An Appraisal of Multi Objective Evolutionary Algorithm for Possible Optimization of Renewable Energy Systems

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***Abstract*—The development of efficient multi objective evolutionary algorithms (MOEAs) can provide an effective tool for solving the optimization of solely renewable electricity systems. This paper presents an appraisal of multi objective evolutionary algorithms. It covers MOEA framework as a key issue in its design, these are including of MOEA based on decomposition, Preference, Indicator, hybridization, and co-evolution. Other MOEA frameworks covered in this paper are Target Region-based Multi Objective Evolutionary Algorithm (TMOEA) and Memetic Algorithm (MA) for multi objective evolutionary algorithms. The computational complexity of MOEAs has been presented. Potential direction for future research is in the area of MOEA application in an exclusively renewable energy system, thereby paving the way for the Internet of Renewable Energy (IoRE).**

***Index Terms*--Computational complexity of multi objective evolutionary algorithm, Evolutionary Algorithm, Multi objective evolutionary algorithm, Multi objective evolutionary algorithm frameworks, Renewable Energy Systems.**

I. INTRODUCTION

The growing environmental pollution, increasing demand and shortage of electricity supply has raised the interest in renewable energy sources. Renewable energy system is a power production system provided only by renewable technologies. The electricity supplied by a single renewable energy source exhibit the character of randomness and unpredictability. Hence, it is necessary to combine various sources of renewable energy sources altogether to solve this problem [1] – [2]. This is an important pattern in which to develop renewable electricity. A purely renewable electricity system will consist of two or more alternative renewable electricity architecture working together. Here, renewable electrical islands and renewable electricity grids will be connected. The former will help to secure electricity to vitally important loads. While the later will feed electricity to crucial and non-crucial loads [3]. Electricity will be generated using only renewable sources of energy like Wind Plants (WPs), Concentrated Solar Plants (CSPs), Photovoltaic Solar Panels (PSPs), Hydro Power Plants (HPPs) and so on. WPs, PSPs, HPPs and CSPs are among the most developed renewable energy sources and have been universally used in renewable electricity generation. Renewable electricity provides clean energy and are free in nature. But due to economic and political hindrances, addition of storage systems and ability of solely renewable electricity generating systems to compensate for irregularity in renewable energy generation process, the cost of electricity from renewable sources is on the high side [4] – [7].

Optimization is a methodology of making a system as fully effective as possible. It is a way of maximizing or minimizing some function with respect to some set, often standing for a range of options obtainable in a certain situation. The function enables the comparability of different options for deciding the best option [8] – [9]. Multi objective optimization examines optimization problems including more than one objective function to be optimized concomitantly. It is used in engineering, economics, logistics etc., when foremost resolutions are obligatory in the existence of trade-offs between two or more opposing objectives [10 – [11]. In the design of renewable energy systems, performance merits are initiated considering the randomness of its sources. While for reliability assessment, its variability is incorporated [12]. In renewable electricity architecture, optimizing the size/rating of the components and deciding the mode of operation are hindrances. Since the cost of renewable electricity grid architecture is high, its optimum rating is needful for minimizing cost while balancing its reliability [7], [12] – [14]. MOEA can be used to optimize renewable electricity systems taking into consideration its cost and reliability [15] – [19].

The paper is structured as follows: Section 2 talks about evolutionary algorithm while Section 3 present detail account of pareto set and multi objective evolutionary algorithm frameworks. Complexity of multi objective evolutionary algorithm is discussed in Section 4. Multi objective evolutionary algorithm based on decomposition and renewable

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energy sources is presented in Section 5 and finally, Section 6 provides conclusion and future research direction.

II. Evolutionary Algorithm (EA)

Evolutionary Algorithm (EA) is regarded as a constituent of evolutionary computation in artificial intelligence. It functions via the selection procedure in which the minimal fit members of a population set are gotten rid of, in contrast the fit members can pull through and carry on till more suitable solutions are decided. EA is a computer application which imitate biological procedures to find an answer to complex problems. Over time, the triumphant members develop to come up with the optimized answer to the problem [20]. Evolutionary algorithm contains four steps in all, these are: initialization, selection, genetic operators, and termination.

Initialization---To start with evolutionary algorithm, a starting population of solutions are first established. The population will comprise of random number of feasible results to the problem, in many instances called members. It is essential that the population covers a broad scope of solutions, since it fundamentally depicts a gene pool. Selection---After a population is generated, members of the population are then assessed as per fitness function. A fitness function takes in the attributes of a member and solutions of a numerical depiction of how feasible a solution is. The fitness of each one of the members is calculated, and a part for top-scoring members are chosen. Genetic Operators---This includes two sub-steps: crossover and mutation. Following the selection of top members, it varies and are normally the top two. They are then utilized to produce the succeeding generation in the algorithm. Using the attribute of the chosen parents, new children are produced that are a mix of the parent's attributes. Afterwards, new genetic material is injected into the generation. If this step is omitted, it is swiftly stuck in local extrema, and optimal results will not be obtained. This is mutation, it is merely done by making different small part of the children such that they no longer completely mirror subsets of parents' genes. Mutation is probabilistic. Termination---Finally, the algorithm should come to an end. This normally happen in two ways: either the algorithm has attained some maximum runtime, or the algorithm has attained some threshold of functioning. At this stage a concluding solution is selected and returned [21]. The general scheme of an evolutionary algorithm is shown in figure 1. Even though EAs can optimize effectively, they do not certainly find the optimal solution. Alternatively, EAs continually, find functioning solutions and quantify performance contrary to one another, which may or may not obtain the perfect best possible solution [22] – [23].

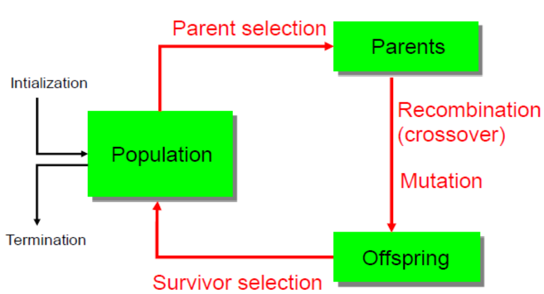

Fig. 1. The general scheme of an evolutionary algorithm [22]

III. Pareto Set and Multi Objective Evolutionary Algorithm (MOEA) Frameworks

Evolutionary algorithms can equally be far-reaching in its utilization of multiple fitness functions. This make difficult the process, in place of identifying a single optimal point, it alternatively ends up with a set of optimal points. The set of optimal results is called the Pareto frontier, and contains elements that are equally optimal in the sense that no solution is most important than any other solution in the frontier. A decider is then utilized to limit the set down to a single solution, founded on the contextual relationship of the problem or some distinct relationship [21]. MOEA is a stochastic probe method with the ability to obtain sets of suitable trade-off solutions, and is a common method utilized to find a solution to Multi Objective Optimization (MOO) problems, The utilization of MOEA makes it feasible to obtain a Pareto set with several optimal solutions, by this means Decision Makers (DMs) make trade-offs between affective responses in order to obtain a solution founded on intended preferences. [24]. A Pareto optimal solution cannot be made better with respect to any objective without worsening at least one other objective. The target of a MOO algorithm is to deduce solutions in the Pareto optimal set. Nevertheless, ascertaining the total Pareto optimal set, for MOO problems, is practically impossible owing to its size. In addition, for many MOO problems, especially for combinatorial optimization problems, proof of solution optimality is computationally infeasible. Hence, a practical approach to MOO is to study a set of solutions, which are the best-known Pareto set that portray the Pareto optimal set [25]. For a feasible region F with objectives f_1 and f_2. Likely solutions that optimize f_1 and f_2 are shown in figure 2, and figure 3, respectively [26]. Figure 2 illustrates f_1 and f_2 being minimized. While figure 3 depicts a situation where f_1 and f_2 are maximized. Note that even though high-quality multiple pareto-optimal solutions can be initiated, the eventual selection of a point on the pareto front is up to the decision makers, who have higher-level information or rules to make decisions. Higher-level information is normally nontechnical, inaccurate, highly subjective, and often not part of MOO problem [27]. MOEA framework is a key issue in its design and are including of:

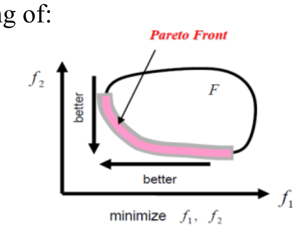

Fig. 2. A Pareto set for a two-objective minimization problem [26]

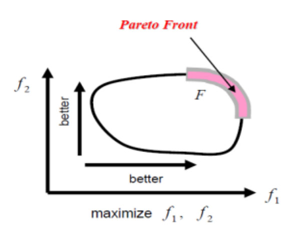

Fig. 3. A Pareto set for a two-objective maximization problem [26]

A. Multi Objective Evolutionary Algorithms based on decomposition (MOEA/D)

MOEA/D is a population founded evolutionary algorithm which uses aggregation method to decompose Multi Objective Optimization Problems (MOPs) into Ns number of single-objective optimization subproblems, optimizing each by using information from the optimization of adjacent subproblems. Hence, MOEA/D presents a general framework which allows the application of a single objective optimization technique to optimize each subproblem. In MOEA/Ds, a scalar objective local search can be utilized in each subproblem in a natural way since its task is for optimizing a scalar objective subproblem. The two most usually utilized decomposition methods are the Weighted Sum Approach and the Weighted Tchebycheff approach. [28] – [30].

B. Multi Objective Evolutionary Algorithms Based on Preference

Preference-based MOEAs is regarded as a collaboration of MOEA and Multiple Criteria Decision Making (MCDM). Preference information given by the DM is utilized to guide the exploration regarding preferred parts of the Pareto Front (PF), in place of approximating the whole PF. Incorporating preferences into MOEA has several merits: Firstly, MOO Problems has more than three objectives, so it is difficult to achieve the whole Pareto Set (PS). As almost all the solutions tend to be non-dominated, selection pressure will be lost when many solutions are associated with PF. Utilizing the preference information as a selection criterion resolves this issue [29] – [30]. Secondly, Solution inspection and selection from the whole PF is not easy. The visualization of high-dimensional space makes it more difficult. If DMs give some vague information about preferences, then only the preferred parts of the PF will be obtained, thus relieving selection burden of DMs. Thirdly, with preference information guiding the exploration, MOEAs only focus on regions favored by DMs. Thereby avoiding computational efforts for finding unwanted solutions, so that preferred solutions are achieved more quickly [31] – [33]. Centered on the role of the DM in the solution process, MOO techniques can be classified into priori, posteriori, and interactive [29].

C. Multi Objective Evolutionary Algorithm (TMOEA) based on Target Region

Target region based MOEAs is aimed at a more fine-grained resolution of the target regions without exploring the whole set of Pareto optimal solutions. Target region is equally called the region of interest (ROI), which is bluntly detailed by the DM. TMOEAs can guide the exploration towards this region and achieve a better converged and distributed set of Pareto optimal solutions within it. Target-region Nondominated Sorting Genetic Algorithm (T-NSGA-II), Target-region S-Metric Selection Evolutionary Multi objective Optimization Algorithm (T-SMS-EMOA) and Target-region R2 indicator-based Evolutionary Multi objective Optimization Algorithm (T-R2-EMOA) are examples of TMOEAs. They follow the original framework of NSGA-II, SMS-EMOA and R2-EMOA. A special ranking criterion and diversity enhancement methods are integrated in the framework. figure 4, illustrates a TMOEA [31], [34] – [36].

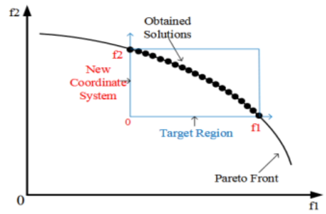

Fig. 4. An illustration of target region-based multi objective evolutionary algorithm (TMOEA) [31]

D. Multi Objective Evolutionary Algorithm based on Indicator

Here, the performance indicators of solution quality measurement are chosen as selection benchmark in an environmental selection. The standard of an approximated PF can be calculated by a scalar indicator such as generational distance and hypervolume. Indicator-based MOEAs uses an indicator to guide the exploration, notably to perform solution selection. A quality indicator is a function that maps N Pareto set approximations to a real number. Indicators can provide distinctive solutions that have no contribution to the indicator, so it can accelerate the evolution of a population toward pareto front when it is chosen as a selection criterion in MOEAs [29], [37] – [38].

E. Multi Objective Evolutionary Algorithm based on Hybridization

Single-objective optimization have shown that hybrid variants of locally explored algorithms and evolutionary algorithms can perform better than their pure mates. This equally holds for continuous search spaces and for differentiable fitness functions. Same is true for MOO. MOEAs has several techniques which have different characteristics and benefits. Hybridizing these techniques is thus a natural way of utilizing their benefits for resolving intricate MOPs. The techniques to use and how to hybridize algorithms should be solved when designing hybrid MOEA. The resulting hybrid algorithms have proven great success over sets of well-chosen functions regarding the convergence rate of algorithms combined. Hybridization approach to MOEA enhances and does not ruin the diversity of solutions obtained [29], [39].

F. Multi Objective Evolutionary Algorithms based on Memetic Algorithm

Memetic algorithms (MAs) are hybrid optimization techniques which places a local exploration workings into the process of evolutionary optimization. This speed up the convergence and helps to obtain a high-performance approximate Pareto front. MAs are evolutionary techniques that hybridize a global exploration of a population with a local search of individuals. MAs helps to resolve a variety of intricate optimization problems and it is more effective than evolutionary optimization techniques alone. MAs offers not only better speed of convergence to evolutionary approach, but it equally offers better accuracy for the final solutions.

MAs are flexible as compared to more traditional search techniques. EAs and MAs does not require a problem to be formulated in a constraint language. It does not ask for the function to be differentiable, continuous, linear, separable, or of any data type. On the contrary, it is applied to problems such as some/almost any way to encode a candidate solution to a problem and means of computing the quality of any such encoded solution which is the objective function [29], [40 – [42].

G. Multi Objective Evolutionary Algorithms based on Coevolution

Co-evolutionary algorithms (CAs) are natural extensions of traditional evolutionary algorithms (EAs). Such extensions consist of the way the fitness function is evaluated for each of the members of a co-evolutionary system. In CAs, the fitness value of everyone is given based on interactions with members from other species. Co-evolution is a reciprocal evolutionary exchange connecting species that interact with one another. The main issue in CAs is that the fitness of an individual from a specie is computed, by relying on individuals of distinct species. There are two main kinds of CAs, regarding how fitness is computed: The first is based on competitive Interactions. Here, fitness of an individual is the result of a series of encounters with individuals from other species. While the second is based on cooperative interactions. Here, fitness of an individual is given by the performance of such individual when collaborating with individuals from other species [43]. CAs has the merits of convergence, diversity and uniform distribution of the non-dominated solution set [44]. The advantages of MOEA frameworks are presented in the table below.

ADVANTAGES OF MOEA FRAMEWORKS

MOEA Frameworks	Advantages
Multi Objective Evolutionary Algorithms based on decomposition (MOEA/D)	1. It allow the application of a single objective optimization technique to optimize each subproblem. 2. It is utilized in each subproblem in a natural way.
Multi Objective Evolutionary Algorithms Based on Preference	1. It helps to resolve the issue of selection pressure. 2. It helps to relieve the selection burden of decision makers. 3. It helps to avoid computational efforts for finding unwanted solutions, thus preferred solutions are achieved more quickly.
Multi Objective Evolutionary Algorithm (TMOEA) based on Target Region	It helps to achieve a better converged and distributed set of pareto optimal solutions.
Multi Objective Evolutionary Algorithm based on Indicator	It helps to accelerate the evolution of a population toward pareto front.
Multi Objective Evolutionary Algorithm based on Hybridization	It enhances the diversity of the solutions obtained.
Multi Objective Evolutionary Algorithms based on Memetic Algorithm	It offers better speed of convergence and better accuracy for the final solutions.
Multi Objective Evolutionary Algorithms based on Coevolution	It helps to achieve convergence, diversity and uniform distribution of the non-dominated solution set.

IV. Computational Complexity of Multi Objective Evolutionary Algorithm

Computational complexity is precisely a function of size, that is the cardinality of an input data set. In computational complexity, time complexity always come to mind except if otherwise specified. A general way to examine computational complexity is to classify problems and algorithms as either "P" or "NP". Here, P stands for "Polynomial" and NP for "Non-deterministic Polynomial". At times NP is understood to mean non-polynomial. Though this is roughly not correct, but it has never been confirmed to be false. The dissimilarity between P and NP is if in any case an algorithm can be resolved in polynomial time or space with a Deterministic Turing Machine (DTM) or if it necessitates a Non-Deterministic Turing Machine (NDTM). NP can be looked at as non-polynomial and is frequently described as intractable. Intractability indicates that a problem cannot be resolved due to its time or space complexity [45] – [46]. The space complexity of MOEAs is uncomplicated; it can be written as $\Theta(n_p)$, where n_p is the population size and n is the cardinality of the input data set. This presumes a fixed population size, but this is required even with algorithms making use of external archiving. For non-evolutionary algorithms, the space complexity can be Non-deterministic Polynomial (NP) since the non-dominated Pareto set can be inestimably infinite. Despite this, EAs, as a rule, supports an exact population size, so the space complexity is linear Polynomial (P). The time complexity of MOEAs is more complex. The upper bound time complexity of an MOEA is controlled by the span of a given chromosome because it can be comprehensively explored in $\Theta(2^{nc})$ time, where n_c is the number of bits needed to encode the chromosome. But since exploring comprehensively has exponential (NP) time complexity in terms of its lower and upper bound, it is too unfit to be feasible. Even though no MOEA employs comprehensive exploration of all workable chromosome permutations, this enable a worst-case bound of $O(2^{nc})$ to be set for the whole class excepting for distinct algorithms shown to have a better bound. Big-oh (O) indicates the asymptotic upper bound, while Big-theta (Θ) designate the asymptotically tight bound [45], [47].

Even though the upper bound of an MOEA is NP, the average case and lower bound may be P. Common MOEAs have complexity that seems to be P. Slower MOEAs like Non-dominated Sorting Generic Algorithm (NSGA) and Strength Pareto Evolutionary Algorithm (SPEA) are given as $O(n_o n_p^3)$, while faster MOEAs like NSGA-II, SPEA2, and Pareto Archived Evolution Strategy (PAES) are given as $O(n_o n_p^2)$, where n_o is the number of objectives. Here, the complexity is the computational complexity involved for advancing a single generation of a population, and not the algorithm's aggregate complexity. Stating an algorithm with respect to a single generation allows it to be compared when the convergence rate of the overall algorithm is unknown. To calculate the actual computational complexity of an MOEA, the complexity for each generation and the number of generations must be known. Although the convergence of

EAs using at least the operations of reproduction and mutation combined with elitism is known, convergence rate is not known. Hence, faster algorithms such as NSGA-II, SPEA2, and PAES are given as $O(n_g n_o n_p^2)$, where n_g is the number of generations. Depending on the stopping criteria, n_g can have complexity from constant to NP. When n_g is not constant, it is a function of the chromosome length, n_c [45], [47].

V. Multi Objective Evolutionary Algorithm Based on Decomposition (MOEA/D) and Renewable Energy Systems

In determining the best combination of PV, wind, battery and fuel generators for a hybrid renewable system configuration. MOEA/D was used for minimizing the lifetime of the system cost, life-time emissions of CO_2 and SO_2, maximization of the system output power and reliability. MOEA/D approach was used to obtain a set of pareto optimal solutions of the system [48]. Thus, this approach can equally be used for purely renewable electricity system shown in figure 5.

In electrical island and grid-connected modes, the optimal design of a purely renewable energy system can be aimed at finding suitable configurations of photovoltaic (PV) panels, wind turbines, hydro power generators, storage schemes and concentrated solar power plants such that the system cost is minimized, and the system reliability/renewable ability corresponding to different modes is maximized. Considering a DMs preference, the most satisfied configuration of a purely renewable energy system can be identified using MOEA/D approach.

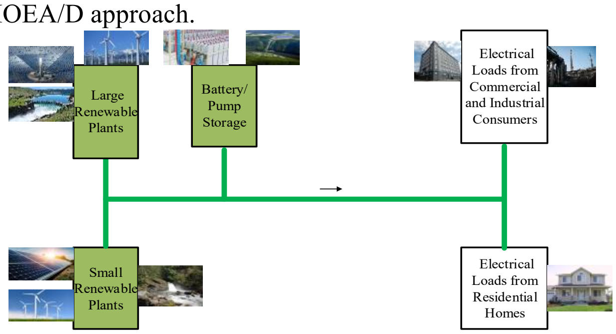

Fig. 5. Illustration of the configuration of a purely renewable energy system

A purely renewable energy system consisting of many renewable energy sources, can be utilized to secure electricity supply. Electricity will be generated using only renewable sources of energy like wind plants, concentrated solar plants, solar panels, hydro plants and so on. This is the future direction of research with regards to the electricity industry. For this reason, there is the need for the Internet of Renewable Energy (IoRE). Probably, this is the first time IoRE is been proposed for effective and reliable electricity supply.

Figure 6 illustrates the relationship between a purely renewable electricity system with electricity consumers via Internet of Renewable Energy (IoRE) platform. The components will be made up of PV power generators, concentrated solar generators, hydro power plants and Wind power generators, the electricity grid, loads, wireless sensors and intelligent controller. In order to meet the continuously varying loads, renewable power generation from an electrical island, which will be made up of PV panels, small wind and hydro plants will be used to secure backup power to extremely important loads. While the utility grid which will be made up of concentrated solar plants, large wind and hydro power generators will feed power to both the extremely important and non-crucial loads. All the installations will be interconnected through an IoRE which will make the purely renewable energy system fully automatic and operates in an efficient manner. The renewable electricity grid will be monitored and controlled using sensors and controllers. MOEA/D will be used in determining the best combination of renewable energy sources such as PV, wind, concentrated solar and hydro plants for the purely renewable energy system.

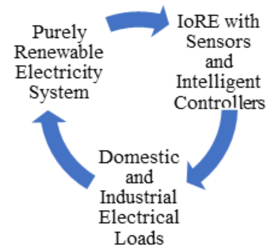

Fig. 6. Relationship between electricity consumers and purely renewable electricity system via IoRE

VI. Conclusion

This paper presents a comprehensive appraisal of multi objective evolutionary algorithm, which can be used for the optimization of purely renewable energy systems. MOEA have proven to produce fantastic results when it comes to optimization of hybrid renewable systems, Hence, MOEAs will be a suitable solution for multi objective optimization of purely renewable energy systems. As future research path, there is need to utilize MOEA for the optimization of purely renewable energy systems. The intended MOEA algorithm we hope to use is MOEA/D. It allows the application of a single objective optimization technique to optimize each subproblem, and it can be utilized in each subproblem in a natural way. Thus, it is hoped that MOEA/D will help to obtain a smart algorithm for a purely renewable energy system in an IoRE platform.

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