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Initialization of a Multi-objective Evolutionary Algorithms Knowledge Acquisition System for Renewable Energy Power Plants

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ABSTRACT

The design of Renewable Energy Power Plants (REPPs) is crucial not only for the investments' performance and attractiveness measures, but also for the maximization of resource (source) usage (e.g. sun, water, and wind) and the minimization of raw materials (e.g. aluminum: Al, cadmium: Cd, iron: Fe, silicon: Si, and tellurium: Te) consumption. Hence, several appropriate and satisfactory Multi-objective Problems (MOPs) are mandatory during the REPPs' design phases. MOPs related tasks can only be managed by very well organized knowledge acquisition on all REPPs' design equations and models. The proposed MOPs need to be solved with one or more multi-objective algorithm, such as Multi-objective Evolutionary Algorithms (MOEAs). In this respect, the first aim of this research study is to start gathering knowledge on the REPPs' MOPs. The second aim of this study is to gather detailed information about all MOEAs and available free software tools for their development. The main contribution of this research is the initialization of a proposed multi-objective evolutionary algorithm knowledge acquisition system for renewable energy power plants (MOEAs-KAS-F-REPPs) (research and development loopwise process: develop, train, validate, improve, test, improve, operate, and improve). As a simple representative example of this knowledge acquisition system research with two selective and elective proposed standard objectives (as test objectives) and eight selective and elective proposed standard constraints (as test constraints) are generated and applied as a standardized MOP for a virtual small hydropower plant design and investment. The maximization of energy generation (MWh) and the minimization of initial investment cost (million €) are achieved by the Multi-objective Genetic Algorithm (MOGA), the Niched Sharing Genetic Algorithm/Non-dominated Sorting Genetic Algorithm (NSGA-I), and the NSGA-II algorithms in the Scilab 6.0.0 as only three standardized MOEAs amongst all proposed standardized MOEAs on two desktop computer configurations (Windows 10 Home 1709 64 bits, Intel i5-7200 CPU @ 2.7 GHz, 8.00 GB RAM with internet connection and Windows 10 Pro, Intel(R) Core(TM) i5 CPU 650 @ 3.20 GHz, 6,00 GB RAM with internet connection). The algorithm run-times (computation time) of the current applications vary between 20.64 and 59.98 seconds.

1. Introduction

An engineering design problem (e.g. new airplane design, new concentrated solar power plant, dam, port, refrigerator, ship, shipyard, spacecraft, etc.) can be defined as a sort of the Multi-objective

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Optimization Problem (MOP). According to [67], a MOP can be defined as "a vector of decision variables which satisfies constraints and optimizes a vector function whose elements represent the objective functions. These functions form a mathematical description of performance criteria which are usually in conflict with each other. Hence, the term "optimize" means finding such a solution which would give the values of all the objective functions acceptable to the decision maker". Some synonymous or similar terms, such as multi-criteria optimization problem, multi-performance optimization problem or vector optimization problem are also used instead of the multi-objective optimization problem [22]. Although almost any design problem is a MOP by its nature, they can be modeled as either a Single Objective Optimization Problem (SOP) or a MOP.

Some design models can cover a few objectives and some others can include some other objectives. Hence, SOPs and MOPs are almost equally important from a research perspective and they must be studied as deep as it can be researched in a timely manner. The definition of both problems is presented in Fig. 1.

SOP	**MOP**
"Minimizing (or maximizing) $\mathrm{f(x)}$ subject to $\mathrm{g_i(x) \leq 0, i = \{1, \dots, m\}}$, and $\mathrm{h_i(x) = 0}$, $\mathrm{j = \{1, \dots, p\}\ x \in \Omega}$. A solution minimizes (or maximizes) the scalar $\mathrm{f(x)}$ where x is a n-dimensional decision variable vector $\mathrm{x = \{x_1, \dots, x_n\}}$ from some universe Ω."	"minimizing (or maximizing) $\mathrm{F(x) = (f_1(x), \dots, f_k(x))}$ subject to $\mathrm{g_i(x) \leq 0, i = \{1, \dots, m\}}$, and $\mathrm{h_i(x) = 0}$, $\mathrm{j = \{1, \dots, p\}\ x \in \Omega}$. A MOP solution minimizes (or maximizes) the components of a vector $\mathrm{F(x)}$ where x is a n-dimensional decision variable vector $\mathrm{x = \{x_1, \dots, x_n\}}$ from some universe Ω. It is noted that $\mathrm{g_i(x) \leq 0}$ and $\mathrm{h_i(x) = 0}$ represent constraints that must be fulfilled while minimizing (or maximizing) $\mathrm{F(x)}$ and Ω contains all possible x that can be used to satisfy an evaluation of $\mathrm{F(x)}$."

Fig. 1. *Definition of SOP and MOP [22].*

The MOPs can be solved by several proposed methods in the literature. These methods are grouped under the "non-preference methods", where the decision maker is not needed, the "a priori methods", where the decision maker expresses his or her preferences before optimization (e.g. ε-Constraint, Weighted Sum), the "a posteriori methods", where the decision maker makes choices amongst Pareto Optimal solutions (i.e. classical algorithms such as hypervolume, normal boundary intersection, ADBASE, normal constraint method, Benson's algorithm, directed search domain; evolutionary algorithms such as vector evaluated genetic algorithm: VEGA and Non-dominated Sorting Genetic Algorithm: NSGA-II), the "interactive methods", where the decision maker guides the process in an interactive way (e.g. Zionts-Wallenius Method, Step Method: STEM, Synchronous NIMBUS Method, Pareto Navigator Method, Geoffrion-Dyer-Feinberg Method: GDF, Interactive Surrogate Worth Trade-Off Method: ISWT, Sequential Proxy Optimization Technique: SPOT, and Pareto Race) [41, 42].

The Multi-objective Evolutionary Algorithms (MOEAs) are a class of the Genetic Algorithms set. The MOEAs have simply two main groups (Non-Pareto-based and Pareto-based) [5]. Moreover, the Pareto-based methods include two main groups (Non-Elitist and Elitist) [5]. There are many MOEAs algorithms in the literature, such as the Lexicographic method, the aggregating functions, the population-based methods under the non-Pareto-based MOEAs, the Multi-objective Genetic Algorithm (MOGA), the Non-Dominated Sorting Genetic Algorithm (NSGA), the Niched-Pareto Genetic Algorithm (NPGA) under the non-elitist Pareto-based MOEAs; the Pareto Archived Evolution Strategy (PAES), the Strength Pareto Evolutionary Algorithm (SPEA), the Strength Pareto Evolutionary

Algorithm 2 (SPEA2), the Nondominated Sorting Genetic Algorithm II (NSGA-II), the ε-dominance NSGA-II, the Adaptive Range Multi-objective Genetic Algorithm (ARMOGA), the ε-dominance ARMOGA (εμ ARMOGA) under the elitist Pareto-based MOEAs; the Multi-objective Messy Genetic Algorithm (MOMGA), the Pareto Envelope-based Selection Algorithm (PESA), the micro-genetic algorithm for multi-objective optimization, the Multi-objective Struggle GA (MOSGA), the Orthogonal Multi-objective Evolutionary Algorithm (OMOEA), the General Multi-objective Evolutionary Algorithm (GENMOP); the Efficient Global Optimization for Multi-objective Problems (EGOMOP), the Hierarchical Asynchronous Parallel Multi-objective Evolutionary Algorithm (HAPMOEA), the Gradient Enhanced Multi-objective Genetic Algorithm (GEMOGA), the Nondominated Sorting Evolutionary Algorithm+ (NSEA+[9]) (see [4, 5, 22, 23, 46]).

This study aims to start finding detailed information about all MOEAs and their available free tools/software in the literature. Besides, their complete comparisons on MOPs are in this research scope. The main goal of this research, development, demonstration, and deployment (RD^3) effort is to develop a very easy and useful multi-objective evolutionary algorithms knowledge acquisition system for renewable energy power plants (MOEAs-KAS-F-REPPs) in the next fifty years with integration and embedding into the original Anatolian honeybees' investment decision support system and the Global Grid Prediction Systems (G^2PS), the Global Grid Electricity Demand Prediction System (G^2EDPS), and the Global Grid Peak Power Prediction System (G^2P^3S) (see [84-89]).

As a simple application example of this research study, only one MOP has been studied with three Multi-objective Evolutionary Algorithms (MOEAs) according to basic parallel or series operating or running of multiple MOEAs principles in the proposed MOEAs-KAS-F-REPPs: the Multi-objective Genetic Algorithm (MOGA) (1^{st} Generation MOEA) [20], the Niched Sharing Genetic Algorithm/Non-dominated Sorting Genetic Algorithm (NSGA-I) (1^{st} Generation MOEA) [100], and the Niched Sharing Genetic Algorithm Version II (NSGA-II) (2^{nd} Generation MOEA) [27].

This paper has four sections. Section 2 presents the review of the literature. Section 3 presents not only the proposed knowledge acquisition and gathering system but also the preliminaries and experiments. Finally, the Section 4 presents the concluding issues and planned following research studies.

2. Literature Review

The current review structure was influenced by Asadi and Sadjadi [6], Banos et al. [10], Iqbal et al. [46], Jebaraj and Iniyan [50], and Coello [21]. A detailed literature review was mainly conducted on the SOPs and MOPs applications in the renewable energy field, focusing on the optimization of the REPP design. The other research fields were also included in this literature review. The literature until 2019 related to this subject was reviewed in two distinct literature review activities and summarized in this section. The first literature review was performed on a more general time frame. The second literature review was performed on a more targeted time frame, related to the recent literature. The key search terms were defined specifically for the online scientific and journal websites (e.g. ACM digital, ASCE online research library, American society of mechanical engineers, Cambridge journals online, directory of open access journals, emerald insight, google scholar, inderscience publishers, journal of applied research on industrial engineering, MedCrave group, science publishing group, springer, Taylor & Francis online/journals, Wiley-Blackwell/Wiley online library, world scientific publishing) in both literature review activities. The main search queries are "Multi-objective evolutionary algorithm" and (operator) "renewable", and "multi-objective evolutionary algorithm" and (operator) "renewable". The search activity was performed in the order of the title, abstract, and full text. This order helped to focus on the appropriate publications.

The application of the Single Objective Optimization Algorithms (SOAs) and the Multi-objective Optimization Algorithms (MOAs) were widely applied in many fields (especially in engineering and financial fields) since the 1970s. The early applications were in the 1970s. The MOPs were mainly solved with classical methods based on the differential calculations in the 1970s. Seo [93] presented one of the first studies that showed a brief survey of the multi-objective optimization techniques for the environmental assessment of the water resource systems in Japan. Blankenship and Fink [34] suggested that a power system control problem was actually a MOP (objective functions of production cost, environmental impact, and system operating security).

Further studies in the same direction were conducted in the 1980s. The MOPs were still mainly solved with the classical methods based on the differential calculations in the 1980s. Yokoyama et al. [113], Chetty and Subramanian [18], and Yang and Chen [110] were focused on the energy management and the power dispatch optimization. Takama and Umeda [103], Rao [75], Acharya et al. [2], Krasławski [56], and García and Prett [36] presented some manufacturing processes optimization research studies. Ramlogan and Goulter [67], Ramologan [73], and Mitchell and Bingham [63] researched on the resources optimization and planning. Shimizu and Hirata [96] presented applications in the electronics.

The bio-inspired algorithms, such as the genetic algorithms, were raised fast in the 1990s, because of their simplicity in comparison with the classical methods and their efficiency and capacity to include new constraints. Hence, the bio-inspired algorithms were mainly preferred to solve the MOPs in the 1990s, in contrast with the classical methods based on the differential calculations in 1970s and 1980s. The bio-inspired algorithms were also favored by the development of faster and economic computational resources in the 1990s. Ishibuchi and Murata [48, 49, 64, 65] developed a multi-objective genetic algorithm (with and without local search) and applied it to solve the flow shop scheduling problem. Tamaki et al. [102] conducted a deep review on the multi-objective optimization by the genetic algorithms. Klemes et.al. [55], Chiang and Jean-Jumeau [19], Gorenstin et al. [37], Hsiao et al. [45] presented some optimal planning and expansion applications of the power systems. Azapagic and Clift [8], Adisa [9] researched on the life cycle assessment optimization.

The bio-inspired algorithms were deeply developed and implemented since the beginnings of the 21st century. Deb et al. [27] developed the widely spread NSGA-II algorithm, which introduced the fast elitist non-dominated sorting concept in 2000. Other metaheuristic algorithms were also developed in that century (e.g. Talbi [101]). Coello and Lechuga [25], Hu and Eberhart [108], Tripathi et al. [104], and Sierra and Coello [98] interested in the particle swarm optimization algorithms. Abbass et al. [1], Kacem et al. [52], and Li and Zhang [58] presented more complicated optimization problems and complex Pareto sets with the capabilities of these algorithms and the greater computational resources. Ashby [7] applied the multi-objective optimization approach for the material options' selection (e.g. Aluminium, Magnesium, Titanium alloys, and cast irons). Zhang and Liu [115] formed a reactive power and voltage control multi-objective problem of a power system and solved it with a new Particle Swarm Optimization (PSO) evolutionary algorithm. Demirkaya et al. [29] aimed to optimize a combined power/cooling cycle (Goswami Cycle) with the NSGA-II (Matlab). Hamdy et al. [39] tried to optimize the nearly-zero energy buildings solutions with the NSGA-II, the pNSGA-II, and the aNSGA-II in the GenOpt. Dovgan et al. [30] applied optimization in a vehicle routing problem with the MODS algorithm (Java). He and Agarwal [40] aimed to optimize the wind turbine airfoil S809's shape with the MOGA in jMetal MOGA. Mansouri et al. [60] applied optimization with the MOGA (MATLAB) in a 3-D well path design problem. Ratono et al. [74] used a Fuzzy-Multi-objective Genetic Algorithm (Fuzzy-MOGA) approach for the enterprise resource planning system selection criteria optimization (Scilab 5.4.1). Campos-Ciro et al. [17] presented a MOP related to an open shop scheduling problem based on a real mechanical workshop made of *m* machines that process *n* jobs. It dealt with different resource constraints related to tools allocation and multi-skills staff assignment. Wood [107] presented an interesting study on the optimization problems of the non-financial key performance indicators (KPIs), a mixed metrics such as earnings before interest tax depreciation and amortization (EBITDA), net present value (NPV), expected monetary value (EMV), capital investment (CAPEX), debt capitalization ratio for the gas and oil assets portfolio strategic decision makers with the simplex (linear) and the evolutionary (non-linear) (genetic) algorithms by the visual basic application (VBA) macros for the Microsoft excel workbooks.

There were also very interesting and worth mentioning studies directly related to the renewable power or energy industry in this century. Anagnostopoulos and Papantonis [3] presented the optimum sizing of two turbines at a small hydropower plant with the objectives of maximization net present value, maximization load coefficient or maximization energy production index and the constraints of the NTUA by the MOEA of EASY EA on the tool of the NTUA. De Simón-Martín et al. [26] optimized single drive parallel kinematics solar tracker mechanism with the objectives of the solar tracker workspace maximization, the mechanism elements' lengths minimization and the constraint of the center mechanism workspace in the field. They solved this MOP with the MOEA of NSGA-II in the Scilab tool. Vazhayil and Balasubramanian [105] presented an electricity generation portfolio optimization problem with two minimization objective functions (i.e. portfolio cost, portfolio standard deviation) in India and solved the defined problem by an Intelligent Pareto search Genetic Algorithm (IPGA). Zhai et al. [118] applied a design optimization for an integrated parabolic trough solar coal-fired power plant. Zhao et al. [116] designed a microgrid in Zhejiang province, China based on the life cycle cost, emissions minimization, and the renewable energy source maximization by a Genetic Algorithm (GA). Yao et al. [111] studied the integrated power distribution and electric vehicle charging systems with two maximization objectives (i.e. overall annual cost of investment, energy losses) by employing the decomposition based Multi-objective Evolutionary Algorithm (MOEA/D). Li and Qiu [57] presented an optimal solution for the Three Gorges Cascade Hydropower System (TGCHS) with two maximization objectives (i.e. power generation of the system and firm power) by employing the NSGA-II algorithm. Shi et al. [94] solved a Hybrid Renewable Energy System design problem (solar, wind, battery, and diesel generator) (HRES) with three minimization objectives (i.e. Annualized Cost of System (ACS), Loss Of Power Supply Probability (LPSP), fuel emissions during one year) by employing the modified Preference-Inspired Coevolutionary Algorithm using goal vectors with enhanced fitness assignment method (PICEA-ng). Wang et al. [106] presented an HRES (PV, wind, diesel, and battery) design problem with four maximization and minimization objectives (i.e. system output power, lifetime system cost, lifetime CO_2 emissions, and lifetime SO_2 emissions) by employing the MOEA/D. Hormozi et al. [44] solved a distribution network reconfiguration and placement distributed generation problem with two minimization objectives (i.e. power loss reduction) by employing the Binary Particular Swarm Optimization Algorithm (BPSO). Kamjoo et al. [54] presented an HRES design problem (solar, wind, and battery) with two maximization and minimization objectives (i.e. reliability and system total cost) by employing the NSGA-II algorithm and integration of the Chance Constrained Programming (CCP) to model. Shukla and Singh [97] optimized a short-term generation scheduling problem with two minimization objectives (i.e. cost and emission) by employing a weighted sum method integrated Weighted Improved Crazy Particle Swarm Optimization (WICPSO) algorithm (PSO variant). Zhao and Yuan [117] solved an HRES (PV, wind, diesel, and battery) design problem with two minimization objectives (i.e. annual total cost and system pollutant emission) by employing the fruit fly optimization algorithm. Ming et al. [62] solved an HRES design problem (solar, wind, battery, and diesel generator) with three maximization and minimization objectives (i.e. system reliability/renewable ability, system cost, and fuel emission) by employing the MOEA/D using Localized Penalty-Based Boundary Intersection (LPBI) method. Qu et al. [72] solved a Dynamic Economic Emission Dispatch (DEED) problem considering electric vehicles and wind power with two minimization objectives (i.e. total fuel cost, total pollution emission) by employing the MOEA/D algorithm. Shi et al. [95] optimized a grid-connected HRES problem with two minimization objectives (i.e. total system cost, and fuel emissions) by employing the PICEA-ng. Biswas et al. [14] optimized the wind farm layouts with two maximization objectives (i.e. output power and wind farm efficiency). Biswas et al. [15] solved an economic-environmental dispatch problem of thermal, wind, solar and small-hydro power combination with two minimization objectives (i.e. cost and emission) by employing two different algorithms (MOEA based on decomposition using superiority of feasible solutions MOEA/D-SF, summation based multi-objective differential evolution using superiority of feasible solutions SMODE-SF). Li et al. [59] solved a solar and wind energy integration into the Combined Cooling, Heating, and Power (CCHP) system design problem with three minimization objectives (i.e. annual total cost, carbon dioxide emission, and loss of energy supply probability) by employing the Preference-Inspired Coevolutionary Algorithm (PICEA-g). Prina et al. [71] applied the EPLANopt model in the energy system of South Tyrol with three minimization objectives (i.e. total annual costs, CO_2 emissions per person, and 100−%RES [%]). Xu et al. [109] solved a Hybrid Energy Storage System (HESS) problem (wind power, energy storage, and local user) with two maximization and minimization objectives (i.e. annual profit and wind curtailment rate) to determine two decision variables (numbers of batteries and super capacitors) by employing the NSGA-II algorithm. They concluded their study with the optimal solution selection with the VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) technique. Yazdi and Moridi [112] optimized the design of cascade hydropower reservoirs with three maximization and minimization objectives (i.e. total amount of produced energy, system reliability, and squared deviation of release from demands) by employing the Non-Dominated Sorting Differential Evolution (NSDE) algorithm. Yuan et al. [114] optimized a standalone HRES design problem with two minimization objectives (i.e. cost of the system in the life cycle and Loss of Power Supply Probability (LPSP) + Energy Excess Percentage (EXC)) by employing the Improved Gravitational Search Algorithm (GSA).

Accordingly, there were many captivating and crucial studies with brilliant ideas in the single objective optimization and multi-objective optimization literature, however, none of the previous publications in the literature proposed a multi-objective evolutionary algorithm knowledge acquisition system for renewable energy power plants (MOEAs-KAS-F-REPPs). Hence, this research study and its first paper are unique with its proposed MOEAs-KAS-F-REPPs.

3. Knowledge Acquisition System Initialization with Preliminaries and Experiments

The knowledge acquisition for the MOEAs in the power industry (e.g. hydro and solar) is a major challenge, because of not only the complexity of the current MOEAs, but also the difficulty of developing generic structured MOPs in the power industry. Zitzler et al. [119] explains the complexity of the current MOEAs and the urgency of a text-based interface for searching algorithms: "these algorithms for each usage scenario becomes time consuming and error-prone"; "application engineers who need to choose, implement, and apply state-of the-art algorithms without in-depth programming knowledge and expertise in the optimization domain"; "developers of optimization methods who want to evaluate algorithms on different test problems and compare a variety of competing methods". This

RD^3 effort aims to overcome these major difficulties in the hydro and solar power industry at first and then all other renewable power industries by some unique MOEAs programming libraries (e.g. MOGA, NPGA, PAES, and εμ ARMOGA), some unique platforms (e.g. Scilab, Scilab Cloud, Python, and GNU Octave), and many standardized SOPs and MOPs. Hence, a multi-objective evolutionary algorithms knowledge acquisition system for renewable energy power plants (MOEAs-KAS-F-REPPs) and its RD^3 is recommended and presented in this study (Fig. 2).

The proposed knowledge acquisition system has five consoles. These consoles are the standardized SOPs & MOPs console, the standardized MOEA console, the literature library console, the expert advice library console and the previous application library console. The library consoles (literature, expert advice, previous applications) collect and store all data and information. Then they feed two processing and storing consoles (standardized SOPs & MOPs, standardized MOEA). In these consoles, the standardization process is performed at first. Then the standardized SOPs & MOPs and also the standardized MOEA are stored in separate sectors and servers. When a new renewable energy power plant problem (e.g. a new solar power plant design, a new small hydropower plant design, a rehabilitation, replacement, and renewal of an operational solar power plant) is asked or requested at any time, the call is answered by the standardized SOPs & MOPs console and an SOP and/or MOP is offered to the users. Concurrently, the call or recall is also answered by the standardized MOEA console and algorithms with the tools are offered to the users. All of these activities may be done automatically or semi-automatically.

In the library consoles (literature library console, experts advice library console, and previous application library console) there are several stored files in several different formats. They may be collected automatically, semi-automatically, or manually (non-automatic) in a regular periodical timely or instantaneous manner. The structure and examples of these library consoles are presented in Table 1.

Table 1. *Structure of library consoles in the proposed MOEAs-KAS-F-REPPs (literature library console, expert advice library console, and previous application library console) (*CV: curriculum vitae).*

Library Consoles	File Types (example)	Reference Documents (example)
Literature Library Console		Papers and reports database
Experts Advice Library Console	Expert 1 Expert 2	CVs* database
Previous Applications Library Console	Scilab	Codes and applications database

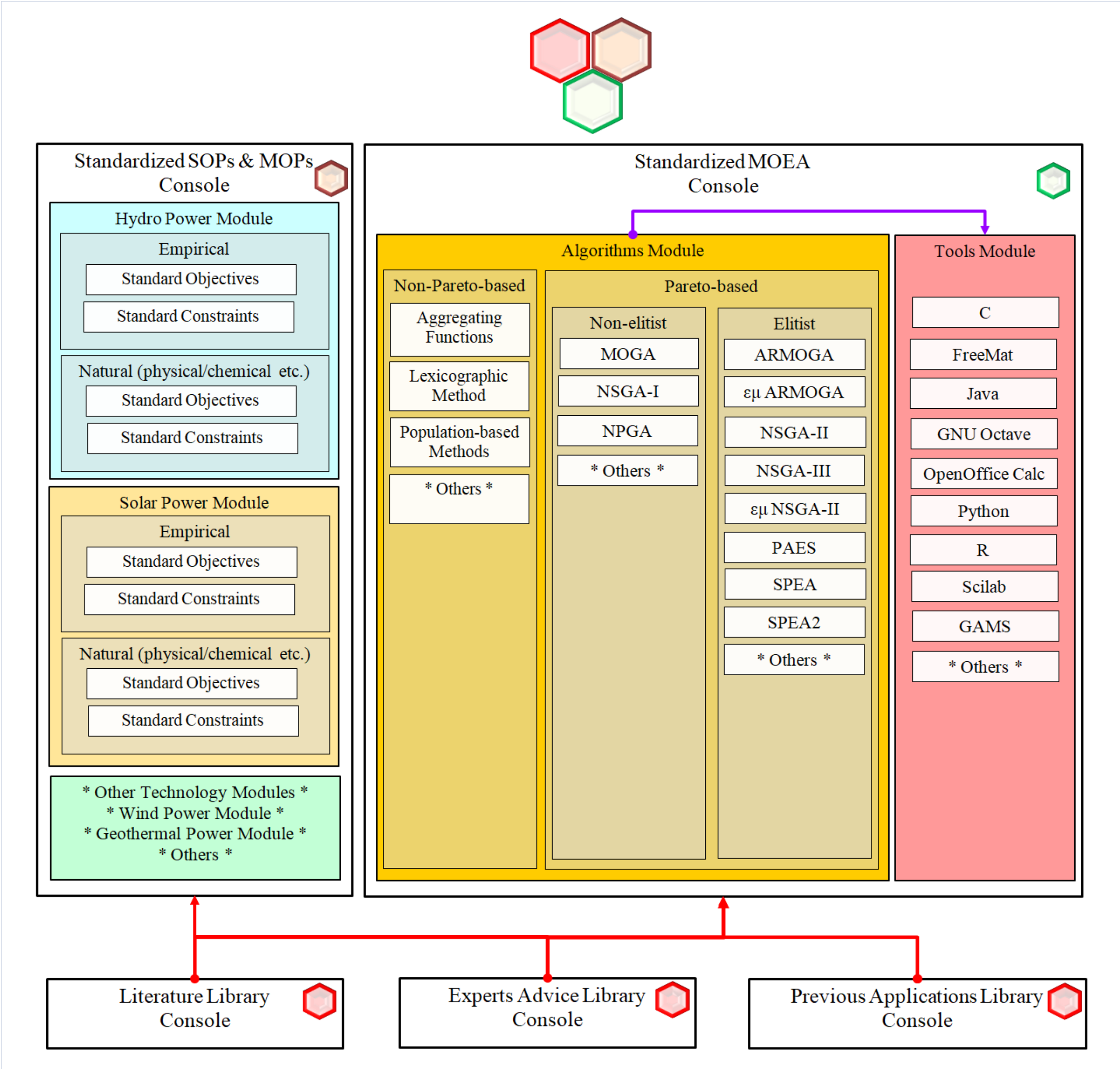

Fig 2. *Multi-objective evolutionary algorithms knowledge acquisition system for renewable energy power plants (MOEAs-KAS-F-REPPs).*

In the standardized SOPs & MOPs console, there are several renewable power technology modules (e.g. Hydro and Solar). These modules have empirical (depending upon experience or observation alone, without using the scientific method or theory, http://www.dictionary.com/browse/empirical?s=t) and natural (based on the state of things in nature, http://www.dictionary.com/browse/natural?s=t) standard objectives and constraints. The standardized objectives and constraints may be acquired automatically, semi-automatically or manually (non-automatic) in a regular periodic timely or instantaneous manner. These standardized SOPs & MOPs are classified according to the different renewable energy technologies (e.g. hydro, solar, wind, and geothermal) and also stored in separate sectors and servers. The structure and some examples of the standardized SOPs & MOPs console are presented in Table 2.

Table 2. *Structure and examples of the standardized SOPs & MOPs console in the proposed MOEAs-KAS-F-REPPs (see also Abbreviations).*

Standardized SOPs & MOPs Console	**Standard Objectives OR Standard Constraints (example)**	**Reference Documents (example)**
Hydro Power Module > Natural (physical/chemical etc.) > Standard Objectives OR Standard Constraints	Small Hydropower Power Plant Installed Capacity $P = \eta_{tr} \times \eta_g \times \eta_t \times \rho_w \times g \times Q \times H_{net}$	Eliasson and Ludvigsson [31]; ESHA [32]; ESHA [33]; IFC [47]; Saracoglu [78]; Saracoglu [79]; Saracoglu [80]; Saracoglu [81]; Saracoglu [82]; Saracoglu [83]
	Small Hydropower Power Plant Total Energy $E = P \times t$ or $E = P \times 8760 \times capacity\ factor$ "*Given that the flow-duration curve represents an annual cycle, each 5% interval on the curve is equivalent to 5% of 8,760 hours (number of hours per year)*" $E = \sum_{i=1}^{20} \left(\frac{P_{5(k-1)} + P_{5k}}{2}\right) \frac{5}{100} 8760(1 - I_{dt})$	IFC [47]; Jindal [51]; RETScreen [76]
Hydro Power Module > Empirical > Standard Objectives OR Standard Constraints	Small Hydropower Power Plant Flow-Duration Curve (FDC) (site and case specific) $Q^* = -10{,}904\ t_Q^3 + 26{,}854\ t_Q^2 - 21{,}72\ t_Q + 5{,}8299$	Current Study (generated in this study)
	Total Investment Cost Equations In Turkey (Million €) Roughly for all: $C_{total} = 1{,}0 \times P$ Large: $C_{total} = 0{,}97 \times P$ Medium: $C_{total} = 0{,}90 \times P$ Small: $C_{total} = 0{,}84 \times P$	Haselsteiner et al. [43]
Solar Power Module > Natural (physical or chemical etc.) > Standard Objectives OR Standard Constraints	Concentrated Solar Power Plant net annual electricity generation (kWh) (without storage) should also be taken into account in this study. $E_{solar} = A_a \times DNI_a \times \eta_{sf} \times \eta_{pa} \times \eta_{pbnet} \times \eta_{trans} \times \eta_{paf}$	Bode and sheer [16]; Gunther et al. [38]

The standardized MOEA console consists of two modules: Algorithms and Tools. In the algorithms module, all Non-Pareto-based and Pareto-based MOEAs will be presented in a detailed manner with their own reference documents. Moreover, the Pareto-based MOEAs will be grouped under Non-elitist and Elitist sets. The tools module will present all free tools in this research field. All of the important definitions and notations (e.g. feasible region, objective region, continuous multi-objective optimization problem, discrete multi-objective optimization problem, Pareto optimal set, and Pareto front) related to the MOEA will be presented very clearly in the manuals of the standardized MOEA console. For instance:

- MOPs may be solved by aggregating multiple objectives into a single objective or by Pareto set approximation [119].
- MOPs may be all minimization objective (1), all maximization objective (2) or minimization of some and maximization others (3).
- A candidate solution which is better than all other candidates for each objective is said to dominate other candidates [13].
- A set of best solutions is identified in which the members are superior among all the candidate solutions when all the objectives are taken into account. This solution set is called Pareto Optimal Front. None of

the solutions included in the POF are better than the other solutions in the same POF for all the objectives being optimized. So, all of them are equally acceptable [13].

These standardized MOEAs are presented according to their classifications in the literature. The core idea of the standardized MOEAs console is presented in Table 5.

Table 3. *The core idea of the standardized MOEAs console in the proposed MOEAs-KAS-F-REPPs (see also electronic supplementary materials).*

Standardized MOEA Console	**Standard Algorithms (example)**	**Reference Documents (example)**
Algorithms Module > Pareto-based > Non-elitist > Multi-objective Genetic Algorithm (MOGA)	MOGA Pseudo Code MOGA Algorithm	Coello et al. [24]; Fonseca and Fleming [20]
Algorithms Module > Pareto-based > Non-elitist > Nondominated Sorting Genetic Algorithm-I (NSGA-I)	NSGA Pseudo Code (NSGA-I) NSGA-I Algorithm	Coello et al. [24]; Srinivas and Deb [99]
Algorithms Module > Pareto-based > Elitist > Nondominated Sorting Genetic Algorithm-II (NSGA-II)	NSGA Pseudo Code (NSGA-II) NSGA-II Algorithm	Coello et al. [24]; Deb et l. [27]

The MOEA aims to find not one solution of a MOP, but the Pareto optimal set in a robust and simple way [5]. Some of the crucial issues related to the application of MOEAs are presented as follows: computationally expensive, flexible, low data dependency, poor scalability, and own ad-hoc encodings require specialized crossover and mutation operators associated to them [5].

A simple representative example of the application of this proposed MOEAs-KAS-F-REPPs is presented in the following paragraphs. It is assumed that there is a real-World Small Hydropower Plant Design and Investment (SHP-DI) problem with the proposed system (MOEAs-KAS-F-REPPs). Hence, it is entitled as Virtual SHP-DI. The presentation of how system aims to work, and when the data and information of the Virtual SHP-DI are given in the system is as follows (see Table 4).

The MOGA, the NSGA-I, and the NSGA-II algorithms (solvers optim_moga, optim_nsga, and optim nsga2) on Scilab 5.5.2 are used in this study. The Scilab is also used by some researchers for optimization, where there can be different unknowns (small<20, medium<50, and large>100); type (binary, integer, and real); objective functions (linear, quadratic, based on min or max, and nonlinear); inequality or equality constrained (linear, quadratic, and nonlinear) or unconstrained models; convex or non-convex optimization MOPs (see Baudin and Steer [11]; Baudin and Couvert [12]; Margonari [61]; Deb [69]; Deb [70]). As a result, the Scilab is an excellent and compelling tool for the kickoff of this RD^3 effort. The Pareto set and the Pareto front of the MOGA, the NSGA-I, and the NSGA-II algorithms on the Scilab 6.0.0 and the commented script for the Scilab 6.0.0 are presented as follows (see Fig. 3 and electronic supplementary materials).

***Table** 4. Standardized MOP (test MOP at the initialization stage of the proposed MOEAs-KAS-F-REPPs).*

Standardized Objective Functions	
Function 1	Energy Generation Maximization (healthy decision maker approach, more ↑ is better ↑)
Function 2	Initial Investment Cost Minimization (healthy decision maker approach, less ↓ is better ↑)
Standardized Constraints For Hydro Power (subject to)	
Function 1	Power Plant Installed Capacity
Function 2	Efficiency of Transformers
Function 3	Efficiency of Generators
Function 4	Efficiency of Turbines
Function 5	The density of Water (kg/m^3)
Function 6	Gravity of Earth (m/s^2)
Function 7	Rated Discharge (m^3/s)
Function 8	Net Head (m)
Function 9	Flow-Duration Curve
Standardized Test Objective Functions For Small HydropowerAt This Initialization Stage	
Function 1	Maximization Energy Generation (MWh) $E = \sum_{i=0}^{100} (P_i * t_i)$ where P_i: power produced or generated (MW) t_i: duration (%) period of time (% percentage of time)
* Please do not use this function in any of scientific, engineering and commercial studies without any further investigations.	
Function 2	Minimization Initial Investment Cost (million €) $C_{total} = -0{,}146 \times {P_i}^2 + 4{,}2918 \times P_i + 2{,}2054$ where P_i: installed capacity in MW
* Please do not use this function in any of scientific, engineering and commercial studies. This function is generated for the small hydropower plant investments in a South East European Grid country. It is a very specific experimental case study function.	
Standardized Constraints For Hydro Power	
Function 1	Power Plant Instantaneous Capacity For Installed Capacity $P_i = \eta_{tr} \times \eta_g \times \eta_t \times \rho_w \times g \times Q_i \times H_{net}$
* Please feel free to use this function in any of scientific, engineering and commercial studies. This is a general function.	
Function 2	Efficiency of Transformers 98−99,5% (a constant value or a function)
Function 3	Efficiency of Generators 90−98% (a constant value or a function)
Function 4	Efficiency of Turbines 89−92% (a constant value or a function)
Function 5	The density of Water (kg/m^3) 998,65 - 992,22 (a constant value or a function)
Function 6	Gravity of Earth (m/s^2) 9,78033 - 9,83203 (a constant value or a function)
Function 7	Rated Discharge (m^3/s) in accordance with Flow-Duration Curve Q_i = -10,904 * t_i^3 + 26,854 * t_i^2 - 21,72 * t_i + 5,8299 where t_i: Duration (%) period of time (% percentage of time)
Function 8	Net Head (m) 1,5−1900 (a constant value or a function)

The genetic algorithms have been introduced in the Scilab thanks to a work by Yann Collette (http://ycollette.free.fr) and allow a high-level programming model for the optimization solvers by some macros. This way, to represent an optimization problem in the Scilab, a cost function (or a multi-objective non-linear cost function) to minimize with or without bound constraints must be introduced first (usually programmed as f). The Macros in the Scilab (optim_"algorithm name") automatically work with a coding of the parameter set (they do not work with the parameters themselves), search from a population of points (which must be initialized), use the payoff information from the objective function (they do not use derivatives or other auxiliary functions), and use the probabilistic transition rules, not the deterministic rules. Moreover, it automatically includes three main GA operators: Reproduction, crossover, and mutation, which can be easily tuned by the parameters functions ("ga_params"). Actually, the parameters module in the Scilab provides the "init_param" function, which returns a new, empty, set of parameters, and the "add_param" function that allows setting individually named parameters, which can be configured with key-value pairs.

The initialization function in the Scilab returns a population as a list made of "pop_size" individuals. If the "init_ga_default" function is used, then a population by performing a randomized discretization of the domain defined by the bounds as minimum and maximum arrays is computed. The MOGA implemented algorithm in the "optim_moga" function from the Scilab is based on Fonseca and Fleming [35], while the NSGA algorithm in "optim_nsga" solver is based on [100], and the NSGA-II algorithm implemented in "optim_nsga2" solver is based on Deb et al. [53].

Fig. 3 shows the results of the implemented MOP given by the different solvers (MOGA, NSGA-I, and NSGA-II). The Pareto front graphs show the solutions of the cost functions (two objective optimization), while the Pareto set graphs represent the values of the variables (net head and capacity respectively) corresponding to the previous solutions. The Pareto front solutions are those who are not dominated by any other solution in the set. Thus, they are located within the borders of the solution set. In the studied case, the first objective function (energy generation) must be maximized and the second objective function (initial investment cost) must be minimized. In order to take into account that both energy generation and initial investment cost values cannot be negative, both functions have to be the sign changed and thus, the first function must be minimized while the second function must be maximized. It can be observed that the MOGA algorithm only found one non-dominated solution (marked in green color), which is similar to the optimal solution found by NSGA algorithm. Nevertheless, NSGA-II algorithm found more non-dominated solutions (optimal Pareto front) thanks to it uses an elitist principle. It emphasizes non-dominated solutions and it uses an explicit diversity preserving mechanism. Thus, a complete Pareto front with the non-dominated solutions is offered, including the optimal solution found by the MOGA and NSGA algorithms.

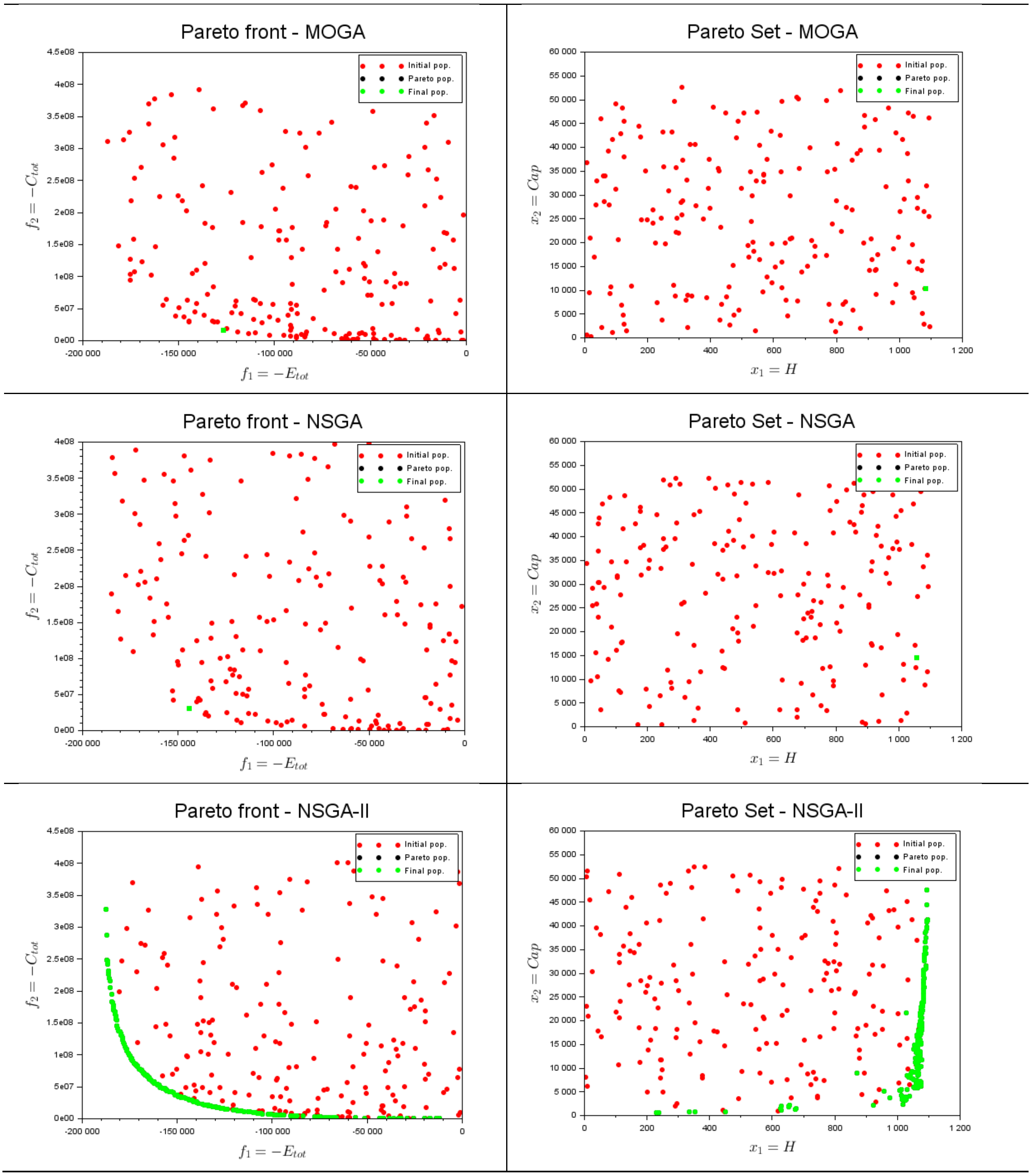

***Fig.** 3. Pareto set & Pareto front of MOGA, NSGA-I, and NSGA-II algorithms on Scilab 6.0.0 (Windows 10 Home 1709 64bits, Intel i5-7200 CPU @2.7 GHz, 8.00 GB RAM).*

The comparison of MOGA, NSGA-I, and NSGA-II algorithms on the Scilab 6.0.0 on a desktop computer with a PC Windows 10 Home 1709 64 bits, Intel i5-7200 CPU @ 2.7 GHz, and 8.00 GB RAM with internet connection and a PC Windows 10 Pro, Intel(R) Core(TM) i5 CPU 650 @ 3.20 GHz, and 6,00 GB RAM with the internet connection is performed and presented in Table 5.

The readers should be aware of the computational cost of these kinds of studies. They may be ranged from milliseconds to weeks (e.g. “1 simulation ≈ 1 ms → 1000 simulations = 1 second” and “1 simulation ≈ 1 hour → 1000 simulations ≈ 42 days” [41].

Table 5. *Runtime (computation time) results for computing the algorithms.*

Computers	Hardware Configuration	MOGA Algorithm Runtime (seconds)	NSGA-I Algorithm Runtime (seconds)	NSGA-II Algorithm Runtime (seconds)
1st PC	Windows 10 Home 1709 64bits, Intel i5-7200 CPU @2.7 GHz, 8.00 GB RAM	46.47	41.82	20.64
2nd PC	Windows 10 Pro, Intel(R) Core(TM) i5 CPU 650 @ 3.20 GHz, 6,00 GB RAM with internet connection	50.32	59.98	28.52
Performance Ratio (1st PC/2nd PC)		%92	%69	%72

4. Conclusion and Future Work

The major contribution of this research paper was its ability to present a new proposed multi-objective evolutionary algorithms knowledge acquisition system for renewable energy power plants (MOEAs-KAS-F-REPPs) and its RD^3 initialization. This new MOEAs-KAS-F-REPPs system will also possibly be evolved into a new multiobjective artificial intelligence system in future. The multi-objective evolutionary algorithms were started to be collected and grouped according to their general classifications in the literature during this research study (e.g. Non-Pareto-based or Pareto-based and Non-Elitist or Elitist). This classification study was a crucial research by itself so that it should be organized and presented in a meticulous manner. All single and multi-objective optimization algorithms in the literature will be tried to be collected and grouped in the following studies. The MOPs functions for the proposed MOEAs-KAS-F-REPPs were started to be generated, collected, and grouped according to their common properties during this research study. For instance, in this paper, two functions in the small hydropower plant designs were generated or collected during this study. All MOPs functions in the literature will be tried to be collected in the following studies. The free tools and software for the proposed MOEAs-KAS-F-REPPs were started to be collected in the literature during this research study. For instance, the information about Python (https://www.python.org/), R (https://www.r-project.org/), and Scilab (https://www.scilab.org/) had been collected and archived during this study. The new proposed system (MOEAs-KAS-F-REPPs) was aimd to integrate all free tools and software under a unique platform that will be researched in a detailed manner. This system will allow the developers and contributors of all free tools and software to be scientifically honored. The RD^3 studies and publications of this new proposed MOEAs-KAS-F-REPPs shall be tried to be developed like Open Source Initiative (https://opensource.org/) and Free Software Foundation (https://www.fsf.org/) approaches. All free tools and software in the literature will be tried to be collected and archived in the following studies.

In future, newly proposed system integration for all multi-objective evolutionary algorithms will be researched and the related help manuals of this new system will be prepared in a detailed manner. Moreover, all functions relevant to renewable energy power plants will be researched, generated, collected, grouped, and presented in this new system. Special and specific research studies will be conducted for a generation, collection, verification, validation, and quality assessment of these MOPs functions in the next years. In addition to these research improvements, all performance measures in the literature for comparison of single and multi-objective optimization algorithms will be found, collected, adapted, and used in new proposed MOEAs-KAS-F-REPPs in the future publications (e.g. algorithm runtime in seconds in this study). Finally, Multi-Criteria Decision Making (MCDM), Multiple–Criteria Decision Analysis (MCDA), Multiple Criteria Decision Aiding (MCDA) methods (e.g. Analytic Hierarchy Process (AHP), Consistency-Driven Pairwise Comparisons (CDPC), and Decision Expert for Education (DEXi)) will be integrated to complete the new proposed MOEAs-KAS-F-REPPs to accomplish and handle the selection of the best alternative REPPs designs and investments (e.g. Ohunakin and Saracoglu [66]; Saracoglu [90, 91, 92]). It is believed that this new proposed MOEAs-KAS-F-REPPs will make it easier to use or apply multi-objective optimization algorithms in REPPs' designs and investments in every design and investment stage in daily engineering life (e.g. Ohunakin and Saracoglu [66]; Saracoglu [90, 91, 92]). Hence, the maximization of source usage (e.g. sun, wind, and water) and the minimization of resource consumption (e.g. raw materials) can be achieved all over the world in this century. It is also thought that similar systems can be developed in other engineering and industry fields too (e.g. Saracoglu [77]).

Abbreviations

P: Power Plant Installed Capacity (MW).
η_{tr}: Efficiency of transformer (98−99,5%).
η_g: Efficiency of generator (90−98%).
η_t: efficiency of turbine.
ρ_w: Density of water (kg/m^3).
g: Gravity (m/s^2) approx: 9.81 m/s^2.
Q: Rated discharge (m^3/s).
H_{net}: Net head (m) (1.5−1900: Technical and technological limits in practice).
E: Generated total energy (MWh).
t: Period of time (h).
Capacity factor (%) (typically 50 % to 60 %).
I_{dt}: Annual downtime losses (%).
Q^*: Small Hydropower Power Plant Flow-Duration Curve (FDC) (site and case specific).
t_Q: Period of time (% percentage of time).
C_{total}: Total Investment Cost Equations For Turkey (Million €).
E_{solar}: Net annual solar electricity generation (kWh).
A_a: Aperture area of solar field (m^2).
DNI_a: Annual direct normal irradiation (kWh/m^2/y).
η_{sf}: solar field efficiency (%) (incl. collector (geometric (incident angle modifier, blocking & shading, intercept, cosine effect), optical), convection, radiation).
η_{pa}: Efficiency due to parasitic (%).
η_{pbnet}: Net power block efficiency (%).
η_{trans}: Heat to power system transfer system efficiency (%).
η_{paf}: Plant availability factor (%).

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