. Agents act like a swarm by sharing information and experience between particles. Authors use a simple example of smart home to show the exchange of information and making decisions to elaborate the basic concepts of DMFSO.

Luo et al. propose in [58] an Improved Efficient and Intelligent Fault-Tolerance Algorithm (IEIFTA). It is used to provide a fast recovery mechanism from path failure due to energy depletion or physical damage with an alternative path. It chooses a path with the optimal fitness from the optimal sensor nodes.

Hurtado et al. propose in [59] an inter-operation of the smart grid (SG) building energy management systems (BEMS). The developed hierarchical agent structure allows lower level agents abstracting the information of their immediate environment into the form of single value information blocks for the higher level agents. A PSO optimizer is proposed to improve the MASs capability in exploiting the buildings flexibility for the SG.

Fang et al. propose in [60] a novel PSO based on two heuristic methods for the recovery of the end-of-use products problem. The inertia weight method of PSO is applied in the encoding scheme to evaluate the total revenue to find good solutions where a particle is represented by the raw material inventory level in manufacturer.

Dai et al. [61] propose a computing resources allocation scheme based on Hybrid Quantum-behaved Particle Swarm Optimization (HQPSO). Authors consider the mobile edge computing (MEC) [83] calculation offloading decision problem. They mathematically model the content of the scene of a wireless communication system with MEC calculation offloading technology. Then the HQPSO is used to optimize the MEC calculation offloading decision.

Jinyi et al. [62] propose a distributed scheme that determines the optimal location and operating channel of SBSs of loT sensor networks to manage the interference and resource allocation. The PSO is used to find the best position and operating channel of SBSs.

Kumrai et al. [63] propose a multi-objective particle swarm optimization (MOPSO) scheme for cloud brokering to find the appropriate connections between clients and service providers to optimize the energy consumption of service providers, the profit of the cloud broker and the response time of requests from clients.

Sangeetha et al. [64] are involved in making a stand-alone cascade control system as an Internet-enabled one without the advent of a dedicated instrument server. The cascaded processes, such as level and flow are independently controlled by PSO proportional, integral-derivative (PID) and proportional-integral (PI) controller, respectively.

3.4. ABC-based IoT systems

Tuba and Bacanin [65] propose a hybridized Bat algorithm with the Artificial Bee Colony algorithm (ABC) to solve Radio Frequency Identification network planning problem. The search procedure of Bat is improved by incorporating onlooker mechanism (BA-OM).

A cross-modified ABC (CMABC) is proposed in [66], to achieve the optimal solution services in an acceptable time and high accuracy. CMABC is used for optimization of IoT service instantiation. Authors build a service model and use CMABC to accomplish its instantiation.

Yi et al. in [67] propose a mechanism to improve the access efficiency of service requests of massive WSNs and make full use of the variable resources at the data access center for IoT. Authors design an optimal algorithm of group migration based on the combination scheme between ABC and chaos searching theory.

Xu et al. [68] consider service optimization problem (SOP). They propose a set of service domain-oriented ABC algorithms (S-ABC) based on the optimization mechanism of ABC and the influence of the service domain features.

The vertical handover management in heterogeneous WSNs is considered in [69]. The network selection is performed by considering various parameters (end-to-end delay, jitter, bit error, packet loss) used by ABC to select the target network with minimum handover delay and time.

Ahmad et al. [70] propose Hadoop-based ABC (HABC) algorithm for feature selection in e-health Big Data IoT. The system is implemented using enhanced MapReduce and HABC algorithm. HABC is used to select features and process large data sets and MapReduce to process other data with Hadoop ecosystem to achieve the efficiency and real-time processing.

Muhammad et al. [71] propose a Hybrid Artificial Bee Colony algorithm with an Efficient Schedule Transformation (HABCA-EST), for searching the optimal number of disjoint subsets to enhance the lifetime of a wireless smart devices network for target coverage application.

Reddy and Babu [72] propose a novel method which combines Gravitational Search Algorithm (GSA) and Artificial Bee Colony (ABC) algorithm to accomplish the efficient cluster head selection. It considers the distance, energy, delay, load, and temperature of the IoT devices during the operation of the cluster head selection process.

3.5. BFOA-based IoT systems

Reddy and Babu [73] propose a novel method which combines Optimal Secured Energy Aware Protocol (OSEAP) and Improved Bacterial Foraging Optimization (IBFO) algorithm for secured energy efficient routing. First, the virtual topology on the basis of network topology is industrialized. All the sensor nodes in the network topology are clustered with the help of a Fuzzy C-Means clustering algorithm. In order to facilitate the protected transfer of messages from the source node to destination node group, key distribution procedure is engaged in OSEAP. The key selection is performed the IBFO algorithm.

Khalid et al. [74] propose a home energy management system which employs load shifting strategy of demand side management to optimize the energy consumption patterns of a smart home. It aims to manage the load demand in an efficient way to minimize electricity cost and peak to average ratio while maintaining user comfort through coordination among home appliances. Therefore, authors propose a hybrid optimization technique combining the GA and the BFOA algorithms (HBG).

3.6. BA-based IoT systems

Balamurugan and Mahalakshmi [75] present modeling and speed control of Brushless DC (BLDC) motor. Then a parameter estimation for BLDC motor is presented. Deep Neural Network (DNN) and BAT optimization algorithm methods are implemented for the estimation of parameters of the BLDC motor using IoT.

Cui et al. [76] report a new velocity update equation in conjunction with the centroid strategy to optimize the cluster-head node selection for Low energy adaptive clustering hierarchy (LEACH) protocol to save the energy cost. Authors propose a new variant of bat algorithm combined with centroid strategy. This new BA variant is capable of not only enhancing the optimization performance and convergence speed but also enlarging the global search space.

3.7. Other SI-based IoT systems

Horng proposes in [77] an innovative adaptive recommendation mechanism for smart parking. It helps drivers to find a parking space quicker and reduce traffic congestion by using cellular automata mechanism and cognitive radio network model. Authors adopt the Artificial Fish Swarm Algorithm to build this two parts parking recommendation mechanism.

Fadel et al. propose in [78] an HBMO-based routing algorithm to be used in cognitive radio sensor networks. The proposed algorithm decreases the probability of packet loss and preserves high link quality among sensor nodes in harsh smart grid spectrum environments.

Garofalo et al. propose in [79] an urban drainage network equipped by sensors and a series of electronically movable gates controlled by a decentralized real-time system based on a gossip-based algorithm which aims to reduce sewer flooding and combined sewer overflows. A gossip-based algorithm is used for computing the average of the degree level as measured by all the agents of a generated network. At convergence stage, the estimated average value is exploited by each gate-agent for tuning its gate so as to bring water levels closer to that average. The algorithm ensures the fault-tolerance property and the system keep working even if an unforeseen event dramatically changes some structural properties (as in the case of obstructions, blockages, damages etc.).

Amjad et al. [80] investigate Pigeon Inspired Optimization(PIO) for Demand Side Management (DMS) in smart grid. PIO is proposed by authors to deal with electric consumption, electric bill, and peak-load-reduction. The aim was to minimize costs, peak to average ratio, and enhance the user comfort by applying Dynamic Pricing Signals (DPS).

Hassan et al. [81] evaluated the performance of Home Energy Management System (HEMS) using Grey Wolf Optimization (GWO) and Bacterial Foraging Algorithm (BFA) techniques inspired by the nature of grey wolf and bacterium respectively. For this purpose, home appliances are categorized into two classes on the bases of their power consumption pattern. GWO gives optimized results as well as fast convergence.

Sun et al. [82] propose an improved cuckoo search (ICS) algorithm to solve the visible light communication (VLC) power coverage problem in smart homes. The proposed ICS algorithm uses chaos theory to optimize the structure of the initial solutions, the quality of the initial solutions can be improved as the chaotic distributions so that it can avoid the non-uniform distribution of the solutions. Also, ICS divides the multidimensional solutions into several areas by using the concept of dimension.

4. Towards SI-based IoT Systems

Modeling IoT-based systems as swarm can help them benefit from the main features of swarm systems (robustness, flexibility, and scalability [5]). These main features can overcome some of the main architectural requirements of IoT-based systems (scalability, robustness, flexibility, and interoperability [84]) [85]:

1. *Robustness:* the system remains operational despite the disturbances from the environment or the malfunction of its individuals. A number of factors contribute to getting this robustness: (1) the swarm is redundant and the loss of an individual can be compensated by another one, (2) coordination is decentralized and the destruction of a particular part of the system is unlikely to stop its operation, (3) individuals are simple; thus less prone to failure, (4) sensing is distributed; hence the system is robust to local perturbances.
2. *Flexibility:* The individuals adapt to changing environmental conditions by coordinating their actions in a way to handle tasks of different nature. Thus, SI-based algorithms can assist devices to deal with the issue of unpredictability that could arise in the conditions of surrounding devices.
3. *Scalability:* SI-based algorithms can support self-organization, collaboration and self-configuration, which allow the swarm to operate under a wide range of group sizes and supports a large number of individuals without impacting performances considerably.
4. *Interoperability:* SI-based systems can handle the heterogeneity and asymmetry in the capabilities and technologies of communicating devices within the IoT just like ants with heterogeneous capabilities leverage on their collective intelligence to optimize the path selection.

From the review of SI-based IoT systems made in Section 3 and the categorization presented in Figure 2, we propose a set of suggestions in order to efficiently apply SI-based algorithms in IoT-based systems:

- Algorithms of category 1 (Figure 2) are matter enough to be applied in IoT-based applications. Also, a large number of SI-based algorithms in category 2 (Figure 2) were widely considered in literature works and need the attention of IoT researchers to be exploited. Unfortunately, algorithms of category 3 (Figure 2) are not yet mature in theory so they have to be avoided in IoT-based systems. Much more work needs to be done on the algorithms theory first.

- SI-based algorithms are suitable mainly for optimization, scheduling, planning, design, and management problems. These kind of problems are everywhere, in investments, production, distribution and so forth. We selected the frequently treated applications of SI-based algorithms that may constitute best practices for IoT-based systems. From Table 1, these problems may include: TSP, JSP, LFC, KP, ELD which could be adapted for several real-world applications. Other applications based on algorithms from category 1 (see Figure 2) may include: Wireless Sensor Networks (WSNs) (routing, energy efficient sensor movement, clustering, data transmission, node search, placement of relay nodes, collaborative mobile sensing, effective cluster head selection, charger deployment in wireless rechargeable sensor networks), RFID (networking planning, optimization for RFID reader deployment, tag design), dynamic routing (railway junction rescheduling, vehicle routing, train routing selection), forecasting (displacement of hydro-power dam, electrical load forecasting, estimation of water resources, travel time estimation, prediction of water temperature in prawn cultures, time series prediction), image processing (multi-level thresholding, MRI brain lesion segmentation, image contrast enhancement, bilinear spectral unmixing of hyperspectral images, remote sensing image registration), feature selection for high-dimensional classification, extraction of photovoltaic module parameters, water allocation and optimal power flow.

- SI-based algorithm's performance strongly depends on algorithmic variations and tuning parameters, thus researcher based on their treated problems can consider hybridizing SI-based algorithms in order to get best performances.

- Swarm robotics is a novel approach to the coordination of large numbers of robots and has emerged as the application of SI to multi-robot systems. IoT is closer to swarm robotics in design rather than to SI since swarm robotics puts emphases on the physical embodiment of individuals and realistic interactions among the individuals and between the individuals and the environment. Devices in IoT can be considered as robots and inspiration from coordination mechanisms in swarm robotics can be adopted to IoT-based systems [5].

5. Conclusion

In this paper, we aimed at introducing a new level of intelligence to IoT-based systems by investigating the potentiality of realizing SI-based IoT systems. It is clear that SI is one of the most efficient paradigms that could present scalable, robust and reliable solutions to dynamic and complex systems such as those based on IoT. The paper treated this issue in three parts. First, we presented definitions about the SI paradigm and discussed many SI-based algorithms with their scope of application. Then, we classified them using a proposed taxonomy. Moreover, we categorized the presented algorithms into three categories according to the maturity of the theories. This categorization helps to formalize which which are the most suitable for future IoT-based systems. We also presented real applications and some potential applications in the industry of SI-based algorithms. In the second part, we presented existing IoT-based systems which use SI-based algorithms and we summarized them in a brief and clear manner through a table. The third part, was reserved to make the link between SI main characteristics and how they could be used in IoT-based systems. Thus, we presented how the main requirements of IoT-based systems can be handled using SI-based algorithms and we introduced useful guidelines on how to properly apply SI-based algorithms in IoT-based systems.

References

[1] R. Parpinelli, H. Lopes, New inspirations in swarm intelligence: a survey, International Journal of Bio-Inspired Computation 3 (1) (2011) 1. doi:10.1504/IJBIC.2011.038700.

[2] S. Garnier, J. Gautrais, G. Theraulaz, The biological principles of swarm intelligence, Swarm Intelligence 1 (1) (2007) 3–31. doi:10.1007/s11721-007-0004-y.

[3] G. Fortino, P. Trunfio, Internet of things based on smart objects: Technology, middleware and applications, Springer, 2014.

[4] O. Zedadra, C. Savaglio, N. Jouandeua, A. Guerrieri, H. Seridi, G. Fortino, Towards a reference architecture for swarm intelligence-based internet of things, in: the Proc. of the 10th International Conference on Internet and Distributed Computing Systems (IDCS 2017), Springer, December 2017, Fiji, pp. 11–13.

[5] B. Christian, M. Daniel, Swarm intelligence. introduction and applications, Natural Computing Series, Springer.

[6] M. Dorigo, M. Birattari, Swarm intelligence, Scholarpedia 2 (9) (2007) 1462.

[7] P.-P. Grassé, La theorie de la stigmergie: essai dinterpretation du comportement des termites constructeurs, Insectes Sociaux 6 (1959) 41–81.

[8] X. S. Yang, X. He, Firefly algorithm: recent advances and applications, International Journal of Swarm Intelligence 1 (1) (2013) 36. doi:10.1504/IJSI.2013.055801.

[9] K. Krishnanand, D. Ghose, Detection of multiple source locations using a glowworm metaphor with applications to collective robotics, in: Proceedings 2005 IEEE Swarm Intelligence Symposium, Vol. 2005, IEEE, 2005, pp. 84–91. doi:10.1109/SIS.2005.1501606.

[10] M. Dorigo, M. Birattari, T. Stutzle, Ant colony optimization, IEEE Computational Intelligence Magazine 1 (4) (2006) 28–39. doi:10.1109/MCI.2006.329691.

[11] D. Karaboga, An idea based on honey bee swarm for numerical optimization, Tech. rep., Technical report-tr06, Erciyes university, engineering faculty, computer engineering department (2005).

[12] B. S. Rani, C. A. Kumar, Multi-objective Swarm Intelligence, Vol. 592 of Studies in Computational Intelligence, Springer Berlin Heidelberg, Berlin, Heidelberg, 2015. doi:10.1007/978-3-662-46309-3.

[13] T. C. Havens, C. J. Spain, N. G. Salmon, J. M. Keller, Roach Infestation Optimization, in: 2008 IEEE Swarm Intelligence Symposium, IEEE, 2008, pp. 1–7. doi:10.1109/SIS.2008.4668317.

[14] X. Feng, J. Zhang, H. Yu, Mosquito host-seeking algorithm for tsp problem [j], Chinese Journal of computers 37 (8) (2014) 1794–1808.

[15] E. Cuevas, M. Cienfuegos, D. Zaldívar, M. Pérez-Cisneros, A swarm optimization algorithm inspired in the behavior of the social-spider, Expert Systems with Applications 40 (16) (2013) 6374–6384. doi:10.1016/j.eswa.2013.05.041.

[16] K. Passino, Biomimicry of bacterial foraging for distributed optimization and control, IEEE Control Systems Magazine 22 (3) (2002) 52–67. doi:10.1109/MCS.2002.1004010.

[17] D. R. Monismith, B. E. Mayfield, Slime Mold as a model for numerical optimization, in: 2008 IEEE Swarm Intelligence Symposium, IEEE, 2008, pp. 1–8. doi:10.1109/SIS.2008.4668295.

[18] J. Kennedy, Swarm Intelligence, in: Handbook of Nature-Inspired and Innovative Computing, Kluwer Academic Publishers, Boston, 2001, pp. 187–219. doi:10.1007/0-387-27705-6_6.

[19] X. S. Yang, S. Deb, Engineering optimisation by cuckoo search, International Journal of Mathematical Modelling and Numerical Optimisation 1 (4) (2010) 330. doi:10.1504/IJMMNO.2010.035430.

[20] H. Duan, P. Qiao, Pigeon-inspired optimization: A new swarm intelligence optimizer for air robot path planning, International Journal of Intelligent Computing and Cybernetics 7 (1) (2014) 24–37. doi:10.1108/IJICC-02-2014-0005.

[21] X.-S. Yang, A New Metaheuristic Bat-Inspired Algorithm, in: Studies in Computational Intelligence, Vol. 284, 2010, pp. 65–74. doi:10.1007/978-3-642-12538-6_6.

[22] M. Eusuff, K. Lansey, F. Pasha, Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization, Engineering Optimization 38 (2) (2006) 129–154. doi:10.1080/03052150500384759.

[23] A. Mutazono, M. Sugano, M. Murata, Energy efficient self-organizing control for wireless sensor networks inspired by calling behavior of frogs, Computer Communications 35 (6) (2012) 661–669. doi:10.1016/j.comcom.2011.09.013.

[24] X.-l. Li, J.-x. Qian, Studies on artificial fish swarm optimization algorithm based on decomposition and coordination techniques, Journal of circuits and systems 1 (2003) 1–6.

[25] C. J. A. Bastos Filho, F. B. de Lima Neto, A. J. C. C. Lins, A. I. S. Nascimento, M. P. Lima, A novel search algorithm based on fish school behavior, in: 2008 IEEE International Conference on Systems, Man and Cybernetics, IEEE, 2008, pp. 2646–2651. doi:10.1109/ICSMC.2008.4811695.

[26] A. Kaveh, N. Farhoudi, A new optimization method: Dolphin echolocation, Advances in Engineering Software 59 (2013) 53–70. doi:10.1016/j.advengsoft.2013.03.004.

[27] S. Mirjalili, S. M. Mirjalili, A. Lewis, Grey Wolf Optimizer, Advances in Engineering Software 69 (2014) 46–61. doi:10.1016/j.advengsoft.2013.12.007.

[28] B. Rajakumar, The Lion's Algorithm: A New Nature-Inspired Search Algorithm, Procedia Technology 6 (2012) 126–135. doi:10.1016/j.protcy.2012.10.016.

[29] B. Wang, X. Jin, B. Cheng, Lion pride optimizer: An optimization algorithm inspired by lion pride behavior, Science China Information Sciences 55 (10) (2012) 2369–2389. doi:10.1007/s11432-012-4548-0.

[30] M. Yazdani, F. Jolai, Lion Optimization Algorithm (LOA): A nature-inspired metaheuristic algorithm, Journal of Computational Design and Engineering 3 (1) (2016) 24–36. doi:10.1016/j.jcde.2015.06.003.

[31] R. Zhao, W. Tang, Monkey algorithm for global numerical optimization, Journal of Uncertain Systems 2 (3) (2008) 165–176.

[32] S. C. Chu, P. W. Tsai, Computational intelligence based on the behavior of cats, International Journal of Innovative Computing, Information and Control 3 (1) (2007) 163–173.

[33] A. Slowik, H. Kwasnicka, Nature Inspired Methods and Their Industry Applications-Swarm Intelligence Algorithms, IEEE Transactions on Industrial Informatics 14 (3) (2018) 1004–1015. doi:10.1109/TII.2017.2786782.

[34] N. E. Karkalos, A. P. Markopoulos, J. P. Davim, Computational methods for application in industry 4.0 (2018).

[35] C. Liu, J. Wang, J. Y. Leung, Integrated bacteria foraging algorithm for cellular manufacturing in supply chain considering facility transfer and production planning, Applied Soft Computing Journal 62 (2018) 602–618. doi:10.1016/j.asoc.2017.10.034.

[36] X. Zheng, Z. Gui, Y. Wang, Support vector machine model based on glowworm swarm optimization in application of vibrant fault diagnosis for hydro-turbine generating unit, in: Information Technology and Mechatronics Engineering Conference (ITOEC), 2017 IEEE 3rd, IEEE, 2017, pp. 238–141.

[37] K. P. Kumar, B. Saravanan, K. S. Swarup, Optimization of Renewable Energy Sources in a Microgrid Using Artificial Fish Swarm Algorithm, Energy Procedia 90 (December 2015) (2015) 107–113. doi:10.1016/j.egypro.2016.11.175.

[38] S. Ali, H. Hasanien, Shuffled Frog Leaping Algorithm for Multi-objective Design Optimization of Transverse Flux Linear Motor, Electric Power Components and Systems 44 (11) (2016) 1307–1315. doi:10.1080/15325008.2016.1155677.

[39] A. Gonzalez-Pardo, J. Del Ser, D. Camacho, Comparative study of pheromone control heuristics in ACO algorithms for solving RCPSP problems, Applied Soft Computing Journal 60 (2017) 241–255. doi:10.1016/j.asoc.2017.06.042.

[40] Y. Lu, W. Hu, Study on the application of ant colony algorithm in the route of internet of things, International Journal of Smart Home 7 (3) (2013) 365–374.

[41] P. Chamoso, F. D. Prieta, F. D. Paz, J. M. Corchado, 12th International Conference Distributed Computing and Artificial Intelligence, Vol. 373 of Advances in Intelligent Systems and Computing, Springer International Publishing, Cham, 2015. doi:10.1007/978-3-319-19638-1.

[42] M. Ebrahimi, E. Shafieibavani, R. K. Wong, C.-H. Chi, A New Metaheuristic Approach for Efficient Search in the Internet of Things, in: 2015 IEEE International Conference on Services Computing, IEEE, 2015, pp. 264–270. doi:10.1109/SCC.2015.44.

[43] V. Suryani, S. Sulistyo, W. Widyawan, Trust-Based Privacy for Internet of Things, International Journal of Electrical and Computer Engineering (IJECE) 6 (5) (2016) 2396. doi:10.11591/ijece.v6i5.9678.

[44] I. Sabbani, M. Youssfi, O. Bouattane, A multi-agent based on ant colony model for urban traffic management, in: International Conference on Multimedia Computing and Systems (ICMCS), IEEE, 2016, pp. 793–798. doi:10.11591/ijece.v6i5.9678.

[45] P. López-Matencio, J. Vales-Alonso, E. Costa-Montenegro, ANT: Agent Stigmergy-Based IoT-Network for Enhanced Tourist Mobility, Mobile Information Systems 2017 (2017) 1–15. doi:10.1155/2017/1328127.

[46] O. Cosido, C. Loucera, A. Iglesias, Automatic calculation of bicycle routes by combining meta-heuristics and GIS techniques within the framework of smart cities, in: 2013 International Conference on New Concepts in Smart Cities: Fostering Public and Private Alliances (SmartMILE), IEEE, 2013, pp. 1–6. doi:10.1109/SmartMILE.2013.6708196.

[47] M. A. Kowshalya, M. Valarmathi, Detection of sybil's across communities over social internet of things, Journal of Applied Engineering Science 14 (1) (2016) 75–83. doi:10.5937/jaes14-10176.

[48] O. Said, Analysis, design and simulation of internet of things routing algorithm based on ant colony optimization, International Journal of Communication Systems 30 (8). doi:10.1002/dac.3174.

[49] Y. Jiang, Q. Ding, X. Wang, A recovery model for production scheduling: Combination of disruption management and internet of things, Scientific Programming 2016. doi:10.1155/2016/8264879.

[50] V. Bellini, T. D. Noia, M. Mongiello, F. N. B, A. Parchitelli, E. D. Sciascio, Reflective Internet of Things Middleware-Enabled a Predictive Real-Time Waste Monitoring System, Springer International Publishing, 2018. doi:10.1007/978-3-319-91662-0.

[51] Y. Hong, L. Chen, L. Mo, Optimization of cluster resource indexing of Internet of Things based on improved ant colony algorithm, Cluster Computing (2018) 1–9doi:10.1007/s10586-017-1496-x.

[52] G. Mahalaxmi, K. E. Rajakumari, Multi-Agent Technology to Improve the Internet of Things Routing Algorithm using Ant Colony Optimization, Indian Journal of Science and Technology 10 (31) (2017) 1–8. doi:10.17485/ijst/2017/v10i31/112338.

[53] Z. Oralhan, B. Oralhan, Y. Yiğit, Smart City Application: Internet of Things (IoT) Technologies Based Smart Waste Collection Using Data Mining Approach and Ant Colony Optimization, International Arab Journal of Information Technology (IAJIT) 14 (4) (2017) 423–427.

[54] P. Thapar, U. Batra, Implementation of ant colony optimization in routing protocol for internet of things, in: Innovations in Computational Intelligence, Springer, 2018, pp. 151–164. doi:10.1007/978-981-10-4555-4_10.

[55] W.-T. Sung, Y.-C. Chiang, Improved Particle Swarm Optimization Algorithm for Android Medical Care IOT using Modified Parameters, Journal of Medical Systems 36 (6) (2012) 3755–3763. doi:10.1007/s10916-012-9848-9.

[56] W. Sung, C. Hsu, IOT system environmental monitoring using IPSO weight factor estimation, Sensor Review 33 (3) (2013) 246–256. doi:10.1108/02602281311324708.

[57] C.-W. Tsai, C.-F. Lai, A. V. Vasilakos, Future Internet of Things: open

issues and challenges, Wireless Networks 20 (8) (2014) 2201–2217. doi:10.1007/s11276-014-0731-0.

[58] S. Luo, L. Cheng, B. Ren, Practical Swarm Optimization based Fault-Tolerance Algorithm for the Internet of Things, KSII Transactions on Internet and Information Systems 8 (4) (2014) 1178–1191. doi:10.3837/tiis.2014.04.001.

[59] L. Hurtado, P. Nguyen, W. Kling, Smart grid and smart building inter-operation using agent-based particle swarm optimization, Sustainable Energy, Grids and Networks 2 (2015) 32–40. doi:10.1016/j.segan.2015.03.003.

[60] C. Fang, X. Liu, P. M. Pardalos, J. Pei, Optimization for a three-stage production system in the Internet of Things: procurement, production and product recovery, and acquisition, The International Journal of Advanced Manufacturing Technology 83 (5-8) (2016) 689–710. doi:10.1007/s00170-015-7593-1.

[61] S. Dai, M. Liwang, Y. Liu, Z. Gao, Hybrid Quantum-Behaved Particle Swarm Optimization for Mobile-Edge Computation Of fl oading in Internet of Things, Vol. 1 of Communications in Computer and Information Science, Springer Singapore, 2018. doi:10.1007/978-981-10-8890-2.

[62] W. Jinyi, Y. Qin, A. Shrestha, S.-J. Yoo, Optimization of cognitive radio secondary base station positioning and operating channel selection for IoT sensor networks, International Conference on Information and Communication Technology Convergence: ICT Convergence Technologies Leading the Fourth Industrial Revolution, ICTC 2017 2017-Decem (2017) 397–399. doi:10.1109/ICTC.2017.8191011.

[63] T. Kumrai, K. Ota, M. Dong, J. Kishigami, D. K. Sung, Multiobjective Optimization in Cloud Brokering Systems for Connected Internet of Things, IEEE Internet of Things Journal 4 (2) (2017) 404–413. doi:10.1109/JIOT.2016.2565562.

[64] A. L. Sangeetha, N. Bharathi, A. B. Ganesh, T. K. Radhakrishnan, Particle swarm optimization tuned cascade control system in an Internet of Things (IoT) environment, Measurement: Journal of the International Measurement Confederation 117 (2018) 80–89. doi:10.1016/j.measurement.2017.12.014.

[65] M. Tuba, N. Bacanin, Hybridized bat algorithm for multi-objective radio frequency identification (rfid) network planning, in: 2015 IEEE Congress on Evolutionary Computation (CEC), IEEE, 2015, pp. 499–506.

[66] L. Huo, Z. Wang, Service composition instantiation based on cross-modified artificial Bee Colony algorithm, China Communications 13 (10) (2016) 233–244. doi:10.1109/CC.2016.7733047.

[67] M. Yi, Q. Chen, N. N. Xiong, The Adaptive Recommendation Mechanism for Distributed Parking Service in Smart City, Sensors 11 (16) (2016) 395–413. doi:10.3390/s1611184.

[68] X. Xu, Z. Liu, Z. Wang, Q. Z. Sheng, J. Yu, X. Wang, S-ABC: A paradigm of service domain-oriented artificial bee colony algorithms for service selection and composition, Future Generation Computer Systems 68 (2017) 304–319. doi:10.1016/j.future.2016.09.008.

[69] M. Khan, S. Din, M. Gohar, A. Ahmad, S. Cuomo, F. Piccialli, G. Jeon, Enabling multimedia aware vertical handover Management in Internet of Things based heterogeneous wireless networks, Multimedia Tools and Applications 76 (24) (2017) 25919–25941. doi:10.1007/s11042-017-4736-4.

[70] A. Ahmad, M. Khan, A. Paul, S. Din, M. M. Rathore, G. Jeon, G. S. Choi, Toward modeling and optimization of features selection in Big Data based social Internet of Things, Future Generation Computer Systems 82 (2018) 715–726. doi:10.1016/j.future.2017.09.028.

[71] Z. Muhammad, N. Saxena, I. M. Qureshi, C. Wook, Hybrid Artificial Bee Colony Algorithm for an Energy Efficient Internet of Things based on

Wireless Sensor Network, IETE Technical Review 34 (S1) (2017) 39–51. doi:10.1080/02564602.2017.1391136.

[72] M. Praveen Kumar Reddy, M. Rajasekhara Babu, Energy Efficient Cluster Head Selection for Internet of Things, New Review of Information Networking 22 (1) (2017) 54–70. doi:10.1080/13614576.2017.1297734.

[73] P. Reddy, R. Babu, An Evolutionary Secure Energy Efficient Routing Protocol in Internet of Things, International Journal of Intelligent Engineering and Systems 10 (3) (2017) 337–346. doi:10.22266/ijies2017.0630.38.

[74] A. Khalid, N. Javaid, M. Guizani, M. Alhussein, K. Aurangzeb, M. Ilahi, Towards Dynamic Coordination Among Home Appliances Using Multi-Objective Energy Optimization for Demand Side Management in Smart Buildings, IEEE Access 6 (2018) 19509–19529. doi:10.1109/ACCESS.2018.2791546.

[75] K. Balamurugan, R. Mahalakshmi, MATHEMATICAL ANALYSIS OF BLDC MOTOR PARAMETER ESTIMATION USING INTERNET OF THINGS, TAGA JOURNAL OF GRAPHIC TECHNOLOGY 14 (2018) 2429–2436.

[76] Z. Cui, Y. Cao, X. Cai, J. Cai, J. Chen, Optimal LEACH protocol with modified bat algorithm for big data sensing systems in Internet of Things, Journal of Parallel and Distributed Computingdoi:10.1016/j.jpdc.2017.12.014.

[77] G.-J. Horng, The Adaptive Recommendation Mechanism for Distributed Parking Service in Smart City, Wireless Personal Communications 80 (1) (2015) 395–413. doi:10.1007/s11277-014-2017-3.

[78] E. Fadel, M. Faheem, V. Gungor, L. Nassef, N. Akkari, M. Malik, S. Almasri, I. Akyildiz, Spectrum-aware bio-inspired routing in cognitive radio sensor networks for smart grid applications, Computer Communications 101 (2017) 106–120. doi:10.1016/j.comcom.2016.12.020.

[79] G. Garofalo, A. Giordano, P. Piro, G. Spezzano, A. Vinci, A distributed real-time approach for mitigating CSO and flooding in urban drainage systems, Journal of Network and Computer Applications 78 (2017) 30–42. doi:10.1016/j.jnca.2016.11.004.

[80] Z. Amjad, S. Batool, H. Arshad, K. Parvez, M. Farooqi, N. Javaid, Pigeon inspired optimization and enhanced differential evolution in smart grid using critical peak pricing, in: International Conference on Intelligent Networking and Collaborative Systems, Springer, 2017, pp. 505–514. doi:10.1007/978-3-319-65636-645.

[81] C. A. ul Hassan, M. S. Khan, A. Ghafar, S. Aimal, S. Asif, N. Javaid, Energy optimization in smart grid using grey wolf optimization algorithm and bacterial foraging algorithm, in: International Conference on Intelligent Networking and Collaborative Systems, Springer, 2017, pp. 166–177. doi:10.1007/978-3-319-65636-615.

[82] G. Sun, Y. Liu, M. Yang, A. Wang, S. Liang, Y. Zhang, Coverage optimization of VLC in smart homes based on improved cuckoo search algorithm, Computer Networks 116 (2017) 63–78. doi:10.1016/j.comnet.2017.02.014.

[83] F. Cicirelli, G. Fortino, A. Guerrieri, A. Mercuri, G. Spezzano, A. Vinci, A metamodel framework for edge-based smart environments, in: 2018 IEEE International Conference on Cloud Engineering (IC2E), IEEE, 2018, pp. 286–291. doi:10.1109/IC2E.2018.00067.

[84] I. Yaqoob, E. Ahmed, I. A. T. Hashem, A. I. A. Ahmed, A. Gani, M. Imran, M. Guizani, Internet of Things Architecture: Recent Advances, Taxonomy, Requirements, and Open Challenges, IEEE Wireless Communications 24 (3) (2017) 10–16. doi:10.1109/MWC.2017.1600421.

[85] O. Bello, S. Zeadally, Intelligent Device-to-Device Communication in the Internet of Things, IEEE Systems Journal 10 (3) (2016) 1172–1182. doi:10.1109/JSYST.2014.2298837.