Mathematical and Computational Applications

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Special Issue
Evolutionary Multi-objective Optimization: An Honorary Issue Dedicated to Professor Kalyanmoy Deb

Edited by
Prof. Dr. Carlos Coello, Prof. Dr. Erik Goodman, Prof. Dr. Kaisa Miettinen, Prof. Dr. Dhish Saxena, Prof. Dr. Oliver Schütze and Prof. Dr. Lothar Thiele

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Interview: Kalyanmoy Deb Talks about Formation, Development and Challenges of the EMO Community, Important Positions in His Career, and Issues Faced Getting His Works Published

Carlos Coello [1], Erik Goodman [2], Kaisa Miettinen [3], Dhish Saxena [4], Oliver Schütze [1,*] and Lothar Thiele [5]

1 Depto de Computacion, CINVESTAV-IPN, Mexico City 07360, Mexico
2 BEACON Center for the Study of Evolution in Action, Michigan State University, East Lansing, MI 48864, USA
3 University of Jyvaskyla, Faculty of Information Technology, P.O. Box 35 (Agora), FI-40014 University of Jyvaskyla, Finland
4 Department of Mechanical and Industrial Engineering, Indian Institute of Technology, Roorkee 247667, India
5 Computer Engineering and Networks Laboratory, ETH Zürich, CH-8092 Zurich, Switzerland
* Correspondence: schuetze@cs.cinvestav.mx

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1. Introducing Kalyanmoy Deb

Kalyanmoy Deb was born in Udaipur, Tripura, the smallest state of India at the time, in 1963. He is the eldest of four siblings. Like him, his other brothers are also engineers, one in academics, one in an industry, and the other is a freelancer. Educated in the IIT system in India, he worked for two years in a reputed engineering design company, before heading for his graduate studies in the USA. After his return to India, he taught at IIT Kanpur for 20 years. He is currently a University Distinguished Professor and Koenig Endowed Chair Professor in the Department of Electrical and Computer Engineering at Michigan State University, USA. Prof. Deb's research interests are in evolutionary optimization and its application in multi-criterion optimization, modeling, and machine learning. He has been a visiting professor at various universities across the world including the University of Skövde in Sweden, ETH Zurich in Switzerland, Aalto University in Finland, Nanyang Technological University in Singapore, and a few IITs in India. He was awarded the IEEE Evolutionary Computation Pioneer Award for his pioneering work in EMO, Infosys Prize, TWAS Prize in Engineering Sciences, CajAstur Mamdani Prize, Distinguished Alumni Award from IIT Kharagpur, Edgeworth-Pareto Award, Bhatnagar Prize in Engineering Sciences, and Bessel Research Award from Germany. He has received an honorary doctorate degree from the University of Jyvaskyla, Finland. He is a fellow of ACM, ASME, IEEE, and three Indian science and engineering academies. He has published over 600 research papers. He is married to Debjani Sarkar, who is an academic specialist at Michigan State University. Their son runs a start-up on AI and their daughter works in a reputed company as a marketing manager.

2. Introducing Evolutionary Multi-Objective Optimization (EMO)

Multi-objective optimization (MO) problems give rise to not one, but a set of Pareto-optimal solutions, each of which makes a trade-off among the associated objectives with another solution. Between a pair of solutions, if one is better on one objective, it must be worse in at least one other objective. Although a single solution is desired as an outcome of a multi-objective optimization task, finding a representative set of Pareto-optimal solutions can be helpful in the process of making a decision. There exist different scalarization-based multi-objective optimization methods that scalarize multiple objectives into a single parameterized one and apply a single-objective optimization method to find the respective optimal solution. Most scalarization techniques ensure that the resulting optimal solution is a Pareto-optimal one but the scalarization technique must be selected carefully to be able to reach any Pareto-optimal solution.

Evolutionary multi-objective optimization (EMO) methods work with a population of solutions in every iteration and can find multiple well-diversified solutions simultaneously. Because of their heuristic nature, they cannot usually guarantee Pareto-optimality, but they approximate Pareto optimal solutions. Early EMO methods could handle two and three objectives well, but the new methods, known as evolutionary many-objective optimization (EMaO) methods, are demonstrated to handle as many as 15 to 20 objectives. EMO and EMaO methods use an implicitly parallel search process introduced by the evolutionary operators, and a partial ordering and diversity-preserving-based selection mechanism. Aided by modular and flexible structures, EMO and EMaO methods are regularly used to solve challenging academic and industrial problems. They have also been commercialized into software packages and public-domain codes for their use at large. The discovery of a representative set of Pareto-optimal solutions has a number of advantages for users. First, the set of solutions can be analyzed to understand the comprehensive nature of possible variations of objectives and their trade-offs, which can provide useful information to the users to follow an informed decision-making task for picking a single preferred solution for deployment. Second, the knowledge of alternate Pareto-optimal solutions can utilize them to use in a platform-based solution philosophy, in which every Pareto-optimal solution can become a potential solution for a different hardware or system platform. Third, an application of machine learning techniques to multiple Pareto-optimal solutions can bring out essential common principles hidden in them. These common principles can reveal valuable insights for constructing optimal solutions for a problem. Fourth, the EMO and EMaO philosophies are increasingly being used to introduce helper objectives in the search process to find optimal solutions for original objectives faster and with more accuracy.

EMO and EMaO methods have uniquely utilized evolutionary algorithm's (EO) population approach to finding and storing multiple optimal solutions. The matching of MO and EO philosophies could not be any better. MO gives rise to multiple alternate solutions and EO's population approach provides a platform to find and capture them. For the past three decades, EMO researchers have not only exploited this match to develop efficient MO algorithms, but they also have launched various related studies to make EMO a field of study with hundreds of PhD theses, commercial and public-domain software, dedicated conference/seminar series, and a record number of publications. Many new ideas for improving existing algorithms, new areas of applications, and new ways to utilize them for various problem-solving areas are continuously emerging. EMO has undoubtedly become a unique and ubiquitous medium for solving multi-objective problems.

It is perhaps an excellent time to celebrate the moment and recognize every EMO researcher's hard work, passion, and collaborative efforts over the past three decades.

3. Interview

The following is an interview with Prof. Kalyanmoy Deb. The editor's question is stated first, followed by Deb's response.

1. Kalyan, thank you very much for taking some of your valuable time for this interview that we are doing as part of the Special Issue dedicated to your 60th birthday. The title of this SI is "Evolutionary Multi-objective Optimization" (EMO) which leads us directly to the first questions, since you are a pioneer and highly impactful and influential proponent of EMO since 1994. Can you recall for us your first steps that, looking back, helped in the formation of what we today call the EMO community?

First of all, I am touched and humbled by your initiative in compiling this Special Issue for the occasion of my 60th birthday. It is a great honor for me. I also take this opportunity to thank all authors and reviewers of the papers published in this Special Issue. My appreciation also goes to the MDPI journal on Mathematical and Computational Applications for publishing this Special Issue.

It has been a long journey, hasn't it! The birth of EMO studies and the start of my academic career as an assistant professor at Indian Institute of Technology Kanpur (IITK) in India, happened almost concurrently. After completing my graduate studies and a short post-doctoral stay in the USA, I returned to India in early 1993 and took the Assistant Professor position at IITK. During my graduate studies (1987–1991), I was fortunate enough to have been exposed to genetic algorithms (GAs)—a fascinating concept for solving search and optimization problems using principles of natural selection and genetics–from the Evolutionary Computation pioneer David Goldberg. A 10-line outline of a plausible GA-based multi-objective optimization algorithm in Goldberg's 1989 pioneering book (Addison-Wesley) caught my attention, while I took the GA course from Goldberg. In an earlier attempt by David Schaffer in 1985, Goldberg observed that a proactive diversity-preserving operator was missing in Schaffer's vector-evaluated GA (VEGA). Having worked on niche-based GAs in my master's thesis, I immediately realized that Goldberg's suggestion for building a working EMO algorithm was just on the horizon. However, by that time, I was already quite advanced with my PhD topic on the development of messy GAs—a variable-length GA that could solve complex problems including deceptive problems, which were found difficult to solve by standard GAs. I temporarily put off my interest on multi-objective optimization research and waited until I had my first graduate student, Nidamurthy Srinivas, at IITK, to begin working on Goldberg's suggestion. The use of non-domination sorting (NS) and niche- preservation based on a sharing function approach in the GA's selection operator confirmed Goldberg's intuition. There came one of the first EMO algorithms—NSGA. We submitted our paper to Evolutionary Computation Journal of MIT Press in 1993 and the paper appeared in print in 1995. Those days, the internet was not that accessible and soon thereafter I came across two other papers which used Goldberg's idea in slightly different ways and produced two other successful EMO algorithms: multi-objective GA (MOGA) and niched Pareto GA (NPGA). Each of these methods showed that a stable population of Pareto- optimal solutions could be found and maintained for successive generations on two-objective problems. In my opinion, these three studies during 1993–1995 have initiated the birth of the EMO field, although there were a few other EMO studies that came soon thereafter which did not use Goldberg's idea literally.

Of course, a few papers or even one great idea does not often fan out to be a successful field of research and application which has lasted for about three decades now. I narrate some of the systematic and chronological developments in which I took a major part. First, more efficient EMO algorithms with fewer tunable parameters and elite preservation appeared. My 2002 NSGA-II paper (IEEE Transactions on Evolutionary Computation (TEVC)) is one such EMO algorithm, in addition to Zitzler and Thiele's Strength Pareto Evolutionary Algorithm (SPEA) and Knowles and Corne's Pareto-Archived Evolution Strategy (PAES). The simplicity and modularity in these algorithms and the availability of their public-domain codes make EMO accessible to researchers and applicationists within and outside the computer science and engineering communities. These algorithms have helped mature the EMO field and attracted many newcomers. Second, with every new algorithm being proposed, I started to realize the need for a test suite through which algorithms can be tested and compared with each other. I found a mechanism in my 1999 test problem construction paper (MIT Press's ECJ) by which existing single-objective challenging test problems can be channeled to construct similarly difficult test problems for multi-objective optimization. That study led to a collaboration with Eckart Zitzler and Lothar Thiele to formulate a two- objective Zitzler-Deb-Thiele (ZDT) test suite with discernable Pareto-optimal fronts. Although largely concurred, ZDT problems are still used as the first problems to test a new algorithm on. Third, with the existence of efficient algorithms to apply to challenging test problems, researchers proposed various performance metrics to measure convergence and diversity of obtained solutions. In my opinion, this three-pronged development of "Algorithm-Test-suite–Performance-metric" allowed more researchers to introduce new ideas and industries to venture into solving their problems for multiple objectives. All these activities started the EMO revolution, and there was no stopping it.

2. The growing interest in EMO even led to, among other things, a new conference series dedicated to this topic, called Evolutionary Multi-Criterion Optimization. Its first edition was held in Zurich (Switzerland) in 2001, and is since been held biannually and very successfully until now. Can you tell us a bit about the evolutionary history of this event series?

The opportunity offered by EMO algorithms to solve problems for multiple objectives attracted many bright PhD students. Journals started to accept EMO papers and major evolutionary computation (EC) conferences accepted EMO-related papers in their regular tracks. It became clear to everyone that EC's population approach provided a unique niche for solving multi-objective problems and EMO was being flagged as a success story of EC. To push the EMO activities further and to let everyone know about others' work closely, I realized that a dedicated conference on EMO was the need of the time. It was December of 1999 and I was on a flight from Delhi to travel to Zurich to examine the PhD thesis of Eckart Zitzler. I pondered on how nice it would be to hold the first EMO conference in Zurich. I expressed my thoughts to Eckart and Lothar, and before I realized it, Lothar was on the phone to find an available date of ETH's auditorium to host the proposed conference. The first international conference on EMO was held in March of 2001 at ETH Zurich with about 50 papers presented. Springer agreed to publish the proceedings under its Lecture Notes in Computer Science (LNCS) series. We prepared the conference for about 60 participants, but 90+ participants attended the conference. If I recall correctly, we had to order extra proceedings from Springer and post them later to many participants. The conference was a huge success, and three proposals for hosting the second one were received. To involve more key EMO researchers in the decision-making of future EMO conference events, Eckart, Lothar and I decided to form an EMO Steering Committee with a total of seven members, which has been recently extended to have 11 members. The steering committee decided to host the conference every two years and adopted a couple of practices from the very first EMO conference: (i) there will be no parallel sessions, so everyone is in the same room for all presentations, thereby giving every paper a wide attention, and (ii) there will be Multi-Criterion Decision-Making (MCDM) events within EMO conferences. Since 2001, the EMO conference series has been held every odd year.

3. For the treatment of multi-objective optimization problems you mainly use evolutionary techniques. However, you have always promoted the use of mathematical programming and multi-criterion decision-making (MCDM) techniques within EMO, which has had a significant impact on the formation of the community. Could you comment on that?

I consider myself a problem solver rather than particularly an EC or an optimization researcher. I strongly believe that a successful researcher should always acquire a good knowledge of the fundamentals associated with the topic before starting to work on it. This not only provides a deeper understanding of the topic for making any fundamental changes, but it also paves the way to know other contemporary approaches as possible alternatives. As you have correctly pointed out, mathematical programming and MCDM fields are two related and contemporary fields which deal with multi-objective problem-solving. While I understand that it is not easy and always uncomfortable to go out of one's own comfort zone and mingle with people in a different field to understand their trades, the trouble is worth taking for two reasons. First, it allows one to evaluate one's methods with other competing methods, and the process can eventually motivate developing hybrid methods. Second, it helps to propagate one's methods to the other contemporary fields.

It was evident from the beginning that multi-objective problem-solving tasks should end up or involve somehow a decision-making activity in arriving at a single preferred solution. I was fortunate to be invited to attend a few MCDM events in 1999 and the years following thereafter, and I came to know the existence of an MCDM field which had been addressing multi-objective problem solving since the early seventies. While they were mainly interested in scalarizing multiple objectives into a single one and in involving a decision-maker directly to provide preference information to move to new scalarized problems iteratively, I realized that EMO studies could definitely benefit by working with MCDM researchers. EMO's ability to find multiple representative near-Pareto solutions can be combined with MCDM-based preference incorporation ideas to make the whole EMO-MCDM approach holistic. To create this merger, I planned a few events.

First, at the EMO-2001 conference, we invited two prominent MCDM researchers: Kaisa Miettinen and Ralph Steuer, both being authors of popular MCDM books, to give a tutorial and a keynote speech on MCDM topics for EMO researchers to be aware of. This tradition has been followed in a number of future EMO conferences.

Second, in 2004, during my Bessel Research Prize visit to the University of Karlsruhe, Germany, I joined hands with my hosts Juergen Branke and Hartmut Schmeck, along with the above-mentioned MCDM researchers, to propose a Dagstuhl Seminar at Schloss Dagstuhl, Saarbrucken, Germany by inviting 30 EMO and 30 MCDM researchers. It was the first time these two groups met and openly exchanged ideas with each other. Of course, EMO being about 20 years younger than MCDM in terms of its inception, EMO researchers strikingly found that many of their ideas were already proposed by their elder counterparts. However, the seminar provided a breeding ground for the two groups to plan future collaborative studies. I must say that MCDM researchers were also exposed to the EMO philosophy and the later publication records of some of the leading MCDM researchers clearly support my assertion. The success of the first Dagstuhl seminar motivated us to repeat it at regular intervals. The epitome of the merger was the publication of an edited book (under Springer's LNCS series, edited by four founding organizers) in which most chapters were jointly written by EMO and MCDM authors.

Third, I was invited to visit Helsinki School of Economics (now Aalto University School of Business) as a Finland Distinguished Professor for two years and to collaborate with Kaisa Miettinen, Jyrki Wallenius and Pekka Korhonen – three stalwarts in the MCDM community. With this collaboration, I had a better appreciation of the MCDM philosophy and met other prominent MCDM researchers who regularly visited the university. I began to combine EMO and MCDM methods, a process which resulted in reference-point-based NSGA-II, reference-direction-based NSGA-II, light-beam-search-based EMO, progressively interactive EMO, and others which also combined EMO with MCDM methods to find a single preferred Pareto-optimal solution at the end.

Fourth, during my Helsinki visit, I also worked with Jyrki and others to make EMO an area topic for the Journal of Multi-Criterion Decision Analysis (Wiley) and served as an area editor from 2009 until 2018.

Fifth, in 2008, I worked with the International Society on MCDM to establish an EMO track within their bi-annual MCDM conferences and reciprocated the same, with the advice of the EMO steering committee, by instituting an MCDM track within EMO conferences soon thereafter. I am happy that these practices are still being continued.

My quest for fundamental understanding has helped me tremendously in evaluating EC's scope as an optimization algorithm compared to mathematical optimization literature, although I must admit that I do not have the adequate mathematical background to understand all of their detailed theoretical intricacies. However, I have been fortunate to have a few colleagues in mathematical optimization and operations research areas with whom I have not only pursued some fundamental convergence studies, but also co-taught multi-objective optimization courses, exposing students to both mathematical and computational worlds of optimization. Using variational principles, we were able to estimate a Karush-Kuhn-Tucker Proximity Measure (KKTPM) for any feasible or infeasible solution from the KKT-based Pareto-optimal set without actually knowing the location of the Pareto-optimal set. Although the KKTPM measure requires computation of derivatives of objective and constraint functions, the idea brought in useful EMO operators aiding guaranteed convergence to EMO studies.

To reiterate the importance of associated knowledge around a field, the next example is illustrative. I was exposed to a resource allocation problem from an industry which involved about 50,000 integer decision variables. While it was a linear programming problem, the integer restriction of variables made all the differences between a fast and guaranteed solution methodology for the real-parameter version of the problem and an exponentially worse algorithm for its integer version. Well-known operations research software packages could not find the optimal solution for 2000 or more variables. We developed a customized EC-based procedure that recombined two or more solutions meaningfully in the context of the problem and used local adjustments to try to make infeasible solutions feasible. The procedure not only found near-optimal solutions (within a maximum of 0.03% deviation from the true optimum) in 2000 or even 50,000 variables, but to a staggering one billion variable version of the problem in polynomial computational time. I believe more such defining contributions are possible and are worth pursuing, but this will require a good understanding of the associated literature and strengths and weaknesses of various alternative methodologies.

4. How do you see the current development of the EMO community?

I am absolutely certain that the EMO field is in good hands. I am happy that a simple idea on the use of a population-based optimization method to find multiple Pareto-optimal solutions simultaneously survived almost three decades and provided EMO researchers with plenty of opportunities to formulate new research ideas, extended to solve various types of problems, and helped merge multiple fields together.

Looking at the recent publications, a major thrust in EMO research today is clearly in the area of evolutionary many-objective optimization (EMaO), which focuses on addressing four or more objectives. While several efficient EMaO algorithms are in place based on reference vectors, the idea is interesting enough to be pursued further.

Another current development in EMO is in the use of machine learning (ML) methods for enhancing performance of EMO and EMaO algorithms. In the past two decades, ML has experienced a surge of activities, mainly due to the availability of data and the need for finding intelligence from data. Evolving a population of solutions and their objective/constraint values within an EMO algorithm can also be seen as a series of evolving data. ML methods can mine the data to reveal interesting search patterns and directions, which in turn can help make EMO methods faster and more reliable. Various such efforts in utilizing ML to improve EMO are underway. On a different note, EMO researchers should also find ways to utilize EC and EMO algorithms for enhancing ML's performance to make EMO an integral part of the current ML revolution.

Surrogate-assisted EMO is another area which is getting significant attention for its own right. Optimizing for a budget of solution evaluations will keep EMO applications practically viable.

Challenging test-problem development for benchmarking EMO algorithms should always be a constant thrust of EMO researchers. I am happy to see the original ZDT and DTLZ-based philosophies are being constantly extended to create more challenging test problems and EMO algorithms are improving consistently as a result.

5. What do you think are the most important challenges EMO has to face in the future?

EMO and EMaO algorithms are now quite capable of addressing different kinds of multi- and many-objective problems, although further improvements are always necessary. They have performed well on challenging test problems and some small-sized engineering problems, but their real test will come when they are extensively applied to large-scale real-world problems. Industries are slowly but surely embracing EMO algorithms for solving two- and three- objective problems mostly (thanks to the use of dedicated commercial software and public-domain codes on EMO!) and it may be a while before they move to addressing more objectives. In the meantime, EMO researchers should advance the current practices as well.

First, more representative problems from real-world problems need to be identified and used to test our best EMaO algorithms for their working. In this direction, a direct collaboration with commercial software companies and researchers in application industries would be helpful.

Second, many-objective problems demand an easy and insightful visualization technique to understand trade-offs among Pareto-optimal solutions. There is a lack of a suitable visualization technique for understanding trade-offs, feasible search spaces, Pareto boundaries, etc., conveniently. Let us accept that the standard parallel coordinate plot (PCP) or radial visualization (RadViz) or scatter plots do not cut it. We may get influenced by high-dimensional data analysis literature for a clue here, but let us understand that our data have a special property – they possess a trade-off among the dimensions, in which generic data analysis folks may not be particularly interested. Hence, EMO researchers may have to find a solution for many-objective Pareto-optimal data visualization themselves.

Third, I strongly believe optimization algorithms must be customized for specific problem classes to make them more efficient both in terms of computational time and solution accuracy. While ML methods can be of help here (as alluded to before), practical use of EMO algorithms must be accompanied by an interactive platform which enables monitoring and aiding in the solution process by real users during the optimization process. Users' many years of experience on the problem can be utilized to customize an algorithm on the fly. Optimization algorithms discover useful variable interactions and patterns through their iterations, and a user's interaction can be made more fruitful if such discoveries can be shared with the user for their feedback on the relevance of the discoveries. Preference-related feedback can also be integrated here for multi-objective problems. We should soon see more such interactive EMO platforms being developed.

In most EMO and EMaO studies, we have focused on developing selection mechanisms for handling multiple objectives and have not spent much time on creation mechanisms for finding new and effective solutions. Unless new and diverse solutions are created by EMO's generation process, the multi-objective selection operator cannot do much. We should start focusing on hybrid genetic and local search methods and focus on creating more solutions directly in places where there is a lack of non-dominated solutions in the current population.

EMO has matured enough now to be applied to address large-scale societal and industrial problems. Problems affecting societies, such as climate change, obesity, forest management, agricultural management problems involving water, energy and food, and others, involve many conflicting objectives in terms of operating and installation costs, environmental effects, sustainability issues, etc., having numerous variables that can be adjusted with time and having constraints which must be satisfied to make a solution implementable. Finding a few alternative Pareto-optimal solutions by EMO algorithms customized to such problems can provide policy-makers with a new and transparent solution approach. Industrial problems such as supply-chain management, large manufacturing system operation, and integrated multi-level design tasks are other areas.

EMO algorithms, like single-objective EC methods, are stochastic and cannot ever have a theoretical convergence proof for any arbitrary problem, as supported by the no-free-lunch theorem. However, an EMO algorithm's population approach and its recombination operator help establish an implicit parallel search, which makes the EMO algorithm unique and different from other optimization methods. Collectively, we should find and focus on addressing problems that are difficult to solve by existing point-based methods, but a clever design of an EMO method can help find acceptable solutions.

6. During your career, you have held numerous important positions. You have already mentioned your times in Dortmund and the ETH Zurich as visiting professor. Your main affiliation has been at the IIT Kanpur in India. After 15 years of service you decided to take a position in Helsinki (Finland). What was your main motivation for that?

I started my professional academic career at IIT Kanpur in India in 1993, when GAs were then mostly unheard of and their practice was questioned in engineering departments. I kept working on some key issues needed to popularize EC and make EC an effective tool for search and optimization in practice. I am happy that a few of these contributions have become popular over the years, including my parameter-less constraint handling approach, real-parameter recombination (SBX) and polynomial mutation operators, multi-objective optimization algorithm (NSGA series), multi-objective test problem construction, two textbooks on optimization, and others. I had the good fortune to have extremely dedicated students with excellent programming skills to help me execute these studies.

From time to time I realized that I needed to get feedback and have real discussions with experts in the field. I took a few opportunities that came my way to visit and interact with key EC experts: University of Dortmund with the Humboldt Fellowship from Alexander von Humboldt Foundation, Germany during 1998–1999, ETH Zurich with visiting professorship in 2001, University of Karlsruhe with Bessel Research Prize Award from Alexander von Humboldt Foundation, Germany in 2003, Nanyang Technological University, Singapore with A* project visit in 2006, Helsinki School of Economics with Finland Distinguished Professorship from the Academy of Finland during 2007–2009, and a number of bilateral project visits between India and European countries. These extended visits not only put me on the right track, but also exposed my work to experts in the field. Although such frequent visits came at the expense of relocating my family, I would recommend to young and isolated researchers to embrace such research visits as opportunities, rather than a disadvantage. I thank my family for their sacrifice and adjustments which I sincerely hope have given them better exposure and made them better individuals.

7. The next—and until now last—major change came in 2011 where you moved to East Lansing (USA) to become Professor and Koenig Endowed Chair at Michigan State University, which definitely came with new challenges for you and your family.

The genetic algorithms research was started in Michigan in early sixties. Michigan State University (MSU) is one of the few universities in USA which traditionally had a strong focus in evolutionary computation field. The BEACON center for the study of evolution in action funded by National Science Foundation (NSF) at MSU enabled a major research collaboration opportunity in various aspects of evolution led by Prof. Erik Goodman. When an endowed chair faculty position was offered to me at MSU, I did not have any second thought. Thus, far, I had the opportunity to work with several MSU colleagues from various disciplines, visiting researchers from various countries, and automobile and chemical industries in Michigan to have a better fulfillment of my research career. The move also provided great educational opportunities to my children at a critical time of their careers.

8. Finally, we come to another topic that might be very interesting, in particular, for younger scholars. We recall a Keynote Talk of yours where you presented a new evolutionary algorithm for a particular resource allocation problem. While the results were amazing, you mentioned that you have faced major issues to get the related paper published. Many readers might assume that publication of a paper that contains such great results and that comes from a renowned researcher like you should just be a formality. Apparently, this is not always the case. Could you comment on that?

Most researchers may have faced such incidents in their careers. Since you mentioned it, let me address it to hopefully make a remark on the current paper review system in our field. What I thought was a great EC-application study which showcased an EC-based solution methodology to solve a billion-variable resource allocation problem (never done before), editors and reviewers of a leading EC journal suggested that I 'compare' my approach with a few recommended existing EC methods. Upon a survey, I found that the suggested EC methods addressed completely different kinds of problems having only 500 to 1000 variables. It was obvious that these methods were generic and would not have worked on a specific problem class involving million to billion-variable integer variables. We developed a customized EC algorithm for solving such large-scale problems and our purpose was to demonstrate that the population-based approach with customized recombination and mutation operators was a better answer to this type of exa-scale optimization problems rather than the standard point-based structured algorithms. I really wanted the paper to appear in an EC-based journal so we, as a community, could celebrate and propagate EC techniques with such defining studies. Anyway, the paper was eventually published in a non-EC journal, after I withdrew the paper from the EC journal.

With this experience and from a few other recent reviews on my papers, I am increasingly convinced that most of our current reviewers expect that every article, to be published, must fall into certain patterns. A paper should have a new idea, but no matter how small or incremental the idea is, it must be compared with many existing algorithms, it must produce page-long tables presenting comparative results, and it must end by citing papers from most renowned authors in the field. Such a mindset of reviewers is harmful for the field in the long run. While there is a need for comparative studies, there is also a need for new and direction-providing papers, addressing bigger issues of the field, providing first-time ideas which cannot be compared with anything from the past, and defining applications that will keep EC alive and meaningful to practitioners. Let us be more inclusive and open-minded.

9. NSGA-III is one of the most cited and most widely used multi-objective evolutionary algorithms. Rumors say that it was also not easy for you to get the two initial works on this algorithm published. Is this true?

It is true that the NSGA-III paper was rejected at first. Apparently, the paper exceeded the strict maximum two-time review policy restriction. Apparently, we failed to follow the suggestion of a reviewer to remove one of the three application problems, as the reviewer thought the paper was too long. I blame it to the lack of patience everyone has these days to pick signals from noise, but it is disturbing to think how many such trivial but harsh decisions are ruining the fate of important studies. I am glad that the decision was overturned eventually and the paper made its way to see the light of day, enriching the journal and EMO community and receiving significant attention to date.

Another not-so-fortunate outcome occurred with the Deb-Thiele-Laumanns- Zitzler (DTLZ) scalable test suite development paper, which never appeared in a journal due to its rejection, but its book-chapter version is probably one of the most highly-cited EMO articles today. I am sure everyone has such examples to cite, but we should all collectively plan for ways and means to reduce such unfortunate events, as these important studies, if can be envisioned by editors and reviewers about their possible future impact, could not only help the field, they will enhance the citation profile of our journals and conferences.

10. Finally, do you have a message for the authors out there that are struggling to get their research published?

I actually have messages for both authors, reviewers and editors. I believe as an author of any work, we should first be “satisfied” and “happy” with our work. If the author is not happy about its content, how can the author convince reviewers or readers to pay attention to it? Thus, my message for authors is to keep improving your work until you think you have tried enough to bring the work to a logical conclusion and in your opinion the work contributes to advance the field. Then, look for a journal/conference which is most suitable for the work. If you are a budding researcher, I understand that you need a good “quantity” of papers, so work on as many ideas as you can, collaborate with as many researchers as you can, and publish. However, once in a while, take a break, and think big and look at your field from 10,000 feet above and identify areas that need deeper attention. Work on these challenging ideas and see if you can make a crack. These works will give you fame, inspire you, and keep you alive.

As to the reviewers, my message is to have a bit of patience. Every article to be conceived worked on and written needs a lot of effort, taking many months to years, which every one of us has experience with. Treat others' papers the same way you would expect your articles to be treated. Here is an idea! Instead of assuming that the article you are reviewing is a reject to start with and looking for positive aspects to decide if you would accept the paper, think the other way. Assume every article is an accept to start with and then evaluate to see if it has enough new messages/results for it to be an accept or reject. Know that every author expects some constructive comments, particularly when the paper is rejected. If you are rejecting the article, please provide enough feedback so that authors find directions to modify it. As a reviewer, always know that you are in some sense in charge of what should be published and what should not be. You need to elevate yourself to decide the article's contribution to the overall growth and advancement of the field. You are a key component in this endeavor and everyone in the EMO community thanks you profusely for your time and efforts.

In my opinion, editors of journals and proceedings are the most influential persons in a field, indirectly controlling the focus of the field. They should not be intermediaries who simply count the number of accepts and rejects to decide the fate of a submission. They are the leaders of the field. They can judge a paper on their own very well and should be courageous enough to change a reviewer's comments and decisions if they think otherwise. Let every stakeholder in the review system (authors, editors and reviewers) care only about our field, its overall advancement and acceptance to contemporary other fields, rather than any other matter.

We have come a long way with all-round and well-grounded activities. Let us all together make the EMO research and application unbiased, top-notch, rewarding, and enjoyable. Let us all feel proud to be a part of the EMO revolution.

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