ISSN:0975-9646

Ankita Golchha et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 6 (1) , 2015, 252-255

Non-Dominated Sorting Genetic Algorithm-II – A Succinct Survey

Ankita Golchha[#], Shahana Gajala Qureshi[*]

[#]*M.Tech (CSE) Scholar, RIT College, Raipur, CSVTU University, Bhilai, Chhattisgarh, India*

[*]*Asst. Professor, Department of (CSE), RIT College, Raipur, CSVTU University, Bhilai, Chhattisgarh, India*

Abstract- **over the period of time a number of algorithms have been proposed for test data generation for automation of software testing. One such algorithm was given by Kalyanmoy Deb in 2002, under the name Non-dominated sorting genetic algorithm-II (NSGA-II). It has been applied for solving number of Optimization problems. In this survey paper we give a succinct overview of the application of NSGA-II.**

Keywords- **NSGA-II**

I. Introduction

The use of technology has increased rapidly over the past years and so has enlarged the usage of software. This makes it important to sustain the quality of the software. Software testing is the most significant critical quality assurance measure consuming at least 50% of software development cost [2]. The automation process of test data generation is a way that will reduce the time taken up by this task. Genetic Algorithm (GA) is used for this purpose.

A number of multi-objective evolutionary algorithms have been suggested earlier. Non-Dominated Sorting Genetic Algorithm (NSGA-II) is an algorithm given to solve the Multi-Objective Optimization (MOO) problems. It was proposed by Deb et.al in 2002 [3], advancing on the concept given by Goldberg 1989 [1]. NSGA-II is one of the most widely used algorithms for solving MOO problems. Rest of the paper is organized as follows: NSGA-II in second section, Succinct Survey in third section and conclusion in fourth section.

II. NSGA-II

A. NSGA-II

The Non-dominated Sorting Genetic Algorithm [3] NSGA-II uses a faster sorting procedure, an elitism preserving approach and a parameter less niching operator. The working is given as follows [4]:

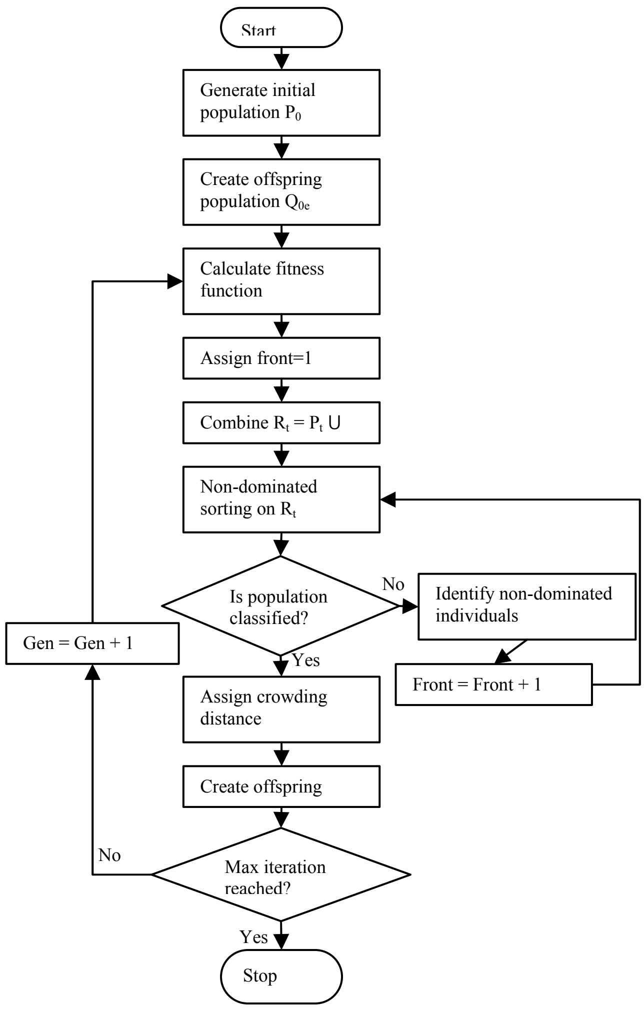

Fig. 1 WORKING OF NSGA II

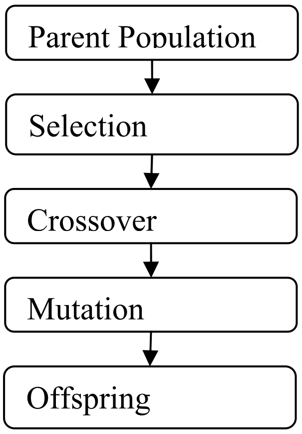

FIG. 2. CREATING OFFSPRING

B. Selection [4]

In original NSGA II *Binary tournament selection (BTS)* is used, where tournament is played between two solutions and better is selected and placed in mating pool. Two other solutions are again taken and another slot in mating pool is filled. It is carried in such a way that every solution can be made to participate in exactly 2 tournaments.

C. Crossover [5]

In NSGA II Simulated Binary Crossover (SBX) is used, which works with two parents solutions and create two offspring. The following step-by-step procedure is followed:

Step 1: Choose a random number $u_i \in [0,1]$,

Step 2: Calculate using equation 1,

Step 3: Compute offspring using equation 2.

The mathematical formulation can be given as follows:

$$\beta_{q_i} = \begin{cases} (2u_i)^{\frac{1}{\eta_c+1}} & \text{if } u_i \le 0.5\,; \\ \left(\frac{1}{2(1-u_i)}\right)^{\frac{1}{\eta_c+1}} & \text{otherwise.} \end{cases} \qquad (1)$$

$$x_i^{(1,t+1)} = 0.5\left[\left(1+\beta_{q_i}\right)x_i^{(1,t)} + \left(1-\beta_{q_i}\right)x_i^{(2,t)}\right],$$
$$x_i^{(2,t+1)} = 0.5\left[\left(1-\beta_{q_i}\right)x_i^{(1,t)} + \left(1+\beta_{q_i}\right)x_i^{(2,t)}\right]. \qquad (2)$$

Here,

u_i : Random number such that $u_i \in [0, 1]$,

η_c : Distribution index (Non-negative real number),

$x_i^{(1,t)}$ & $x_i^{(2,t)}$: Parent solutions,

$x_i^{(1,t+1)}$ & $x_i^{(2,t+1)}$: Offspring solutions.

D. Mutation [5]

In NSGA II Polynomial mutation is used, which mutates each solution separately, i.e. one parent solution gives one offspring after being mutated. The mathematical formulation can be given as:

$$y_i^{(1,t+1)} = x_i^{(1,t+1)} + (x_i^{(U)} - x_i^{(L)})\bar{\delta}_i \,, \qquad (3)$$

Where,

$$\bar{\delta}_i = \begin{cases} (2r_i)^{1/(\eta_m+1)} - 1 & \text{if } r_i < 0.5, \\ 1 - [2(1-r_i)]^{1/(\eta_m+1)}, & \text{if } r_i \ge 0.5. \end{cases} \qquad (4)$$

Here,

r_i : Random number such that $u_i \in [0, 1]$,

η_m : Distribution index (Non-negative real number),

$x_i^{(1,t+1)}$: Parent solution,

$x_i^{(U)}$: Upper bound of parent solution,

$x_i^{(L)}$: Lower bound of parent solution,

$y_i^{(t+1)}$: Offspring solution.

E. Crowded Tournament Selection [6]

To get an estimation of the density of solutions close to a particular solution i in the population, we take the average of the two solutions on the either side of solution i along each of the objective. This quantity d_i is the Crowding Distance. The following algorithm is used to calculate the crowding distance of each point in the set $\mathcal{F}$.

Assignment procedure: Crowding-sort($\mathcal{F}, <_c$)

Step 1: Call the number of solutions in $\mathcal{F}$ as $l = |\mathcal{F}|$. For each i in the set, first assign $d_i = 0$.

Step 2: For each objective function $m = 1, 2, \dots, M$, sort the set in worse order of f_m. Find sorted indices vector $I_m = \text{sort}(f_m, >)$.

Step 3: For $m = 1, \dots, M$, assign a large distance to the edge solutions, $d_{I_1^m} = d_{I_l^m} = \infty$, and for all other solutions $j = 2$ to $(l-1)$, assign:

$$d_{I_j^m} = d_{I_j^m} + \frac{f_m^{(I_{j+1}^m)} - f_m^{(I_{j-1}^m)}}{f_m^{max} - f_m^{min}}$$

III. SUCCINCT SURVEY

All In 2007 [6], author described a fast analytical model of a variable-speed induction machine which calculated both motor performances and sound power level of electromagnetic origin. This model was then coupled to Non-dominating Sorting Genetic Algorithm (NSGA-II) in order to perform global constrained optimizations with respect to several objectives (e.g. noise level, efficiency and material cost). As induction machine design involves both continuous and discrete variables, a modified NSGAII algorithm handling mixed variables was detailed. Finally, some optimization results were presented and analysed by the aid of several visualization tools. These new designs improved electromagnetic noise level by acting on both electromagnetic exciting forces characterization (orders and frequencies) and excited structure characterization (natural frequencies, radiation efficiency).

In 2007 [7], author stated that MO-NSGA-II strengthens the dominance-based predecessor, NSGA-II, by guiding the search process with reference points. In the paper, they further improve MO-NSGA-II by enhancing its mating selection mechanism with a hierarchical selection and a neighbourhood concept based on the reference points. Experimental results confirmed that the proposed ideas leaded to a better solution quality.

In 2007 [8], author studied the performance of the Fast Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) for handling such many-objective optimization problems is presented. In its basic form, the algorithm is not well suited for the handling of a larger number of objectives. To overcome this problem, substitute distance assignment schemes are proposed that can replace the crowding distance assignment, which is normally used in NSGA-II. For a number of many-objective test problems, all proposed substitute distance assignments resulted into a strongly improved performance of the NSGA-II.

In 2008 [9], author examined the effectiveness of scalability of evolutionary multiobjective optimization (EMO) algorithms to many-objective problems through computational experiments on multiobjective knapsack problems with two, four, six, and eight objectives. They explained and various scalability improvements approaches and examined their effects on the performance of NSGA-II through computational experiments. Experimental results clearly show that the diversity of solutions is decreased by most scalability improvement approaches while the convergence of solutions to the Pareto front is improved.

In 2009 [10], author presents an application of Elitist Non-dominated Sorting Genetic Algorithm version II (NSGAII), to multi-objective generation expansion planning (GEP) problem. The GEP problem is considered as a two-objective problem. The first objective is the minimization of investment cost and the second objective is the minimization of outage cost (or maximization of reliability). To improve the performance of NSGA-II, two modifications are proposed. One modification is incorporation of Virtual Mapping Procedure (VMP), and the other is introduction of controlled elitism in NSGA-II. A synthetic test system having 5 types of candidate units is considered here for GEP for a 6-year planning horizon. The effectiveness of the proposed modifications is illustrated in detail.

In 2009 [11], author introduced a general class of continuous multi-objective optimization test instances with arbitrary prescribed PS shapes, which could be used for studying the ability of multiobjective evolutionary algorithms for dealing with complicated PS shapes. It also proposed a new version of MOEA/D based on differential evolution (DE), i.e., MOEA/D-DE, and compares the proposed algorithm with NSGA-II with the same reproduction operators on the test instances introduced in this paper. The experimental results indicate that MOEA/D could significantly outperform NSGA-II on these test instances. It suggests that decomposition based multiobjective evolutionary algorithms are very promising in dealing with complicated PS shapes.

In 2009 [12], author analysed the functionality transition in the evolution process of NSGA-II and an enhanced NSGA-II with the method of controlling dominance area of solutions (CDAS) from the viewpoint of front distribution. They examine the relationship between the population of the first front consisting of non-dominated solutions and the values of two metrics, NORM and ANGLE, which measure convergence and diversity of Pareto-optimal solutions (POS), respectively. They also suggest potentials to further improve the search performance of the enhanced NSGA-II with CDAS by emphasizing the parameter S, which controls the degree of dominance by contracting or expanding the dominance area of solutions, before and after the boundary generation of functionality transition. Furthermore, they analyse the behaviour of the evolution of the enhanced NSGA-II with CDAS using the best parameters combination and compare its performance with two other algorithms that enhance selection of NSGA-II.

In 2012 [13], author proposed a better modified version of a well-known Multi-Objective Evolutionary Algorithm (MOEA) known as Non-dominated Sorting Genetic Algorithm-II (NSGA-II). The proposed algorithm included a new mutation algorithm and was been applied on a bi-objective job sequencing problem. The objectives were the minimization of total weighted tardiness and the minimization of the deterioration cost. The results of the proposed algorithm were compared with those of original NSGA-II. The comparison of the results shows that the modified NSGA-II performs better than the original NSGA-II.

In 2012 [14], author attempted to establish a comprehensive mathematical model for correlating the interactive and higher-order influences of various machining parameters on the predominant machining criteria, i.e. metal removal rate and surface roughness through response surface methodology (RSM). The adequacy of the developed mathematical models was also been tested by the analysis of variance (ANOVA) test. The process parameters were optimized through Nondominated Sorting Genetic Algorithm-II (NSGA-II) approach to maximize metal removal rate and minimize surface roughness. A non-dominated solution set was obtained and reported.

In 2012 [15], author presented an algorithm based on modified non-dominated sorting genetic algorithm (NSGA-II) with adaptive crowding distance for solving optimal economic emission dispatch (EED) problems in electric power system. Economic emission load dispatch problems are multiobjective optimization problems and are the right field for testing and application of NSGA-II algorithms. NSGA-II is reported to have performed excellently on many bench mark test cases of multiobjective optimization problems. However, modification of NSGA-II with adaptive crowding distance improved further the performance of the algorithm as the modified crowing distance enhances the capability of creating more potential and diverse solutions. The performance of the algorithm was tested on a test case of EED problem. The results were impressive and encouraging.

In 2013 [16], author’s work included multi-objective evolutionary algorithm techniques such as Genetic

Algorithm (GA) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) approach for solving Voltage Stability Constrained-Optimal Power Flow (VSC-OPF). Multi-Objective OPF, formulated as a multi-objective mixed integer nonlinear optimization problem, minimizes fuel cost and minimizes emission of gases, as well as improvement of voltage profile in the system. The above method were tested on standard IEEE 30-bus test system and simulation results were done for base case and the two severe contingency cases and also on loaded conditions. This simulation results were carried out using NSGA-II and are found that voltage stability is improved in NSGA-II than multi-objective GA of the proposed algorithm than the other approaches.

IV. CONCLUSIONS

The NSGA-II has been used for a wide variety of applications in a number of different fields. For some applications the NSGA-II has been used in its basic form where as for some applications it has been modified in different ways. The above paper gives a succinct overview of all the applications and modifications.

REFERENCES

[1] Goldberg, and David E., "Genetic Algorithm in Search, Optimization and Machine Learning", Addison Wesley, **1989**.

[2] L.J. Eshelman, and J.D. Schaffer, "Real-Coded Genetic Algorithms and Interval-Schemata", In Whitley, L.D., Editor, Foundations Of Genetic Algorithms 2, Morgan Kaufmann, San Mateo, California, pp. **187-202**, **1993**.

[3] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A Fast and Elitist Multiobjective Genetic Algorithm: Nsga-II", IEEE Transactions on Evolutionary Computations, 6(2): pp. **182–197**, **2002**.

[4] K. Deb, "Multi Objective Optimization Using Evolutionary Algorithms", Chichester, U.K., Wiley, pp. **245-253**, **2013**.

[5] F. Herrera, M. Lozano and J.L. Verdegay, "Tackling Real-Coded Genetic Algorithms: Operators and Tools for Behavioural Analysis", Artificial Intelligence Review 12: pp. **265–319**, **1998**.

[6] J. Le Besnerais, V. Lanfranchi, M. Hecquet, and P. Brochet, "Multiobjective optimization of induction machines including mixed variables and noise minimization".

[7] Shao-Wen Chen and Tsung-Che Chiang, "Evolutionary Many-objective Optimization by MO-NSGA-II with Enhanced Mating Selection", IEEE World Congress on Computational Intelligence (WCCI), IEEE Congress on Evolutionary Computation (CEC), pp. **1397 – 1404.**

[8] Mario K¨oppen and Kaori Yoshida, "Substitute Distance Assignments in NSGA-II for Handling Many-Objective Optimization Problems", LNCS 4403, Springer-Verlag Berlin Heidelberg, pp. **727–741**, **2007.**

[9] Hisao Ishibuchi, Noritaka Tsukamoto, Yasuhiro Hitotsuyanagi, and Yusuke Nojima, "Effectiveness of Scalability Improvement Attempts on the Performance of NSGA-II for Many-Objective Problems", GECCO'08, July **12-16**, **2008.**

[10] P. Murugana, S. Kannana, S. Baskarb, "NSGA-II algorithm for multi-objective generation expansion planning problem", Electric Power Systems Research 79, pp. **622–628, 2009.**

[11] Hui Li and Qingfu Zhang, "Multiobjective Optimization Problems with Complicated Pareto Sets, MOEA/D and NSGA-II", IEEE Transactions on Evolutionary Computation, Vol. 13, No. 2, Pp **284-302**, April **2009.**

[12] Tsuchida, K., Sato, H., Aguirre, H., and Tanaka, K., "Analysis of NSGA-II and NSGA-II with CDAS, and Proposal of an Enhanced CDAS Mechanism", Journal of Advanced Computational Intelligence Vol.13 No.4, **2009.**

[13] Susmita Bandyopadhyay, "Modified NSGA-II for a Bi-Objective Job Sequencing Problem", Intelligent Information Management, **319-329, 2012.**

[14] Chinnamuthu Senthilkumar, Gowrishankar Ganesan, Ramanujam Karthikeyan, "Optimization of ECM Process Parameters Using NSGA-II", Journal of Minerals and Materials Characterization and Engineering, **931-937, 2012.**

[15] Biswajit Purkayastha and Nidul Sinha, "Optimal Combined Economic and Emission Load Dispatch using Modified NSGA-II with Adaptive Crowding Distance", International Journal of Information Technology and Knowledge Management, Volume 2, No. 2, pp. **553-559**, July-December **2010.**

[16] Sandeep Panuganti, Preetha Roselyn John, Durairaj Devraj, Subhransu Sekhar Dash, "Voltage Stability Constrained Optimal Power Flow Using NSGA-II", Computational Water, Energy, and Environmental Engineering, , 2, **1-8** , January **8**, **2013.**