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Advancement in the twentieth century in artificial immune systems for optimization: review and future outlook

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Abstract
Research in Artificial Immune Systems (AIS) for optimization has attracted attention in recent years. Exploration and adoption of the inspired immune theories in clonal selection, immune network, negative selection, and danger signaling is becoming a popular basis for algorithm design for solving optimization problems, especially on multi-objective optimizations. Novel algorithms are design, benchmarked and applied to real life applications. This paper aims to review and outlook on the latest development of AIS-based algorithms in the recent decade. An analysis of the AIS applications is also discussed.

Keywords: Artificial immune systems, future outlook, optimization

1 Introduction

In the context of evolutionary algorithms on optimization, Artificial Immune Systems (AIS) have already attracted much attention with their biologically inspirations from 1990s. The vast majority of the development of AIS-based algorithms are based on the immunological theories of clonal selection (Burnet, 1957, 1959), immune networks (Jerne, 1974), and negative selection (Balicki, 2006). Algorithms developed have been applied to various fields including pattern matching and recognition (de Castro and Von Zuben, 1999; Watkins, 2003), data clustering (de Castro and Timmis, 2002), container transportation (Wong et al., 2008), network routing (Lau and Wong, 2005; Keko et al., 2004), electromagnetic design (Campelo et al., 2005), etc. This paper aims to provide a review on the latest development on AIS algorithms for optimization and suggests future directions of development on this emerging field.

2 Nomenclature of AIS

AIS has attracted many researchers due to its appealing characteristics and corresponding functions. To summarize the functionalities of the AIS theories, Table 1 summarizes the common adaptations of these theories in optimization.

Clonal selection theory describes the clonal expansion and selection in the immune system. When antibodies with highest binding affinity on a B-cell bind with an antigen, the B-cell becomes activated and starts to proliferate. New B-Cell clones are produced that are exact copies of their parent B-cell. Otherwise they undergo somatic hypermutation (Berek and Ziegner, 1993) and produce antibodies that are specific to the invading antigens. The clonal selection principle (Burnet, 1959) describes the basic properties of an adaptive immune response to an antigenic stimulus and is an alternative view to the position presented in the previous section. It establishes the idea that only those cells capable of recognizing an antigenic stimulus will proliferate, thus being selected against those that do not. Clonal selection operates on both T-cells and B-cells. The B-cells, in addition to proliferating or differentiating into plasma cells, can differentiate into long-lived B memory cells. The process of clonal expansion, binding, selection, cloning, proliferating and memory are often adopted by multi-objective optimization algorithms.

Jerne (1974) proposed the Immune memory and network theory in which the immune system is capable of achieving immunological memory by the existence of a mutually reinforcing network of B-cells. The cells not only stimulate each other but also suppress the connected B-cells. This suppression function is a mechanism by which the over-stimulation of B-cells is regulated in order to maintain a stable memory. The immune network acts as a self-organizing and self-regulatory system that captures antigen information ready to launch an attack against any similar antigens.

Negative selection describes the inhibition or death of a given lymphocyte upon being activated. It models the behavior of the elimination of antibodies that react against self-antigens which cause auto-immune diseases. The theory has been applied to intrusions detection (Forrest et al., 1994), fault detection, and optimization (He and Han, 2007).

Danger theory (DT) (Matzinger, 1994) proposed a measurement of the level of threat represented by a given antigen. The danger signal response of the T-cells in the immune system depends on the activation signals from Antigen-presenting cells (APC). Matzinger states that the T-cell and the immune response they orchestrate occurs not because of the self-nonself but due to the dynamic and constantly-updated response to danger based on the cellular damage detected by APC. The DT has been applied to the design of intrusion detection system (Aickelin et al., 2003) for computers and anomaly detection. It can also be applied to the exploration of Pareto front in optimization problems by sending the danger signals to guide the evolution operators towards specific trade-offs between multi-objective optimization problems.

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Functionalities	AIS Theories
Inheritance	Cloning
Storage, elitism, memory	Memory cell
Population valuation, fitness evaluation, population selection	Clonal selection principle
Diversification, inheritance	Hypermutation
Re-sampling,	Affinity maturation
Interaction	Immune network theory
Elimination, diversification	Negative selection
Exploration, Optimal search signaling	Danger theory

Table 1. Nomenclature of Artificial Immune Systems

3 Multi-objective Optimization

With the complexity of the real world problems, there often occur multiple objectives instead of single objective in various optimization problems. These objectives are often contradicting, existing a set of solutions for the multiple objective cases which cannot simply compare with each other (Vrugt and Robinson, 2007). This gives rise to a set of Pareto optimal solutions or non-dominated solutions. This solution cannot be further improved without causing a simultaneous degradation in at least one other objective, representing globally optimal solutions to the tradeoff problem. Consider a multi-objective optimization problem with minimizing or maximizing a vector function having n decision variables and m objectives:

$$y = f(x) = [f_1(x), \ldots, f_m(x)] \quad (1)$$

where x denotes the decision vector, and y is the objective space. The problem is bounded by search space X where $x = (x_1, \ldots, x_n) \in X$. The result on achieving the multi-objective problem would come to a set of Pareto-optimal solutions (Coello, 1999). Traditionally, there are a lot of stochastic techniques solving the multi-objective optimization problems. These methods usually could generate the Pareto set but the solutions obtained are sometimes limited to local optimal approximations and do not guarantee to identify optimal trade-offs. Evolutionary algorithms became popular because of their ability to generate new solutions in various dimensions to increase the diversity of the populations. AIS is one of such novel evolutionary algorithms that raised attentions in the late 1990s.

4 Development of AIS

Among the evolutionary algorithms, AIS is a novel biologically-inspired computation paradigm emerged in recent years. Research in AIS becomes popular in the late 1990s with Ishida et al. (1998) conducted a comprehensive overview of AIS. Dasgupta (1998) published some of the early work on AIS with theories, models, simulations, and applications. Other early works include de Castro and Von Zuben (1999, 2000), de Castro and Timmis (2002).

Year	Author(s)	Highlights
1998	Ishida et al.	A book on immune system
1998	Dasgupta,	A book on theoretical immunology and AIS
1999	de Castro & Von Zuben	Reported immune theories, applications, and future works
2000	de Castro & Von Zuben	Reported a survey on AIS applications
2002	de Castro & Timmis	A textbook on AIS
2004	Wang et al.	A survey of AIS optimization methods and applications
2007	Dasgupta	Reported over 800 literatures in AIS
2007	Timmis	Reviewed current state of AIS research and challenges
2007	Campelo et al.	An overview of AIS on multi-objective optimization
2008	Hart & Timmis	Overviewed of the past, the present and the future of AIS

Table 2. Reviews on the development of AIS

5 AIS-based algorithms for optimization

5.1 CLONALG and aiNet

In optimization, one of the pioneering AIS-based algorithms is CLONALG developed by de Castro and Von Zuben (2002) based on an early development in 1999. The algorithm named Clonal Selection Algorithm (CSA) adopted the Clonal Selection Principle and Affinity Maturation Principle for pattern matching and optimization. de Castro and Von Zuben then combined the principles of the immune network theory further with CSA and CLONALG to developed Artificial Immune Network (aiNet) (de Castro and Von Zuben, 2001). Other algorithms are subsequently developed with foundation based on CLONALG (de Castro and Timmis, 2002; Watkins et al., 2003; Coelho and Von Zuben, 2006; Zhao et al., 2008).

A number of limitations were suggested by Garrett (2004) regarding the Function definition, size of population subset to be cloned, efficiency of evaluation and selection stage, and the number of fitness function evaluations of CLONALG.

de Castro and Timmis developed a discrete immune network model aiNet which is an enhancement using the concepts from CLONALG by incorporating immune network theory (de Castro and Von Zuben, 2001). In the network model, each cell is a real-valued vector in the Euclidean shape-space. The affinity between the two cells is represented by their Euclidean distance. The model adopted clonal selection on the selection of antibodies. It also applied the network suppression to increase the diversity and allow interaction between the cells. During the iterations of the algorithm, a population of cells is optimized through the affinity proportional mutation. Similar cells are eliminated to avoid redundancy and new cells are randomly generated. The cells in the network interact with each other until the terminal condition is met. The algorithm is shown to be successfully applied to solve multi-modal optimization functions.

5.2 ACS and TS aiNet

Based on the foundation of CLONALG, Watkins et al. (2003) proposed the Parallel Immune-inspired Algorithm through the parallelization of CLONALG. The input set of the algorithm is divided by a number of processes involved in the parallel job. Each process evolves corresponding memory cells and a root process gathers them for a final simulated result. The result shows a more efficient computation but yet the improvement of decentralized exploration and immune-inspired learning algorithm are proposed. Garrett (2004) developed Adaptive Clonal Selection (ACS) by enhancing a number of processes and parameters in CLONALG. The mutation parameter, number of antibodies selected for cloning, and the number of clones produced for each antibody are changed to automatic parameters.

5.3 Opt-aiNet, copt-aiNet, dopt-aiNet, Omni-aiNet, Parallel immune-inspired algorithm, VAIS, and VIS

Research based on aiNet extended aiNet to opt-aiNet (de Castro and Timmis, 2002), copt-aiNet (Gomes et al., 2003), dopt-aiNet (de Franca et al., 2005), and Omni-aiNet (Coelho and Von Zuben, 2006). Freschi and Repetto (2005) developed a multi-objective version of the opt-aiNet called Vector Artificial Immune System (VAIS). Vector Immune System (VIS) (Freschi and Repetto, 2006) is also developed as a modified version of VAIS. Tabu Search Artificial Immune Algorithm (TS aiNet) is also proposed by Zhao et al. (2008) based on aiNet.

After the proposed aiNet developed for data analysis and clustering tasks, a modified version of aiNet, called opt-aiNet, is specially designed for multimodal optimization problems. The algorithm was modified to combine exploitation with exploration of the fitness landscape. The search method is designed based on local search intertwine with global search. It proposed a dynamic search for an optimum population size based on the network suppression threshold and defined stopping criterion. Gomes et al. (2003) further proposed Artificial Immune Network for Combinatorial Optimization (copt-aiNet) which is modified from opt-aiNet for combinatorial optimization tasks. de Franca (2005) also proposed Artificial Immune Network for Dynamic Optimization (dopt-aiNet) for solving time-varying fitness functions. Artificial Immune Network for Omni-optimization (omno-aiNet) was further suggested by Coelho and Von Zuben (2006) which incorporates the mechanism of opt-aiNet and dopt-aiNet, and presents a population capable of adjusting its size during the execution of the algorithm.

Freschi and Repetto (2005) introduced VAIS as a multi-objective version of opt-aiNet. It incorporates the immune network theory to allow antibodies recognizing each other and further stimulate or suppress during proliferation. It also designed with a memory population storing the non-dominated solutions and Gaussian mutation diversifying the population. Unlike opt-aiNet, the suppression mechanism is modified to consider similarity in the objective space instead of the parameter space in the optimization problems. Later, VAIS is modified into VIS (Freschi and Repetto, 2006) and applied to constrained and unconstrained benchmarking problems.

Zhao et al. (2008) developed TS-aiNet by further incorporating the mechanism of Tabu search algorithm and the aiNet. A tabu list is introduced in the algorithm for taboos cells with no affinity values improvement in the network. The mutation of diversity search in the process of global optimization is improved using Gauss mutation. The algorithm is shown to have better convergence and stability in the search space when compared with CLONALG and aiNet when applied in the multi-modal optimization problems.

5.4 ISPEA

Immune Strength Pareto Evolutionary Algorithm (ISPEA) (Meng and Lui, 2003) is an improvement on Strength Pareto Evolutionary Algorithm (SPEA) (Zitzler et al., 2001) by adding immune characteristics into the algorithm design to restrain the degeneracy of the evolution process. An immune operator is proposed by the use of vaccine extraction, vaccination, and immune selection. It shows from the test functions that ISPEA performs well with scattered Pareto solutions obtained and restrains the degeneracy through the evolution process. However, lack of discussions is made on the sensitivity and control on the population size and corresponding crossover and mutation parameters. Examples could also be performed using ISPEA to demonstrate its effectiveness and contribution to real life applications.

5.5 MOIA and CMOIA

Luh et al. (2003) proposed Multi-objective Immune Algorithm (MOIA) to search for Pareto optimal solutions in multi-objective optimization problems. It adopts the adaptive immune responses, gene fragment recombination, and antibody diversification of biological immune system to allow an efficient exploitation and exploration in optimal search of optimization problems. It is also compared with SPEA and indicated that MOIA outperformed the SPEA. Constrained multi-objective immune algorithm (CMOIA) (Luh and Chueh, 2004) is further developed by introducing the concept of cytokines on handling constraints in optimization problems.

5.6 MISA

Multi-objective Immune System Algorithm (MISA) is developed by Coello Coello and Nareli (2005) to solve both constrained and unconstrained multi-objective optimization problems. Pareto dominance and mutation have been used in the algorithm. Both uniform and non-uniform mutations are applied in the algorithm. The proposed algorithm is compared with three other evolutionary algorithms, namely micro-genetic algorithm for multi-objective optimization (microGA) (Coello Coello and Toscano Pulido, 2001), Nondominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2000) and Pareto Archived Evolution Strategy (PAES) (Knowles and Corne, 2000). The results show that the proposed algorithm is a viable method to solve multi-objective optimization problems.

5.7 RCSA

Campelo et al. (2005) proposed a real-coded clonal selection algorithm (RCSA) and applied it to electromagnetic design optimization. The algorithm is in real-coded in order to cater real-valued variables in electromagnetic problems. The main features adopted from immune metaphor are the clonal selection, cloning, and mutation. After verifying with the test functions, RCSA is shown successfully applied in optimizing superconducting magnetic energy storage (SMES) device in the electromagnetic problems.

5.8 PAIA

Population Adaptive-based Immune Algorithm (PAIA) is developed using clonal selection theory and immune network theory (Chen and Mahfouf, 2006). Besides adopting Clonal selection principles and Immune network theory, the algorithm is designed to allow the population adaptive at each iteration step during the simulation process. This could achieve having the population size adaptive to the problem and reduce the evaluation times on the iterations. The algorithm is compared with NSGA-II, SPEA, and VIS. It shows the AIS-based algorithm offers advantages over the traditional population-based GA schemes.

5.9 AISDR

Lau and Wong (2005) proposed a framework, called Artificial Immune System-based Dynamic Routing (AISDR), for solving routing selection problems. The framework covers the AIS features on recognition, selection, learning, memory, and adaptation capabilities. An AISDR algorithm incorporating clonal selection, affinity maturation, and immunological memory characteristics is developed. It is then applied on route selection in container transportation and logistics.

5.10 HAIS

An immunity-based hybrid evolutionary algorithm called Hybrid Artificial Immune Systems (HAIS) was proposed by Wong et al. (2008) to solve both unconstrained and constrained multi-objective optimization problems. It adopted Clonal selection and Immune suppression theories with a sorting scheme to attain Pareto optimal. The algorithm was verified on successfully attaining global optimal solutions in the benchmarking functions. It is compared with other evolutionary algorithms and applied to optimize the global container repositioning in maritime logistics.

5.11 MOBAIS

Castro and Von Zuben (2008) recently tried to investigate the ability of AIS on building blocks to solve high quality partial solutions coded in the problem functions and developed an algorithm called Multi-Objective Baysian Artificial Immune System (MOBAIS). As traditional AIS algorithms on evolving the population do not consider the relationship among the variables of the problem, this results the disruption of the high-quality partial solutions. Castro and Von Zuben replaced the mutation and cloning operators with a probabilistic model for sampling new solutions in MOBAIS. The performance of the algorithm was evaluated and compared to three other algorithms using a multi-objective knapsack problem. The result is positive and MOBAIS shows a better performance on the sensitivity of population size, and identification of building blocks.

Apart from the algorithms highlighted, Table 3 shows a list of recent AIS-based algorithms developed for solving optimization problems. A summary of the immune theories adopted in various algorithms has also been shown in Table 4.

Year	Author(s)	Algorithm	AIS Theories on Optimization	Application
1999	de Castro & Von Zuben	Clonal Selection Algorithm (CSA)	Clonal Selection Principle; Affinity Maturation	Pattern matching; Optimization
2001	de Castro &Von Zuben	aiNet	Immune Network Theory	-
2002	de Castro &Timmis	Opt-aiNet	Clonal Selection; Affinity Maturation	Information compression; Data clustering
2002	de Castro & Von Zuben	CLONALG	Clonal Selection	-
2003	Kelsey & Timmis	B-Cell Algorithm (BCA)	Clonal Selection; Affinity maturation - somatic hypermutation operator; Genetic Algorithm	-
2003	Watkins et al.	Parallel immune-inspired algorithm	Clonal Selection, Affinity Maturation	Pattern recognition; Function Optimization
2003	Meng & Liu	Immunity Strength Pareto	Vaccine extraction; Vaccine Immune	-

		Evolutionary Algorithm (ISPEA)	Selection	
2003	Chueh et al.	Multi-objective Immune Algorithm (MOIA)	Somatic mutation, Gene fragment recombination, Antibody diversification	-
2004	Keko et al.	GA with added immune operator	GA (Crossover and Edge-Recombination Operator), Immune Operator	Distribution Network Routing Problem
2004	Garrett	Adaptive Clonal Selection (ACS)	Adaptive clonal selection	-
2004	Li et al.	Artificial Immune Algorithm for MO Optimization (AIAMOO)	Affinity of antibodies measurement, Network Suppression, Mutation	Solve optimization functions
2004	Luh & Chueh	Constrained Multi-objective Immune Algorithm (CMOIA)	Somatic mutation, Gene fragment recombination, Antibody diversification schemes, concept of cytokines	Optimal design of truss structure
2005	Coello Coello & Cortés	Multiobjective Immune System Algorithm (MISA)	Clonal Selection, Uniform & Non-uniform mutation, Pareto dominance	-
2005	Campelo et al.	Real-coded clonal selection algorithm (RCSA)	Clonal Selection	Electromagnetic design optimization
2005	Lau & Wong	Artificial Immune System Dynamic Routing (AISDR)	Clonal Selection	Routing selection
2005	de Franca, et al.	dopt-aiNet (Artificial Immune Network for Dynamic Optimization)	Cloning, Gene duplication, Gaussian mutation, Cell line suppression	-
2005	Freschi & Repetto	Vector Artificial Immune System (VAIS)	Gaussian mutation, Immune suppression	-
2005	Lin	Real-time Dynamic Danger Theory Model (RDDT)	Danger Theory	-
2006	Coelho & Von Zuben	Omni-aiNet	Cloning, Hypermutation, Selection, Gene Duplication	Solve optimization functions
2006	Chen & Mahfouf	Population Adaptive based Immune Algorithm (PAIA)	Clonal Selection, Immune Network Theory	-
2006	Freschi & Repetto	Vector Immune System (VIS)	Clonal Selection, Suppression, and Hypermutation	-
2007	Gong et al.	Differential Immune Clonal Selection Algorithm (DICSA)	Clonal Selection, Differential Evolution Paradigm	-
2007	Dong et al.	Immune memory clonal selection algorithm (IMCSA)	Immune Memory, Clonal Selection	Designing stack filters for noise suppression
2007	He & Han	Binary differential evolution algorithm	Negative selection	-
2007	Gong et al.	Differential Immune Clonal Selection Algorithm (DICSA)	Clonal Selection, Differential Evolution Paradigm	-
2007	Lau & Tsang	Suppression Control Algorithm (SCA)	Immune network theory, Suppression	
2008	Lau & Tsang	Parallel Suppression Control Algorithm (PSCA)	Immune network theory, Suppression	Parallel implementation of SCA
2008	de Castro & Von Zuben	Multi-Objective Bayesian AIS (MOBAIS)	Estimation of Distribution Algorithm, Bayesian network	Multi-objective Knapsack Problem
2008	Tan et al.	Evolutionary multi-objective immune algorithm (EMOIA)	Clonal Selection, Immune Memory, Information-theoretic based density preservation mechanism, Entropy-based density assessment (EDAS)	-
2008	Zhao et al.	Tabu Search Artificial Immune Algorithm (TS aiNet)	Immune Network Theory, Tabu Search, Gauss mutation, Markov chain	-
2008	Ge et al.	A PSO and AIS-Based Hybrid Intelligent Algorithm	Vaccination Model, Receptor editing	Job-shop scheduling

2008	Wong et al.	Hybrid Artificial Immune System (HAIS)	Clonal selection, immune suppression, hypermutation	Container repositioning
2008	Aragon et al.	T-Cell Model	Process of T-Cell, Mutation	-
2009	Gong et al.	Secondary response clonal multi-objective algorithm (SRCMOA)	Clonal Selection, Secondary Response, Affinity Maturation, Pareto-strength based fitness assignment strategy	-
2009	Batista et al.	Real-coded distributed clonal selection algorithm (DCSA)	Clonal Selection	Electromagnetics
2009	Yildiz	A hybrid optimization algorithm based on AIS & hill climbing local search algorithm	Clonal Selection, Affinity Maturation, Hill climbing optimization search algorithm	Milling Operation, i-beam design problem, machine tool spindle design

Table 3. AIS-based optimization algorithms

AIS theories	Immune Inspired Optimization Algorithms
Clonal selection	CLONALG, aiNet, Opt-aiNet, Omni-aiNet, CSA, BCA, ACS, HAIS, MISA, RCSA, PAIA, DICSA, Parallel immune-inspired algorithm, VIS, EMOIA, AISDR, HAIS, DCSA
Somatic mutation	CMOIA, BCA, CMOIA, HAIS
Affinity maturation	CSA, aiNet, Opt-aiNet, Parallel immune-inspired algorithm
Immune network theory	aiNet, TS aiNet, PAIA, SCA, PSCA
Negative selection	Binary differential evolution algorithm
Danger Theory	RDDT

Table 4. Optimization algorithms developed based on AIS

6 Future Outlook

Considering the future development and directions of AIS in optimization, there are a number of suggestions put forward including Wang et al. (2004) who emphasized on the appropriate selection and deployment of immune theories and mechanisms, Campelo et al. (2007) suggested the exploration of the Negative Selection and Danger theory, and Timmis (2008) commented that the investigations of AIS has achieved some success but reached an impasse due to lack of theoretical advances, naive immune inspired approach and limited applications track records. He supplemented a number of recommendations to the AIS community that could be considered in order to move forward on the AIS development.

With the development of AIS algorithms for optimization in this decade, it is important to position and define future directions. Four outlooks are suggested: exploration of novel immune theories such as the mechanism of neutrophils, analysis of distinct advantages of AIS as compared to other evolutionary algorithms, integration of AIS with other techniques, and promotion of the applications of AIS algorithms to solve a diverse spectrum of industrial problems.

Currently, the majority of the optimization algorithms adopt the clonal selection and somatic mutation as the computation basis, and the issue of whether the underlying principles are fully explored is still under active consideration. Other immune theories are also yet to be discovered. The concept of negative selection and danger theory to bring new insights to search algorithms for global optimum could be further investigated. Danger signal as modeled by the danger theory could possibly guide the detection of Pareto front. The theory also includes interactions among immune operators, which may enhance the convergence of optimal solutions. Definitive benchmarking with other evolutionary algorithms, neural network-based algorithms and genetic algorithms will help setting landmarks and further establish the contributions of immunity-based algorithms for optimization.

Based on the strengths of AIS-based algorithms developed so far, taking a further step to integrate these algorithms with other optimization techniques would enhance the flexibility and possibly improve the performance of the hybrid approach. As engineers, we would definitely like to see more applications of the immune theories and algorithms to solving practical industrial optimization problems.

7 Conclusion

With the emerging success stories of AIS to the field of optimization, this paper provides a comprehensive review on the development of AIS-based algorithms for optimization. Active development with the introduction of hosts of algorithms for tackling single and multiple objective optimization problems will be found. Also, other pioneering integrations of the immune theory with other evolutionary algorithms will be reported. We believed that are much opportunity for development in this field of research and would like to see the growth of AIS in the theoretical as well as practical directions.

Reference

Aickelin, U., Bentley, P., Cayzer, S., Kim, J., McLeod, J., 2003. Danger Theory: The Link between AIS and IDS?

2nd International Conference on Artificial Immune Systems, Edinburgh, UK, Sept. 1-3 (2003), pp. 147-155.

Balicki, J., 2006, Negative selection with ranking procedure in tabu-based multi-criterion evolutionary algorithm for task assignment, CS, ICCS 2006, Pt 3, pp. 863-870, Springer-Verlag, Lecture Notes in Computer Science Vol. 3993.

Burnet, F.M., 1957. A Modification of Jerne's Theory of Antibody Production Using the Concept of Clonal Selection. The Australian Journal of Science 20: 67-69.

Burnet, F.M., 1959. *The Clonal Selection Theory of Acquired Immunity*, Cambridge University Press.

Campelo, F.; Guimaraes, F.G.; Igarashi, H.; Ramirez, J.A., 2005. A clonal selection algorithm for optimization in electromagnetics, Magnetics, IEEE Transactions on Volume 41, Issue 5, May 2005, pp. 1736 – 1739.

Campelo, F., Guimaraes, F. G., and Igarashi, H., 2007, Overview of Artificial Immune Systems for Multi-objective Optimization, Lecture Notes in Computer Science, Evolutionary Multi-Criterion Optimization, LNCS 4403, pp. 937–951, 2007.

Chen J., Mahfouf, M., 2006. A Population Adaptive Based Immune Algorithm for Solving Multi-Objective Problems. In: Bersini, H., Carneiro, J. (eds.) ICARIS 2006. LNCS, vol. 4163, pp. 280-293. Springer, Heidelberg.

Coelho, G.P., Von Zuben, F.J., 2006, Omni-aiNet: An Immune-Inspired Approach for Omni Optimization. In: Bersini, H., Carneiro, J. (eds.) ICARIS 2006. LNCS, vol. 4163, pp. 294-308

Coello Coello, C.A., and Nareli C.C., 2005. Solving Multiobjective Optimization Problems Using an Artificial Immune System, Genetic Programming and Evolvable Machines, Volume 6, Number 2, pp. 163-190.

Coello Coello, C.A., and Toscano Pulido, G., 2001. Multiobjective optimization using a micro-genetic algorithm, in Proceedings of GECCO'2001, Spector, et al. (Eds.), Morgan Kaufmann Publishers: San Francisco, CA, 2001, pp. 274–282.

Dasgupta, D., 1998, *Artificial immune systems and their applications*, Berlin, Springer, 1998.

de Castro, L.N. and Timmis, J., 2002, An artificial immune network for multimodal function optimization, in Proc. IEEE Congr. Evolutionary Computation, 2002, vol. 1, pp. 699–674.

de Castro L. N., and Timmis, J., 2002, Artificial immune systems: a new computation intelligence approach, London; New York: Springer, c2002.

de Castro, L.N., and Von Zuben F.J., 1999, AIS-Part I Basic Theory and Applications, School of Electrical and Computer Engineering, State University of Campinas, Brazil, TR DCA 01/99, Dec 1999.

de Castro, L.N., and Von Zuben F.J., 2000, Artificial Immune Systems: Part II–A Survey of Applications.

de Castro, L.N., and Von Zuben F.J., 2001, "aiNet: An Artificial Immune Network for Data Analysis" in Data Mining: A Heuristic Approach, Abbass, H.A., wt al. (eds.), Idea Group Publishing, USA, Chapter XII, pp. 231-259.

de Castro and Von Zuben, 2002, Learning and Optimization Using the Clonal Selection Principle, Evolutionary Computation, IEEE Transactions on Volume 6, Issue 3, June 2002, pp. 239 – 251.

de Franca, F. O., Von Zuben, F. J., de Castro, L. N. 2005. "An Artificial Immune Network for Multimodal Function Optimization on Dynamic Environments." In: Proc. GECCO, Washington, DC, USA, pp. 289–296, 2005.

Deb, K., Agrawal, S., Pratab, A., and Meyarivan, T., 2000. A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II, in Proc. of the Parallel Problem Solving from Nature VI Conference, Schoenauer, M., et al. (Eds.), Springer: Paris, France, pp. 849–858. Lecture Notes in Computer Science No. 1917.

Forrest, S., Perelson, A., Allen, L., Cherukuri, R., 1994, Self-nonself discrimination in a computer. In: Proc. of the IEEE symposium on research security and privacy, pp. 202-212.

Freschi, F., and Repetto, M., 2005, Multiobjective optimization by a modified artificial immune system algorithm. 4th International Conference on Artificial Immune Systems, Banff, Alberta, Canada, August 14-17, Lecture Notes in Computer Science 3627 (2005) 248-261.

Freschi, F., and Repetto, M., 2006. VIS: An artificial immune network for multi-objective optimization. Engineering Optimization Vol. 38, No. 8, pp.975-996.

Gomes, L.C.T., de Sousa, J.S., Bezerra, G.B., de Castro, L.N., Von Zuben, F.J., *Copt-aiNet and the Gene Ordering Problem*, In: Information Technology Magazine, Catholic University of Bras'ılia, vol.3, no.2, pp. 27-33, 2003.

He, X., and Han, L., 2007, A novel binary differential evolution algorithm based on artificial immune system, Evolutionary Computation, 2007. CEC 2007. IEEE Congress on 25-28 Sept. 2007, pp. 2267 - 2272

Ishida, Y., Hirayama, H., Fujita, H., Ishiguro, A., and Mori, K., 1998, *Immunity-Based Systems--Intelligent*

Systems by Artificial Immune Systems, Corona Pub. Co. Japan, 1998 (in Japanese).

Jerne, N.K., 1974. Towards a Network Theory of the Immune System. *Ann. Immunol. (Inst. Pasteur)*, 125C, pp. 373-389.

Keko, H., Skok, M., Skrlec, D., 2003. Artificial immune systems in solving routing problems, EUROCON 2003. Computer as a Tool. *The IEEE Region* 8, pp. 62 -66, Vol. 1, September 22-24.

Knowles, J. D. and Corne D.W., 2000. "Approximating the nondominated front using the pareto archived evolution strategy," Evolutionary Computation, vol. 8, no. 2, pp. 149–172, 2000.

Lau, Y. K. H. and Lu, S. Y. P., 2008. A Lagrangian based Immune-inspired Optimization Framework for Distributed Systems, IEEE International Conference on System Man and Cybernetics (SMC 2008), 12 – 15 October, Singapore.

Lau, Y. K. H. and Tsang, W. W. P., 2007. A parallel computation-based immunological framework for global optimization, Proceedings 7th International Conference on Optimization: Techniques and Applications (ICOTA7), Japan, 12 – 15 December, Vol. 5, pp. 229 – 233.

Lau, Y.K.H. and Tsang, W.W.P., 2008. A Parallel Immune Optimization Algorithm for Numeric Function Optimization, Evolutionary Intelligence, 1(3): 171 – 185

Lau, Y.K.H., and Wong, E.Y.C., 2005. An AIS-Based Dynamic Routing (AISDR) Framework. In Christian Jacob et al. (Ed.), *ICARIS 2005, Banff, Alberta, Canada, 14 – 16 August 2005*, pp. 56-71. Springer.

Li, C.H., Zhu, Y.F., Mao, Z.Y., 2004. A novel artificial immune algorithm applied to solve optimization problems, Control, Automation, Robotics and Vision Conference, 2004. ICARCV 2004 8th Vol. 1, 6-9 Dec. 2004 pp. 232 – 237.

Lin, H., 2005, A Real-time Dynamic Danger Theory Model for Anomaly Detection in File Systems, MSc. Thesis, August 2005, Department of Computer Science, University of York

Luh, G.C., Chueh, C. H., and Liu W.W., 2003, MOIA: Multi-objective Immune Algorithm. Engineering Optimization, 35 (2): pp. 143-164, 2003.

Luh, G.C., and Chueh, C.H., 2004, Multi-objective optimal design of truss structure with immune algorithm, Computers & Structures, Vol. 82, Issues 11-12, May 2004, pp. 829-844.

Matzinger, P., 1994, Tolerance Danger and the Extended Family. Annual reviews of Immunology, 12, pp. 991-1045.

Meng, H., and Liu, S., 2003, ISPEA: improvement for the strength Pareto evolutionary algorithm for multiobjective optimization with immunity, ICCIMA 2003. Proc. Fifth International Conference on 27-30 Sept. 2003 pp. 368 – 372.

Garrett, S.M., 2004, Parameter-free, adaptive clonal selection, Congress on Evolutionary Computing (CEC 2004), Portland Oregon, USA, Volume 1, pp. 1052-1058.

Timmis, J., 2007, Artificial immune systems – today and tomorrow, Nat Comput (2007) 6: pp. 1-18.

Vrugt, J.A., Robinson, B.A., 2007. Improved evolutionary optimization from genetically adaptive multimethod search. *Proc. of the National Academy of Sciences of the USA (PNAS)*, vol. 104, no. 3, pp. 708-711.

Wang, X., Gao, X. Z., Ovaska, S. J., 2004. Artificial Immune Optimziation Methods and Applications – A Survey, IEEE International Conference on Systems, Man and Cybernetics.

Watkins A., Bi, X., Phadke, A., 2003, Parallelizing an immune-inspired algorithm for efficient pattern recognition, In Intelligent Engineering Systems through Artificial Neural Networks, Vol. 13, edited by Dagli, C., et al., pp. 225-230. ASME Press.

Wong, E.Y.C., Yeung, H.S.C., and Lau, H.Y.K., 2008, Immunity-based hybrid evolutionary algorithm for multi-objective optimization in global container repositioning, Journal of EAAI, Article in Press, 17 Dec 2008.

Zhao, Y., Yin, Y., Fu, D., Zhou, Z., Yin, P., Wang, J., 2008, Application of improved artificial immune network algorithm to optimization, ISSCAA 2008. 2nd International Symposium on 10-12 Dec. 2008 pp. 1 – 6.

Zitzler, E., Laumanns, M., Thiele, L., 2001. SPEA2: Improving the strength pareto evolutionary algorithm, Swiss Federal Institute of Technology, Tech-Rep. TIK-Rep, 103.