An Optimisation Algorithm Inspired by Dendritic Cells

N.M.Y. Lee and H.Y.K. Lau

Abstract Clonal Selection Algorithm (CSA) has been widely adopted for solving different types of optimization problems in the field of Artificial Immune Systems (AIS). Apart from the effector functions of *hypermutation* and *proliferation* providing the diversity of solutions in CSA, the metaphors of dendritic cells (DCs) also enthuse a wide-range of effector control functions, for examples, *cytoarchitecture* and *differentiation* for formulating and developing a powerful solution-evolution engine in optimization algorithms. In order to demonstrate the capability of providing a set of good Pareto fronts with regards to the defined objective functions, the interactions and collaboration of the DC-inspired features are studied in this paper. A real-world problem is studied to demonstrate the functionality of the algorithm in terms of its convergence and diversity of solutions. The experimental results also reveal that the framework produces promising solutions in a scheduling problem, particularly the increased problem size in daily real-life operations.

1 Introduction

Artificial Immune Systems (AIS) has widely been adopted for solving optimization problems, including multi-objective optimization [1, 2], combinatorial optimization [3, 4], constrained optimization [5] and functional optimization framework. In the literature, these optimization problems have usually been solved by the *Clonal Selection Algorithm* [6] that is underpinned by the *Clonal Selection Theory* introduced by Burnet [7]. This immunological principle explains that (i) pattern recognition, (ii) differentiation of the antigenic components and (iii) affinity

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measurement of antigens are incorporated in the regulation the synthesis of antibodies. With respects to the invading antigens, a specific and adaptive immune response is resulted according to the inherent features in the theory for producing optimal solution as summarised in [8], These features include:

- Diversify the population of antibodies by genetic changes in *hypermutation*
- Retain a set of high affinity pattern for *proliferation* and differentiation on the antibodies that have been in contact with the antigens

Foregoing researches studied the paradigm of the clonal selection algorithm and has demonstrated promising results in solving a wide range of optimization problems, particularly in escaping from local optima by the diversification of the population of solutions as mentioned in numerous studies [9]. Apart from the inspiration of the lymphocytes in the adaptive immune system, a novel computational paradigm is introduced that is enthused by the dendritic cells (DCs) in the innate immune system in this study. The proposed DC-inspired computational framework not only encompasses the features from the clonal selection theory as aforementioned, the mechanisms and behaviour of DCs in the metaphor of maturation and migration (as summarised in Table 1) are further enhance the capabilities of decision-making and solution-evolution over the classical DCA proposed by Greensmith [10]. In brief, the intrinsic immuno-features introduced in the proposed DC-inspired framework including,

(i) Threat quantification—that enriches the Discrimination of Self/non-self and Danger Theory that adopted in the DCA and affinity measures in the clonal selection algorithm
(ii) Signal interactions embedded in the cascading pathways/network—the proposed framework is a signal driven optimization algorithm instead of a cell-driven algorithms that have been modeled in the aforementioned AIS algorithms such as clonal selection algorithms [8, 11]

Table 1 Comparison of the proposed framework and the classical Clonal Selection Algorithm in solving optimization problems

Features	The proposed framework	The Clonal Selection Algorithm
Quantification of the solutions (for decision-making)	Threat of the solutions	Affinity measures of the solutions
Communication path(s)	i. Receptors between the dendritic cells and pathogens ii. Between the signal cascading network	i. Antibodies and antigens
Control Operators (for solutions)	i. Differentiation ii. Proliferation iii. Cytoarchitecture iv. Endocytosis	i. Hypermutation ii. Proliferation

(iii) Resulted effector control functions—the controls (e.g. *Cytoarchitecture* and *Endocytosis*) are mediated by mature DCs instead of the antibodies behave in the Clonal Selection Algorithms.

The aforementioned features, namely, the proposed signal cascading network and architecture, are going to enhance the classical DCA. In addition, the orchestral interactions of these characteristics further enhance for the problem solving capabilities in optimisation problems such as diversification of the evolved solutions, instead of limiting to the domains of classification and intrusion detection [12, 13] that are mainly inspired by the danger theory [14]. In the applications of solving detection problems, the sampled data sets (antigens) in the classical DCA are sensed by detectors (DCs) that are further migrated and transformed according to the emitted concentration of cytokines that are regulated by the embedded signals (i.e. PAMPs, safe and danger signals). Such mimic demonstrates a highly adaptive classification paradigm to the sampled data set instead of providing evolution mechanisms to the solutions, as the classical DCA that had been implemented for a decision-making of the unexpected event (as the intrusions) in a dynamic scheduling problem [15]. Whilst the DCA performs the decision-making, the optimal solutions were often evolved based on the AIS mechanisms including clonal selection algorithm and affinity maturation [16, 17]. These AIS-based computing paradigms are efficient in producing high quality of solutions in terms of good acceleration of the solutions convergence and diversity. On the other hands, hybridisation AIS paradigms with the traditional artificial intelligence (AI) are also popular in solving complex engineering problems. For instances of hybridisation of AIS with (i) genetic algorithm (GA) [18, 19] and (ii) particle swarm algorithm (PSA) [20, 21], AIS approaches further address the limitations of the classical approaches such as the efficiency of solution-generation and voiding the premature convergence of evolved solutions respectively, in particular to combinatorial optimisation problems.

Details of the proposed DC-inspired features are given in Sect. 2.2 in the paper. The rest of the paper is organised as follows—the roles of DCs in the human immune system are given in Sect. 2. The competence and performance of the proposed framework is evaluated with a combinatorial optimization problem that is presented in Sect. 3. Discussion and recommendations are presented in the last section.

2 Dendritic Cells and the Optimization Framework

Human DCs are the sentinels [22] in the innate immune system, which capture and process antigens in periphery tissues (such as skin). Subsequently, the cells further migrates to the lymphoid organs and secrete signal molecules (e.g. cytokines and chemokines) for providing a primary inflammatory response, presenting antigens onto the cells and stimulating T-cells in the adaptive immune system. With the

Table 2 The key processes of the DC-induced adaptive immune responses

Process	Description and output of process	Involved immune cells and molecules
Antigen capturing/processing	Discrimination of safe and threat of the invading pathogens	Receptors onto DCs and pathogens, namely, Toll-like receptors (TLRs) and pattern recognition receptors (PRRs) respectively
Maturation and migration	(i) Up-/down-regulation of stimulatory molecules (in maturation) (ii) Intracellular signalling in the signal cascading network (in migration)	Signal molecules and transcription factors in the intracellular pathways and network
Regulation of effector control functions	Regulate and control the fate and migratory properties of DCs and their subpopulation—in terms of (i) the population of the DCs, (ii) phenotypical and functional properties of DCs and (iii) migratory properties	DCs

revealed immunological knowledge of DCs, the paradigm of these cells and molecules provides a powerful computing tool for the evolution of high-quality solutions as given below.

2.1 Human Dendritic Cells

DC-induced adaptive immunity is a three-fold process that involves (i) antigen capturing and processing, (ii) maturation and migration and (iii) initiation of effector control functions, as summarised in Table 2.

Upon DCs encountering the invading pathogens, the magnitude of the microbial threat can be scaled through the formation of synapse [23], including

(i) Microbial viability that refers to the dead or alive of the pathogens. Usually, more vigorous response reacts to viable ("live") microorganisms instead of the "dead".
(ii) Virulence factors, such as toxins, that may harm to the host by causing diseases and illnesses.
(iii) Microbial invasion dictates the magnitude of the immune responses, and the responses are increased from (a) external environment, (b) non-sterile tissues such as skin, (c) sterile tissue and to (d) systematic circulation (e.g. blood).

The resulted threat of pathogens propagates to the downstream signal cascading network that is embedded underneath each activated surface receptors regulates the maturation and the migration properties of DCs. In the process of maturation, the

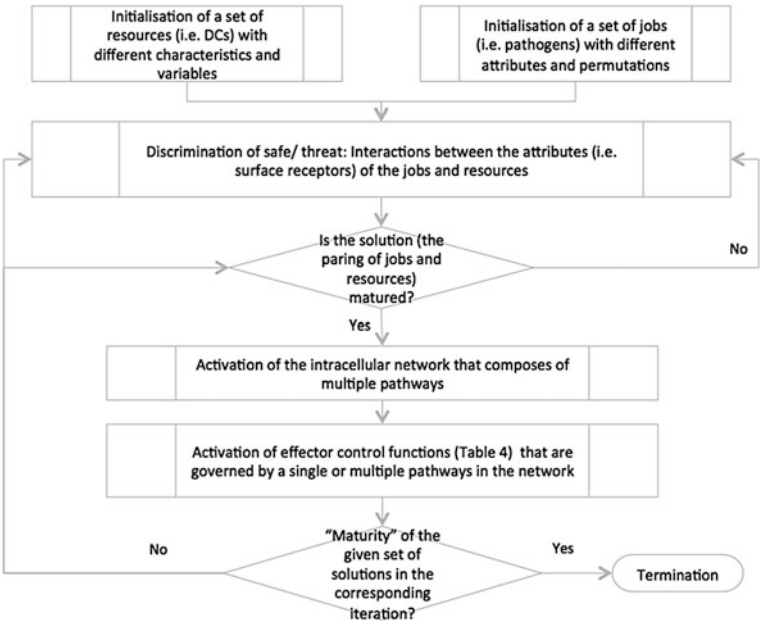

Fig. 1 The DC-mediated framework for solving an optimization problem such as combinatorial optimization problem

phenotype of the surface receptors and their functionalities are changed according to the quantification of the perceived threat. In the context of migration, on the other hand, the migratory prosperities (e.g. kinetic, migratory speed and adhesiveness of the DCs) and immunity control (e.g. antigen up-taking and proliferation of the cells) are regulated upon the activation of T-cell in drained lymph nodes.

The metaphors of threat quantification and the signal cascading network are underpinned the design principles for decision-making and solution-evolution processes in the proposed framework (Fig. 1), are described in the next section.

2.2 The DC-Mediated Framework

The framework (Fig. 1) comprises (i) the macrostructure of the framework and (ii) the microstructure of the network implanted in an individual DC distributed in the framework—a cascading structure facilitates the signal propagation in the solution-evolution process with respects to the quantified threat of the attacks. The macrostructure features the interactions between the artificial components, namely, pathogens and DCs. The analogy is summarised in Table 3.

The framework composes of two key components, namely, DCs and pathogens, which are imitated as resources and jobs in the domain of scheduling problems. Their interactions commenced from (i) the surface receptors (i.e. attributes) of

Table 3 The analogy of the components in the human immune system and the proposed framework for solving combinatorial optimization problems

Human Immune System	The DC-inspired framework
Dendritic cells	Variable(s) of the resources (solutions)
Pathogens	Permutation of the jobs (problem)
Surface receptors/pathogenic recognition molecules (on DCs and pathogens)	Attributes (of the variable and permutation)

Toll-like receptors/Chemokine receptors (TLRs/CCRs) and pathogen-associated molecular patterns (PAMPs) to (i) the signal molecules along the pathways result in producing high quality of solutions as aforementioned, which is distinct from the classical AIS algorithms in particular to the structure of the framework for solving optimisation problems. The framework imitates the DC and its extra- and intra-cellular features, including the surface receptors, signal molecules and its structured pathways—these features leading the signal (i.e. quantified threat) cascading upon the activation of the corresponding effector control functions, which stipulate a robust control to the population of solutions in a given environment.

As illustrated in Fig. 1, the mechanisms (such as the discrimination of threaten solutions) and interactions are adopted as the regulators or control in the decision-making and solution evolution process (Table 4) in the cascading network. Per each iteration, the mechanism begins with a process of decision-making that refers to the differentiation of safe and threat of the solutions according to the factors behaved by DCs [23], which is followed by the activation of the downstream signalling process along the pathways that governs the magnitude of the DC inspired effector control functions. And, these metaphors and features are critical to determine the derived solution, are given in the following sections.

Table 4 Behaviours and immuno-mechanism revealed from dendritic cells and the corresponding analogy

Immuno-mechanisms in Human Immune System	DC-inspired mechanisms in the proposed framework
Discrimination of safe/threat (i) Microbial viability (ii) Virulence factors (iii) Microbial invasion	Differentiate the safe and threat signals of the solutions (i) Feasibility of solutions (ii) Performance of the objective functions (iii) Impacts to the domain
Signal cascading in an intracellular network	Solutions evolution for each paring of variable and permutation
Activation of effector control functions (i) Proliferation and Differentiation (ii) Endocytosis and Cytoarchitecture	(i) The control functions of *proliferation* and *differentiation* regulate the quantities of mature and immature solutions (ii) *Endocytosis* and *Cytoarchitecture* mentioned on the left are used to diversify the generated solutions by changing the attributes of the jobs and resources, such as the permutation of jobs, preference of the jobs, and the availability of the resources

2.2.1 Threat Quantification

In the context of differentiation of safe and threat (signals), signals are emitted from the interacted pathogens can be identified and quantified thru an extracellular signal cascading as the factors given in Sect. 2.1. In other words, the signals of safe and threat associated with the solutions, are estimated based on (i) the feasibility of solutions, (ii) objective functions in the domain (e.g. minimisation of makspan and utilisation of resources in the real-life scheduling problems), and (iii) the impacts of the obtained solutions to the domain. The resulted signal(s) (denoted by $Threat_{DC}$ as presented in Eq. (1)) is estimated the evolved solutions from the perspectives of viability/feasibility of solutions, performance of the objective functions and the corresponding impact to the solutions, that are mimicked the threat components inspired by DCs as aforementioned. The quantified threat further compares with the threshold (δ_{Threat}) that estimated in an iterative manner. More importantly, this may induce the downstream decision-making process if $Threat_{DC} = 1$ in the intracellular network that is implanted in each solution.

$$Threat_{DC} = \begin{cases} 1 & if\ f(feasbility, objectives, impacts) \geq \delta_{Threat} \\ 0 & otherwise \end{cases} \tag{1}$$

2.2.2 Signal Cascading Network and Effector Control

The stimulation and suppression of the proposed effector functions (as summarised in the above table) are regulated by signal molecules in the signal cascading network. The adopted signal molecules are responsible for single or multiple control functions in the network. With regards to the DC-inspired controls, some of them have also been demonstrated in the classical CSA, such as proliferation. In the proposed framework, here, *proliferation* and *differentiation* are taken the roles in adjusting the population and quality of the solutions that are labelled as *safe* and *threat* respectively. Furthermore, the varieties of solutions are regulated by *endocytosis* and *cytoarchitecture* which are the attributes reformation/modification to the variable (of resources) and permutation (of given batch of jobs). The orchestra of various effector control functions is hypothetically a good metaphor for obtaining high quality Pareto font.

3 Experimental Studies

The capabilities of the proposed framework and its performance in terms of convergence and diversity of solutions are investigated in a resource allocation problem that is a class of combinatorial problem. Typically, the optimal resources configuration [24], resources utilization [25] and the shortest dwell time [26] of

completing a batch of jobs are the crucial performance indicators in the given domain. In this study, the framework is studied with numerical simulation based on the following objective function,

$$\max f(x) = \sum_{k=1}^{k'} \frac{Occupancy\ of\ resource\ k\ (denoted\ by\ \phi_k)}{Total\ availablity\ of\ resource\ k} \tag{2}$$

where

$$k = 1, 2, \ldots k' \ \left(k' \text{ is the index of the resource}\right)$$

$$\phi_{\mathrm{k}} = \begin{cases} 1 & \text{Resources is being occupied by a job} \\ 0 & \text{otherwise} \end{cases}$$

Each individual job (denoted by u, where $u = 1, 2, \ldots u'$) is constrained by a workable timeframe between the earliest commencement time and latest completion time depending on the delivery time of the job and the service commitment to the customers.

Experiments are conducted in two scenes according to the size of the problem, (i) 100 jobs and (ii) 300 jobs. As aforementioned, the quality of the solutions is investigated in terms of the convergence and diversity of solutions that are elaborated in the following sections.

3.1 Quality of Solutions

With respects to the objective as defined above, there is a significant improvement of the convergence of the solutions (Fig. 2) with respects to the objective function as defined above. The results also revealed that the percentage of resource utilization has been increased by 10 % in both test environments particularly in the early stage of the evolution process. By comparing the cases of (i) 100 jobs and (ii) 300 jobs, case (ii) produces a set of better solutions in terms of utilization. As observed, some of the solutions have achieved a high utilization rate of up to 43 %.

Despite the limited number of iterations performed, the potential of the proposed framework in evolving good "potential" candidate solution(s) is clearly demonstrated.

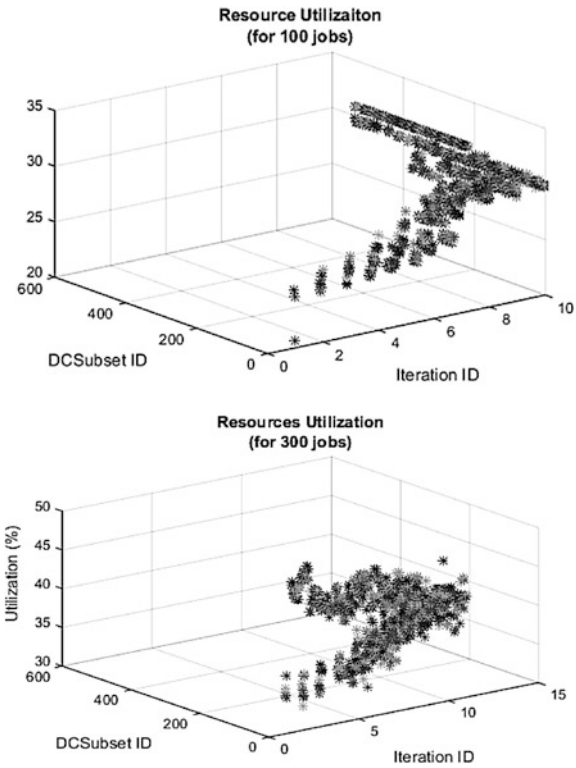

Fig. 2 Convergence of the solutions in resources allocation problems with the sizes of (i) 100 jobs and (ii) 300 jobs

3.2 Diversity of Solutions

Apart from the convergence of solutions, the diversity of the solutions is also investigated. To study the diversity of solutions, the means, maximum and minimum of the objective function (Eq. (2)) are analysed, as depicted in Fig. 3.

The experimental results shown above further illustrate an upward trend in the convergence of the obtained solutions as discussed in last section. In addition, the solutions are evolved and differentiated in a diverse manner. By comparing the solutions obtained in the earliest iterations, the diversity of solutions performed better with a problem with 300 jobs, as compared to a smaller scale problem of 100 jobs under the identical configurations of the number of proliferated and differentiated solutions. On the other hand, the quantities of proliferated and differentiated cells potentially expand the diversity by enlarging the population size of solutions.

Based on the experimental results presented in this section, the framework demonstrates its capability in obtaining optimal solutions especially for a problem with 300 jobs than in a problem with 100 jobs, in terms of convergence and diversity of solutions.

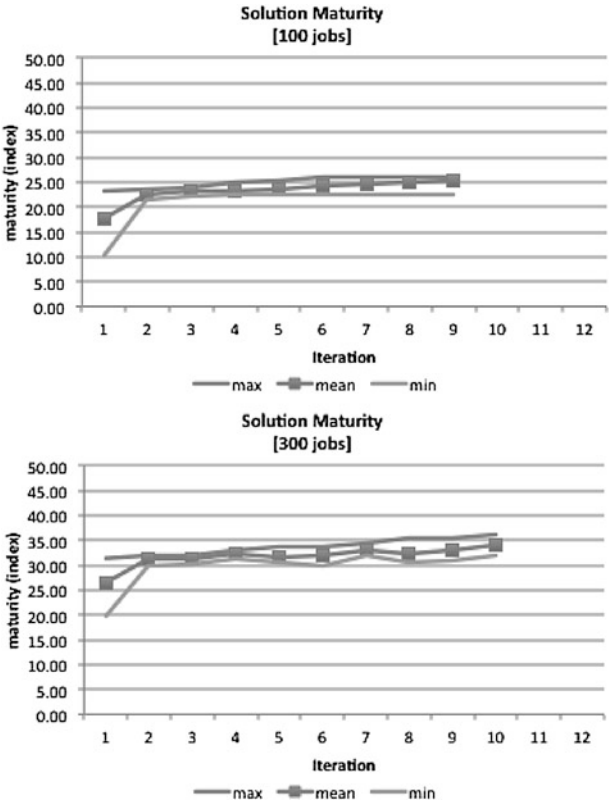

Fig. 3 Diversity of the solutions in resources allocation problems with the scale of (i) 100 jobs and (ii) 300 jobs

4 Conclusions

The key immuo-features and mechanisms of the proposed framework provide a novel approach for the development or evolution of optimal solutions, are inspired by DCs. It is a signal-driven optimization framework, in which, signals are generated from scaling the threat of the solutions, and further regulates the proposed control functions to the generated solutions. In this paper, the functions of the framework have demonstrated problem-solving capabilities, including the convergence and diversity of solutions in solving combinatorial optimization problems. According to the preliminary experimental results, the framework performs well when the number of jobs increased in the combinatorial scheduling problems. In this study, a case with 300 jobs gives satisfactory results in terms of the convergence and diversity of solutions.

As of the proposed framework, forthcoming development of the framework includes the investigation of the abilities of the framework with regards to the

(i) features of the framework and (ii) the behaviour in the search/evolution process. More significantly, benchmarking with other AIS and AI approaches are also considered in the future, in particular to affirming the optimality of the solutions.

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