Multiobjective evolutionary algorithms knowledge acquisition system for renewable energy power plants

Burak Omer Saracoglu

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Abstract

Engineers have to present the best of best solutions amongst the best solutions to engineering problems or engineering design problems (EP, EDP, EPs, EDPs). Hence, EPs or EDPs are indeed Multiobjective Optimization Problems (MOPs). Although all EPs or EDPs are MOPs in reality, only a few of them can be modeled as MOPs, some of them can be modeled as Single-Objective Optimization Problems (SOPs) and most of them cannot even be modeled as MOPs or SOPs, because of the difficulties of EPs or EDPs and optimization studies. According to these basic facts, a multiobjective evolutionary algorithm knowledge acquisition system for renewable energy power plants (MOEAs-KAS-F-REPPs) is proposed to deal with those difficulties. The proposed MOEAs-KAS-F-REPPs will help engineers in the renewable energy field to work with the most appropriate and satisfactory MOPs in their daily work routine. The proposed knowledge acquisition system in its Research, Development, Demonstration, Deployment, and Diffusion ($RD^3\&D$) stages are explained in a concise style. A representative example based on some experimental test MOPs with some linear, quadratic, polynomial functions is also presented with a brief descriptive way to show how the proposed knowledge acquisition system will operate after its $RD^3\&D$ stages. According to the proposed MOEAs-KAS-F-REPPs design, the representative example has selective and elective proposed standard objectives and constraints (as test objectives and constraints). A standardized MOP is developed and saved into its own console for a virtual small hydropower plant design and investment (VSHPDI). The Pareto Optimal solutions are found by only one algorithm (NSGA-II) in the Scilab 6.0.1 on a desktop computer configuration (Windows 10 Pro, Intel(R) Core(TM) i5 CPU 650 @3.20 GHz, 6,00GB RAM with internet connection). The algorithm run-times of the current applications are between 29,489 and 50,666 seconds. All data and information are stored for the next applications and improvements according to the $RD^3\&D$ philosophy of the proposed MOEAs-KAS-F-REPPs.

Keywords: multi-objective optimization, multiobjective problem, multiobjective evolutionary algorithm, scilab, renewable energy

Abbreviations

1GOAHIDSM, 1st generation original anatolian honeybees' investment decision support methodology; ACBIDSS, autonomous or semi-autonomous computer-based intelligent decision support system; EALC, experts advice library console; G^2CSEDPS, global grid consumption side electricity demand prediction system; G^2CSPS, global grid consumption side prediction systems; G^2CSP^2S, global grid consumption side price prediction system; G^2CSP^3S, global grid consumption side peak power prediction system; G^2EDPS, global grid electricity demand prediction system; G^2PS, global grid prediction systems; G^2P^3S, global grid peak power prediction system; G^3SCPS, global grid generation side cost prediction system G^3SEGPS, global grid generation side electricity generation prediction system; G^3SPS, global grid generation side prediction systems; G^3SP^3S, global grid generation side peak power prediction system; LLC, literature library console MOEA, multiobjective evolutionary algorithm; MOEAs-KAS-F-REPPs, multiobjective evolutionary algorithm knowledge acquisition system for renewable energy power plants; MOO, multiobjective optimization; MOP, multiobjective optimization problem; NSGA-II, non dominated sorting genetic algorithm II; PALC, previous application library console; RD^3&D, research, development, demonstration, deployment, and diffusion; SCGCC, standard constraints generation & collection console; SDVGCC, standard design variables generation & collection console; SMOEAC, standardized MOEA console; SOGCC, standard objectives generation & collection console; SSOPMOPC, standardized SOPs & MOPs console; ST, standardized tools; STC, standardized tools console; SOO, single-objective optimization; SOP, single-objective optimization problem; SSOPMOP, standardized SOPs & MOPs; SMOEA, standardized MOEA

Introduction

Engineers are very different from scientists.

“Scientists discover the world that exists; engineers create the world that never was.”

“A scientist studies what is, whereas an engineer creates what never was.” Theodore von Karman.[1,2]

Engineers have an important responsibility for this World. They have to present the best of best solutions. At first, they have to find the best solutions to reach to the best of best solutions. All of these best solutions are solutions to some engineering problems or engineering design problems (EPs, EDPs). Some of the well-known engineering design problems are as such car, airplane, bridge, building, power plant design problems. All of those engineering design problems have many objectives and constraints in real life. Engineers try to design and build the safest, the most reliable, the most comfortable, the most economical, the most environmental-sound friendly cars, airplanes, buildings, and power plants. As a result, all EDPs are a sort of Multi objective Optimization Problem (MOP) (synonymous terms: multi criteria optimization problem, multi performance optimization problem or vector optimization problem.[3]

There are many EDPs in the renewable energy engineering field. One of them is to design, invest, build and operate %100 renewable power grid. Those grids may be modeled in national, multinational or global wise. There are many research, development, demonstration, deployment, and diffusion (RD^3&D) subjects in %100 renewable power grid topic. One of them is the Global Grid Prediction Systems (G^{2}PS) and its enclosed RD^3&D studies (i.e. Global Grid Electricity Demand Prediction System (G^{2}EDPS), Global Grid Peak Power Prediction System (G^{2}P^{3}S), Global Grid Generation Side Prediction Systems (G^{3}SPS), Global Grid Generation Side Electricity Generation Prediction System (G^{3}SEGPS), Global Grid Generation Side Peak Power Prediction System (G^{3}SP^{3}S), Global Grid Generation Side Cost Prediction System (G^{3}SCPS), Global Grid Consumption Side Prediction Systems (G^{2}CSPS), Global Grid Consumption Side Electricity Demand Prediction System (G^{2}CSEDPS), Global Grid Consumption Side Peak Power Prediction System (G^{2}CSP^{3}S), Global Grid Consumption Side Price Prediction System (G^{2}CSP^{2}S)).[4–11] These systems aim to predict the consumption and generation in the interconnected power grid at consumers, power plants, and regions levels. They will hopefully operate the grid effectively and efficiently. Another group of those RD^3&D subjects is related to the investment decision support system and their associated tools of the renewable power plants in %100 renewable global power grid or %100 renewable power grids.

1st generation Original Anatolian Honeybees’ investment decision support methodology (1GOAHIDSM), the autonomous or semi-autonomous computer-based intelligent decision support system (ACBIDSS) and their connected studies shall help to present the best investment options and take appropriate renewable power plant investment decisions and actions.[12–22] While all parts and pieces of %100 renewable power grid have been researched and developed in a scientific manner like in the above subjects, the design of renewable power plants could not be forgotten by researchers.

A captivating RD^3&D subject deals with the MOPs obstacles in the design of renewable power plants. That subject is a proposed multiobjective evolutionary algorithm knowledge acquisition system for renewable energy power plants (MOEAs-KAS-F-REPPs).[23] All RD^3&D efforts of the proposed MOEAs-KAS-F-REPPs complete those other RD^3&D efforts, that are interrelated and interacted with each other and related to presentation of the best design options of the REPPs. Moreover, all those RD^3&D studies serve actually one purpose as to design, invest, build, and operate the best of best grid in the considerations of all good and favorable objectives (e.g. economical, environmental-sound friendly, emission-reducing, electromagnetic free, reliable, safe, secure). This e-book presents some of the details of the proposed MOEAs-KAS-F-REPPs that shall help all engineers in practice and research areas to present the best of best renewable power plant design solutions in the next decades.

Single objective optimization & multiobjective optimization

There are many terminologies, notations, definitions and preliminaries of single objective optimization (SOO) and multiobjective optimization (MOO) subject. Only a few basic ones in SOO and MOO research are presented in this document as follows.

Branke et al.[24] defined the optimization term in the following sentence. “Optimization is the task of finding one or more solutions which correspond to minimizing (or maximizing) one or more specified objectives and which satisfy all constraints (if any)”. Bandyopadhyay & Saha,[25] defined it as “Optimization deals with the study of those kinds of problems in which one has to minimize or maximize one or more objectives that are functions of some real or integer variables.” Branke et al.[24] also defined the single-objective optimization term by defining single-objective optimization problem (SOP) as “A single-objective optimization problem involves a single objective function and usually results in a single solution, called an optimal solution.”Bandyopadhyay& Saha,[25] defined the MOO as “(multicriteria or multiattribute optimization) deals with the task of simultaneously optimizing two or more conflicting objectives with respect to a set of certain constraints.” Rao[26] defined it as “an area of multiple criteria decision-making that is concerned with mathematical optimization problems involving more than one objective function to be optimized simultaneously”. Newaz et al.[27] defined SOO and MOO as “Single objective would be the opposite of multi-objective optimization. In other words, standard optimization with a single objective functions. Multi-objective optimization means optimizing two or more conflicting objectives with respect to a set of certain constraints.” SOO research is as important as MOO research in the engineering perspective. Their mathematical representative definitions are presented in the literature as in Table 1.

Table 1 SOP and MOP definitions (Source: Coello et.al., 2002)

General Single-Objective Optimization Problem	"Minimizing (or maximizing) $f(\boldsymbol{x})$ subject to $g_i(\boldsymbol{x}) \le 0$, $i = \{1,\ldots,m\}$. and $h_i(\boldsymbol{x}) = 0$, $j = \{1,\ldots,p\}$ $\boldsymbol{x} \in \Omega$. A solution minimizes (or maximizes) the scalar $f(\boldsymbol{x})$ where $\boldsymbol{x}$ is a *n*-dimensional decision variable vector $\boldsymbol{x} = \{x_1,\ldots,x_n\}$ from some universe Ù ."Constraints: $g_i(\boldsymbol{x})$ and $h_i(\boldsymbol{x})$ $\boldsymbol{x}$ can be a vector of continuous or discrete variables" f can be continuous or discrete
General Multiobjective Optimization Problem	"minimizing (or maximizing) $F(\boldsymbol{x}) = (f_1(\boldsymbol{x}),\ldots,f_k(\boldsymbol{x}))$ subject to $g_i(\boldsymbol{x}) \le 0$, $= \{1,\ldots,m\}$, and $h_j(\boldsymbol{x}) = 0$, $j = \{1,\ldots,p\}$ $\boldsymbol{x} \in$ Ù . A MOP solution minimizes (or maximizes) the components of a vector $F(\boldsymbol{x})$ where $\boldsymbol{x}$ is a *n*-dimensional decision variable vector $\boldsymbol{x} = \{x_1,\ldots,x_n\}$ from some universe Ω. It is noted that $g_i(\boldsymbol{x}) \le 0$ and $h_i(\boldsymbol{x}) = 0$ represent constraints that must be fulfilled while minimizing (or maximizing) $F(\boldsymbol{x})$ and Ω contains all possible $\boldsymbol{x}$ that can be used to satisfy an evaluation of $F(\boldsymbol{x})$." Constraints: $g_i(\boldsymbol{x})$ and $h_i(\boldsymbol{x})$ The number of equality constraints p ($h_j(\boldsymbol{x}) = 0$, $j = \{1,\ldots,p\}$) must be less than the number of decision variables n ($\boldsymbol{x} = \{x_1,\ldots,x_n\}$). If $p \ge n$ then the problem is overconstrained, so that there is nothing to be optimized. $(f_1(\boldsymbol{x}),\ldots,f_k(\boldsymbol{x}))$ Objective functions may be in the same units (commensurable) or in different units (non-commensurable).

Single objective optimization

There is only one objective function to optimize in the SOPs. There is only one unique solution in the SOO as presented by "Although single-objective optimization problems may have a unique optimal solution,..."[3]

Some SOPs in the literature are Yasar,[28] and Cinar et al.[29] There are many SOO solution methods and algorithms in the literature such as HUMANT (HUManoid ANT), Simplex method, interior point methods, dynamic programming, simulated annealing (SA), genetic algorithms, branch and bound algorithm, cutting-plane algorithm, branch and price algorithm, Tabu search.[24,30–32] All of these methods have some advantages and disadvantages so that they should be studied very well.

The current RD^3&D scope of the proposed MOEAs-KAS-F-REPPs does not include any SOO solution methods and algorithms, however, that scope can be included in the next years and the proposed system can expand to cover all SOO solution methods and algorithms.

Multiobjective optimization

There are many objective functions to optimize in the MOPs, so that there is not one unique solution unlike with the SOPs, but there are a set of feasible solutions as mentioned by "Although single-objective optimization problems may have a unique optimal solution, MOPs usually have a possibly uncountable set of solutions on a Pareto front. Each solution associated with a point on the Pareto front is a vector whose components represent trade-offs in the decision space or Pareto solution space." Hence, the MOPs needs a sort of decision-making system or at least one decision-maker to select the final option of the decision variable values $\left(x_i^* = \{x_1^*,\ldots,x_n^*\}\right)$ where x_i^* represents the Pareto optimal set.[3]

Some MOPs in the literature are Sunar & Kahraman,[33] de Simon-Martin et al,.[34] Dehnavi and Esmaeili,[35] Oral et al.[36] There are many MOO solution algorithms in the literature such as Multiobjective Evolutionary Algorithms (MOEAs) (e.g. Multi-Objective Genetic Algorithm (MOGA), Nondominated Sorting Genetic Algorithm (NSGA), Niched-Pareto Genetic Algorithm (NPGA), Strength Pareto Evolutionary Algorithm (SPEA), Strength Pareto Evolutionary Algorithm 2 (SPEA2), Pareto Archived Evolution Strategy (PAES), Vector Evaluated Genetic Algorithm (VEGA), Nondominated Sorting Genetic Algorithm II (NSGA-II), **ε**-dominance NSGA-II, Adaptive Range Multi-Objective Genetic Algorithm (ARMOGA), ε-dominance ARMOGA (εμ ARMOGA), Multiobjective Messy Genetic Algorithm (MOMGA), Pareto Envelope-based Selection Algorithm (PESA), Micro-Genetic Algorithm for Multiobjective Optimization, Multiobjective Struggle GA (MOSGA), Orthogonal Multi-Objective Evolutionary Algorithm (OMOEA), General Multiobjective Evolutionary Algorithm (GENMOP), Efficient Global Optimization for Multi-Objective Problems (EGOMOP), Hierarchical Asynchronous Parallel Multi-Objective Evolutionary Algorithm (HAPMOEA), Gradient Enhanced Multiobjective Genetic Algorithm (GEMOGA), Nondominated Sorting Evolutionary Algorithm+ (NSEA+9), Weighted based genetic algorithm (WBGA), Random Weighted Genetic Algorithm (RWGA), S Metric Selection Evolutionary Multiobjective Optimisation Algorithm (SMS-EMOA), Scatter Tabu Search Procedure for Non-Linear Multiobjective Optimization (SSPMO), Multi Objective Ant Colony Optimization (MOACO), Progressive Multi-Objective Optimization (PMOO), NSGA-II strengthened dominance relation (NSGA-II/SDR), an enhanced inverted generational distance (IGD-NS) based MOEA with reference point adaptation (AR-MOEA).[36–43] All of these methods have some advantages and disadvantages so that they should be studied very well.

The current RD³&D scope of the proposed MOEAs-KAS-F-REPPs includes only the MOEAs, not any other MOO solution algorithms, but that scope will be extended in future and the proposed system shall expand to cover all MOO solution methods and algorithms.

Multiobjective evolutionary algorithms knowledge acquisition system for renewable energy power plants

There are some commercial off-the-shelf (shrink-wrapped, canned) MOO software. One of the well known is the modeFRONTIER (https://www.esteco.com/modefrontier). This software product is presented as such "comprehensive solution for process automation and optimization in the engineering design process" by its company. Simplex and Powell algorithms for the SOO, and MOGA II, NSGA II, ES, ARMOGA, MOPSO, MOSA, Hybrid Fast, MOGT, SANGEA, and MEGO algorithms for the MOO are available in the modeFRONTIER. pilOPT is presented as an autonomous tool in it. Another software product is the OPTIMUS (https://www.noesissolutions.com/our-products/optimus). This product is presented as such "is the industry-leading Process Integration and Design Optimization (PIDO) software platform, bundling a powerful range of capabilities for Engineering Process Integration, Design Space Exploration, Engineering Optimization and Robustness & Reliability." by its company. Differential evolution, self-adaptive evolution, simulated annealing, efficient global optimization, particle swarm optimization, and covariance matrix adaptation evolution strategy are available in the OPTIMUS. The optiSLang (https://www.dynardo.de/en/software/optislang.html) is another product in this market. Nonlinear programming quadratic line search (NLPQL), adaptive response surface method, particle swarm optimization are available in the optiSLang. None of them focuses on the REPPs designs and renewable power industry.

There are also some open source software, libraries, platforms, and tools. Some of the worth-mentioning ones are Multi-objective NSGA code in C, Multi-objective NSGA-II code in C, Epsilon-MOEA in C and C++, Basic Differential Evolution (DE) in C, Omni-Optimizer, improved Archive-based Micro Genetic Algorithm (AMGA2) (http://www.iitk.ac.in/kangal/codes.shtml), A Platform and Programming Language Independent Interface for Search Algorithms (PISA) with its own optimization problems (variator) and optimization algorithms (selector) (i.e. Set Preference Algorithm for Multiobjective Optimization (SPAM), Sampling-based HyperVolume-oriented algorithm (SHV), Hypervolume Estimation Algorithm for Multiobjective Optimization (HypE), Demonstration Program (SEMO), Simple Evolutionary Multiobjective Optimizer (SEMO2), Fair Evolutionary Multiobjective Optimizer (FEMO), SPEA2, NSGA2, Epsilon-Constraint Evolutionary Algorithm (ECEA), Indicator Based Evolutionary Algorithm (IBEA), Multiple Single Objective Pareto Sampling (MSOPS), Epsilon MOEA (EPSMOEA) in C, Simple Indicator Based Evolutionary Algorithm (SIBEA) in Java) (https://sop.tik.ee.ethz.ch/pisa/?page=pisa.php), ParadisEO in C++ with NSGA, NSGA-II and IBEA algorithms (http://paradiseo.gforge.inria.fr/), jMetal in Java with its own optimization algorithms (i.e. steady-state version of NSGA-II (ssNSGAII), NSGAIIadaptive, NSGAIIrandom, SPEA2, PAES, PESA-II, OMOPSO, MOCell, AbYSS, MOEA/D, Densea, CellDE, GDE3, FastPGA, IBEA, SMPSO, SMPSOhv, SMS-EMOA, dMOPSO, WASFGA*, GWASFGA*) (http://jmetal.sourceforge.net/), MCDMlib ("a collection of test data sets for a variety of Multiobjective optimization problems") (http://xgandibleux.free.fr/MOCOlib/), MOEA Framework (a free and open source Java library for developing and experimenting with MOEAs) (http://moeaframework.org/). None of them focuses on the REPPs designs and renewable power industry.

There are also some open source tools on the commercial software such as the PlatEMO on the MATLAB® MathWorks ("a MATLAB-based EMO platform"), that includes 50 existing MOEAs (e.g. SPEA2, PSEA-II, NSGA-II, ε-MOEA, IBEA, MOEA/D, SMS-EMOA, MSOPS-II, MTS, AGE-II, MOMBI-II, RVEA, dMOPSO) and 110 MOPs (Tian et.al., 2017b). None of them focuses on the REPPs designs and renewable power industry.

The proposed multiobjective evolutionary algorithms knowledge acquisition system for renewable energy power plants (MOEAs-KAS-F-REPPs) RD³&D project aims to study and analyze the advantages and disadvantages of these software, libraries, platforms, and tools; cooperate with their developers to integrate some of the available powerful properties, and focuses on the renewable energy power plants to present a very easy end-user system for daily engineering usage. The proposed MOEAs-KAS-F-REPPs is grouped under the open source software, libraries, platforms, and tools. This main RD³&D aim is a major challenge.

The proposed MOEAs-KAS-F-REPPs are a knowledge acquisition system. The definitions of knowledge, knowledge acquisition, knowledge support system, and knowledge acquisition tools are as follows: knowledge: "what people understand about things, concepts, ideas, theories, procedures, practices and the way do things around here",[44] knowledge acquisition: "is the acquisition of knowledge for a special purpose e.g. the expert's answer to a certain question",[45] "is the process of obtaining knowledge from a domain expert as knowledge source and is used to solve artificial intelligent problems; when and/or where the experts are not available. Acquiring adequate and high-quality knowledge is the most costly, time-consuming and difficult part of knowledge engineering",[46] knowledge support system: "at the top of the hierarchy are experimental systems integrating knowledge acquisition and performance tools in systems designed to support knowledge base updating and extension as part of ongoing applications", knowledge acquisition tools: "at the next level are the tools for automating knowledge engineering for KBS, through automatic interview procedures, modeling expert behavior, and analysis of knowledge in textual form."[47]

The proposed MOEAs-KAS-F-REPPs (Figure 1) aims not only to collect and unite widespread SOPs' objectives, SOPs' constraints, MOPs' objectives, MOPs' constraints, SOPs as a whole, MOPs as a whole in the renewable power industry and in the academic literature, and all software programs, solvers and tools in the multiobjective evolutionary algorithms research on a proposed web-based platform and desktop-based platforms (user preference), but also to build a common continuous online meeting place for all people in this interest field. In the end, there shall be a scripting-free or coding-free and also problem formulating or developing free (functions and equations generation free) platform, that can be used by daily routine application engineers to optimize all daily engineering projects and designs of the REPPs.

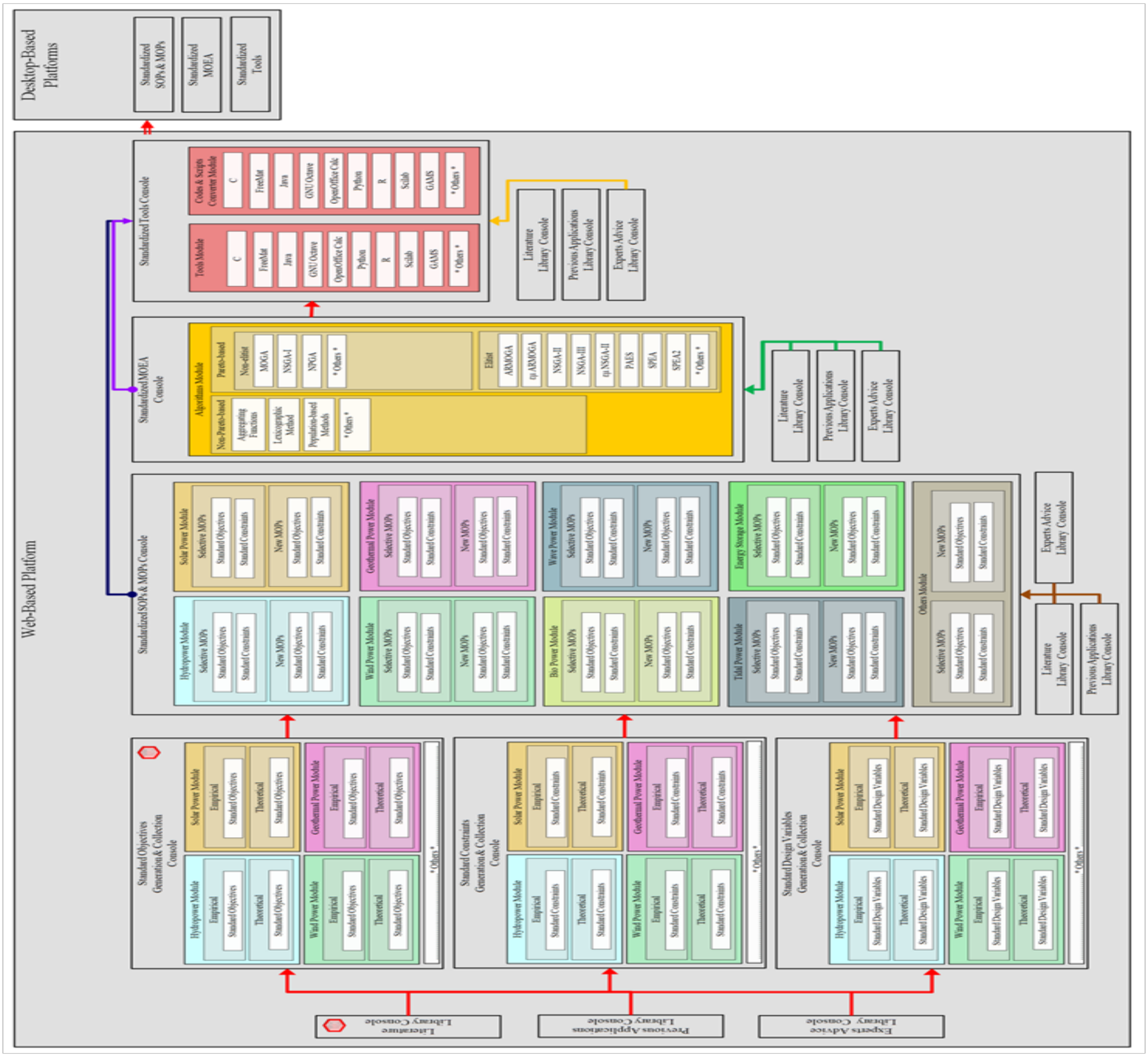


Figure 1 The proposed Multiobjective Evolutionary Algorithms Knowledge Acquisition System for Renewable Energy Power Plants (MOEAs-KAS-F-REPPs).

The proposed MOEAs-KAS-F-REPPs will hopefully deal with the difficulties of the current modeling, scripting, and solving of the MOPs and presenting the MOEAs solutions and results. The difficulties of the current MOEAs and MOPs studies are explained by several authors (i.e. time consuming, error-prone, requiring in-depth programming ability, requiring optimization expertise by Zitzler et al.[48] The proposed MOEAs-KAS-F-REPPs will overcome these difficulties by its two platforms (i.e. web-based platform, desktop-based platforms). The proposed MOEAs-KAS-F-REPPs is planned to be mainly a web-based platform. However, a desktop-based platform is also planned for all users. All or some part of the proposed MOEAs-KAS-F-REPPs may be downloaded and installed on the desktop computers and laptops. In any case, the users will have user accounts on the web-based platform and all user applications (e.g. MOEAs, MOPs) will be collected and stored on the web-based platform. The proposed MOEAs-KAS-F-REPPs will succeed in dealing with those difficulties mentioned above paragraphs by its nine consoles “Literature Library Console: LLC”, “Experts Advice Library Console: EALC”, “Previous Application Library Console: PALC”, “Standard Objectives Generation & Collection Console: SOGCC”, “Standard Constraints Generation & Collection Console: SCGCC”, “Standard Design Variables Generation & Collection Console: SDVGCC”, “Standardized SOPs & MOPs Console: SSOPMOPC”, “Standardized MOEA Console: SMOEAC” and “Standardized Tools Console: STC” on its proposed web-based platform and its “Standardized SOPs & MOPs: SSOPMOP”, “Standardized MOEA: SMOEA”, and “Standardized Tools: ST” on its proposed desktop-based platforms.

The “Literature Library Console: LLC” has its own sub-consoles (6 sub-consoles) for “SOGCC”, “SCGCC”, “SDVGCC”, “SSOPMOPC”, “SMOEAC” and “STC”, because objectives, constraints, design variables, SOPs & MOPs, MOEA, and tools are studied and will be researched by many researchers and academics in several research fields with different research aims, that do not have any common research interest set in practice. Similarly, “EALC”, “PALC” have their own 6 sub-consoles for “SOGCC”, “SCGCC”, “SDVGCC”, “SSOPMOPC”, “SMOEAC” and “STC”. The library consoles (literature, experts advice, previous applications: LLC, EALC, PALC) are designed to collect and store necessary data and information. Their aim is to supply necessary data and information for other 6 consoles (e.g. “SOGCC”, “SSOPMOPC”). “LLC” contains all relevant documents in the literature in its own scope and content with some standardized formats. The objectives, the constraints, the design variables, the SOPs & MOPs, the MOEA and the tools in the literature are collected automatically, semi-automatically, or manually (non-automatic) in a regular periodical timely or instantaneous manner.

Any user may add new documents to the LCC. Also, any user may search any document in the LCC. The “EALC” contains all experts information in their own research fields at some standardized formats (Table 2). Experts are also users in the proposed MOEAs-KAS-F-REPPs, however, this condition is not a necessity. Some experts would prefer to be out of the proposed system, however, their expert information will be presented very well. The experts information is collected automatically, semi-automatically, or manually (non-automatic) in a regular periodical manner. More importantly, their advice or recommendations are collected and stored in an organized manner in this console. Those advices and recommendations support the linked consoles (e.g. “SOGCC”, “SSOPMOPC”). As a result, all experts will be very active in the proposed MOEAs-KAS-F-REPPs. The “PALC” contains all SOPs and MOPs that are applied in the previous applications (scripts, codes, applications) on the proposed MOEAs-KAS-F-REPPs. Also, it collects and stores applied SOPs and MOPs on different information sources such as websites and software. The first RD^3&D studies focus on only manual regular periodical timely or instantaneous collection actives for all of these 3 consoles. The automatic, semi-automatic collection tools of these 3 consoles will be researched during that RD^3&D period. At the end of the RD^3&D period, the proposed MOEAs-KAS-F-REPPs will collect everything automatically. These main ideas and approaches in this part of the system give some powerful features in the core modeling and structuring of the system. Millions or billions of data and information ((literature, experts advices, previous applications) based on several sources will be collected and stored in the proposed MOEAs-KAS-F-REPPs. They will be presented whenever the users call or request them.

The “Standard Objectives Generation & Collection Console: SOGCC”, “Standard Constraints Generation & Collection Console: SCGCC”, and “Standard Design Variables Generation & Collection Console: SDVGCC” are developed for creating, collecting and storing objectives, constraints and design variables. The data and information are collected from any sources such as software (i.e. the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, the National Renewable Energy Laboratory (NREL), System Advisor Model (SAM) https://sam.nrel.gov/), websites, literature, and experts. They are linked to the “LLC”, “EALC”, and “PALC”. They include all renewable power technology modules in the current RD^3&D study approach of the MOEAs-KAS-F-REPPs. These modules are hydro (hydropower), solar (solar energy), wind (wind energy), geothermal (geothermal energy), bio (bioenergy), wave (wave energy), tidal (tidal energy), energy storage (e.g. pumped storage, compressed air energy storage, battery energy storage system) and others (all others as reserve and expansion) in the current RD^3&D study approach of the MOEAs-KAS-F-REPPs. The users can use any of them, whenever they would like to solve any MOP. However, there will be a sign-on and sign-in procedure for each of them.

Each module has its own two main groups of standard objectives, constraints, and design variables. These are entitled as empirical and theoretical standard objectives, constraints, and design variables in its current RD^3&D study status. They are defined according to the classification of the functions related to the standard objectives, constraints, and design variables. The "empirical" term means "based on experience or scientific experiments and not only on ideas",[49] "Based on, concerned with, or verifiable by observation or experience rather than theory or pure logic",[50] "derived from or relating to experiment and observation rather than theory",[51] "originating in or based on observation or experience".[52] The "theoretical" term means "based on the ideas that relate to a subject, not the practical uses of that subject",[53] "Concerned with or involving the theory of a subject or area of study rather than its practical application",[54] "A theoretical study or explanation is based on or uses the ideas and abstract principles that relate to a particular subject, rather than the practical aspects or uses of it"[55] "existing only in theory: hypothetical gave as an example a theoretical situation".[56] The exact classification of functions as either empirical standard objectives and constraints or theoretical standard objectives and constraints have not been done in the current $RD^3\&D$ stage yet. Hence, some functions are presented as empirical and theoretical at the same time lately. The up to date list of standard objectives and constraints in their linguistic forms of the proposed MOEAs-KAS-F-REPPs is given in Table 3.

Table 2 Experts Advice Library Console Experts Information Example

No	Name&Surname	Website	Contact	Expertise	Supportive to consoles
1	Jussi Hakanen	http://users.jyu.fi/~jhaka/en	jussi.hakanen@jyu.fi	MOIMD*	SMOEAC
2	Kathrin Klamroth	https://www.opt.uni-wuppertal.de/de/ag-opt/mitarbeiter/klamroth.html	klamroth@math.uni-wuppertal.de	MOPs	SOGCC SCGCC SDVGCC SSOPMOPC
3	Daene C. McKinney	http://www.caee.utexas.edu/prof/mckinney/	daene@aol.com	EO**	SOGCC SCGCC SDVGCC SSOPMOPC

*MOIMD, multiobjective optimization interactive method development; **EO, energy optimization

Table 3 Some standard objectives, constraints and decision variables in linguistical forms

No	Function Classification	Function Type	Linguistic Functions	Objective	Constraint	Complexity	Objective Type
1	Theoretical	Technical	Power Plant Installed Capacity	✔	✔	Simple	Maximization Minimization
2	Theoretical	Technical	Available Power Rate	✔	✔	Simple	Maximization
3	Theoretical	Technical	Electricity Generation	✔	✔	Simple	Maximization
4	Theoretical	Technical	Capacity Factor	✔	✔	Simple	Maximization
5	Theoretical	Technical	Energy Yield	✔	✔	Simple	Maximization
6	Empirical	Technical	Power Availability	✔	✔	Simple	Maximization
7	Empirical	Technical	Land Use	✔	✔	Composite	Minimization
8	Empirical	Technical	Total Area	✔	✔	Composite	Minimization
9	Empirical Theoretical	Technical	Specific Land Area	✔	✔	Composite	Minimization
10	Empirical	Technical	Material Consumption	✔	✔	Composite	Minimization
11	Empirical Theoretical	Technical	Emissions During Construction	✔	✔	Composite	Minimization
12	Empirical Theoretical	Technical	Emissions During Operation	✔	✔	Composite	Minimization
13	Empirical Theoretical	Technical	Emission Reductions	✔	✔	Composite	Maximization

Table Continued

14	Empirical Theoretical	Technical	Environmental Impact	✔	✔	Composite	Minimization
15	Empirical Theoretical	Technical	System Reliability	✔	✔	Composite	Maximization
16	Empirical Theoretical	Technical	Economic Life	✔	✔	Composite	Maximization
17	Empirical Theoretical	Technical	Technical Life	✔	✔	Composite	Maximization
18	Empirical Theoretical	Technical	Waste Amount During Construction	✔	✔	Composite	Minimization
19	Empirical Theoretical	Technical	Waste Amount During Operation	✔	✔	Composite	Minimization
20	Empirical Theoretical	Technical	Energy Payback Time	✔	✔	Composite	Minimization
21	Empirical	Financial*	Investment Cost	✔	✔	Simple	Minimization
22	Empirical	Financial*	Total Operation Cost	✔	✔	Simple	Minimization
23	Empirical	Financial*	Total Maintenance Cost	✔	✔	Simple	Minimization
24	Empirical Theoretical	Technical	Material Costs	✔	✔	Composite	Minimization
25	Empirical Theoretical	Technical	Manhour Costs	✔	✔	Composite	Minimization
26	Theoretical	Financial*	Levelized Cost Of Electricity	✔	✔	Composite	Minimization
27	Theoretical	Financial*	Levelized Avoided Cost of Electricity	✔	✔	Composite	Minimization
28	Empirical	Technical	Credibility	✔	✔	Composite	Maximization
29	Empirical	Technical	Bankability	✔	✔	Composite	Maximization
30	Empirical	Financial*	Revenue	✔	✔	Composite	Maximization
31	Empirical Theoretical	Financial*	Profit	✔	✔	Composite	Maximization
32	Empirical Theoretical	Financial*	Benefit-Cost Ratio	✔	✔	Composite	Maximization
33	Empirical Theoretical	Financial*	Profitability	✔	✔	Composite	Maximization
34	Empirical Theoretical	Financial*	Cash Available for Distribution	✔	✔	Composite	Maximization
35	Empirical Theoretical	Financial*	Profit Before Interest and Taxes	✔	✔	Composite	Maximization
36	Empirical Theoretical	Financial*	Earnings Before Interest, Taxes, Depreciation, And Amortization	✔	✔	Composite	Maximization
37	Empirical Theoretical	Financial*	Earnings Before Interest and Taxes	✔	✔	Composite	Maximization
38	Empirical Theoretical	Financial	Earnings Before Interest but After Taxes	✔	✔	Composite	Maximization
39	Empirical Theoretical	Financial*	Net Present Value	✔	✔	Composite	Maximization
40	Empirical Theoretical	Financial*	Internal Rate of Return	✔	✔	Composite	Maximization
41	Empirical Theoretical	Financial*	Payback Period	✔	✔	Composite	Minimization

Table Continued

42	Empirical Theoretical	Financial*	Return on Capital	✔	✔	Composite	Maximization
43	Empirical Theoretical	Financial	Return on Equity	✔	✔	Composite	Maximization
44	Empirical Theoretical	Financial*	Weighted Average Cost of Capital	✔	✔	Composite	Minimization
45	Empirical Theoretical	Financial*	Project Life Coverage Ratio	✔	✔	Composite	Maximization
46	Empirical Theoretical	Financial*	Loan life Coverage Ratio	✔	✔	Composite	Maximization
47	Empirical Theoretical	Financial*	Debt-Service Coverage Ratio	✔	✔	Composite	Maximization

*Financial term is interchangeable with the economic term.

Similar linguistic terms: available power rate or loss of power supply probability, lifespan or technical life

Each standard objective, constraint and design variable is grouped under its own renewable energy technology module. Each renewable energy technology module is stored in a separate sector. When a renewable energy technology module is called by a user, all standard objectives, constraints and design variables in that renewable energy technology module are presented to the user. The users will be able to work on these consoles and modules so that they will be capable of studying and revising those functions and presenting new functions directly. The proposed MOEAs-KAS-F-REPPs will collect and store all those kinds of data and information. Some of the experimental test standard objective, constraint, and design variables have already been researched to present some test standard objective, constraint and design variables to the researchers in the following RD³&D stages. For instance; Hydropower Module >Theoretical OR Empirical >Standard Objectives OR Standard Constraints OR Standard Decision Variables

Small Hydropower Power Plant Installed Capacity (MW) (alternative experimental test functions) based on Eliasson & Ludvigsson,[57] ESHA,[58] ESHA,[59] IFC, [60]; Saracoglu,[14] Saracoglu,[15] Saracoglu,[16] Saracoglu,[17] Saracoglu;[18] Saracoglu[19] and this study

$$P_i = \eta_{tr} \times \eta_g \times \eta_t \times \rho_w \times g \times Q_i \times H_{net} \quad (1)$$

$$P_i = \eta_{tr} \times \eta_g \times \eta_t \times \rho_w \times g \times Q_i \times H_{net_i} \quad (2)$$

$$P_{ij} = \eta_{tr} \times \eta_g \times \eta_t \times \rho_w \times g \times Q_i \times H_{net\,j} \quad (3)$$

$$P_i = \eta_{tr_i} \times \eta_{g_i} \times \eta_{t_i} \times \rho_{w_i} \times g_i \times Q_i \times H_{net} \quad (4)$$

$$P_{ij} = \eta_{tr_i} \times \eta_{g_i} \times \eta_{t_i} \times \rho_{w_i} \times g_i \times Q_i \times H_{net\,j} \quad (5)$$

Energy Generation (MWh) (alternative functions) based on IFC, 2015; Jindal, 2010; Saracoglu and de Simon Martin, 2018 and this study

$$E = \sum_{i=0}^{1} \left(P_i * t_i\right) \quad (6)$$

$$E = \int_0^1 \left(P_i * t_i\right) \quad (7)$$

$$E = P \times t \quad (8)$$

$$E = P \times 8760 \times capacity\ factor \quad (9)$$

Total Investment Cost (million €) in a South East European Grid state (alternative functions) based on Saracoglu and de Simon Martin, 2018 and this study

$$C_{total} = 2{,}2426 \times P_i - 0{,}1122 \ \ (R^2\text{: } 0{,}952) \quad (10)$$

$$C_{total} = -0{,}146 \times P_i^2 + 4{,}2918 \times P_i + 2{,}2054 \ \ (R^2\text{: } 0{,}9814) \quad (11)$$

$$C_{total} = -0{,}0313 \times P_i^3 + 0{,}5854 \times P_i^2 - 0{,}0202 \times P_i + 1{,}00864 \ \ (R^2\text{: } 0{,}9998) \quad (12)$$

$$C_{total} = 1{,}2373 \times e^{0{,}2518 \times P_i} \ \ (R^2\text{: } 0{,}9068) \quad (13)$$

$$C_{total} = 8{,}9388 \times \ln\left(P_i\right) + 3{,}8966 \ \ (R^2\text{: } 0{,}9086) \quad (14)$$

Total Investment Cost (million €) in Turkey based on Haselsteiner et.al., 2009

$$C_{total} = 1{,}0 \times P_i \ \ \text{(roughly for all hydropower plants)} \quad (15)$$

$$C_{total} = 1{,}970 \times P_i \ \ \text{(large hydropower plants)} \quad (16)$$

$$C_{total} = 0{,}90 \times P_i \ \ \text{(medium hydropower plants)} \quad (17)$$

$$C_{total} = 0{,}84 \times P_i \ \ \text{(small hydropower plants)} \quad (18)$$

Credibility (alternative functions) based on this study

$$Credibility = \sqrt{\frac{E}{C_{total}}} \quad (19)$$

$$Credibility = \frac{1}{LCOE} \quad (20)$$

$$Credibility = \sqrt{\frac{1}{LCOE}} \quad (21)$$

Credibility: "Offering reasonable grounds for being believed", "actuarial credibility: the weight to be given to data relative to the weight to be given to other data" (Dean, 1997)

Discharge (m³/s) (flow duration curve) based on Saracoglu and de Simon Martin, 2018 and this study

$$Q_i = -4{,}7606 \times t_i + 3{,}4255 \ \ (R^2\text{: } 0{,}7792) \quad (22)$$

$$Q_i = 6,4532 \times t_i^2 - 9,9055 \times t_i + 3,7729 \quad (R^2: 0,9065) \tag{23}$$

$$Q_i = -13,151 \times t_i^3 + 24,669 \times t_i^2 - 15,607 \times t_i + 3,9371 \quad (R^2: 0,9349) \tag{24}$$

$$Q_i = 18,899 \times e^{-16,5 \times t_i} \quad (R^2: 0,4804) \tag{25}$$

$$1,0 \le Q_i \le 3,0 \tag{26}$$

Efficiency of Transformers (98−99,5% (a constant value or a function)) Saracoglu and de Simon Martin, 2018 and this study

$$\eta_t = 0,99 \tag{26}$$

$$0,98 \le \eta_t \le 0,995 \tag{27}$$

$$0,99 \le \eta_t \le 0,995 \tag{28}$$

Efficiency of Generators (90−98% (a constant value or a function)) Saracoglu and de Simon Martin, 2018 and this study

$$\eta_g = 0,955 \tag{29}$$

$$0,90 \le \eta_g \le 0,98 \tag{30}$$

$$0,95 \le \eta_g \le 0,98 \tag{31}$$

Efficiency of Turbines (89−92% (a constant value or a function)) Saracoglu and de Simon Martin, 2018 and this study

$$\eta_{tr} = 3,3187 \times Q_i^3 - 13,631 \times Q_i^2 + 17,432 \times Q_i + 83,421 \quad \left(R^2: \ 0,949\right) \tag{32}$$

$$\eta_{tr} = 0,92 \tag{33}$$

$$0,89 \le \eta_{tr} \le 0,92 \tag{34}$$

$$0,90 \le \eta_{tr} \le 0,92 \tag{35}$$

Density of Water (kg/m³) (998,65-992,22 (a constant value or a function)) Saracoglu and de Simon Martin, 2018 and this study

$$\rho_w = 998,65 \tag{36}$$

$$998,65 \le \rho_w \le 992,22 \tag{37}$$

Gravity of Earth (m/s²) (9,78033-9,83203 (a constant value or a function)) based on SensorsONE, 2018; Saracoglu and de Simon Martin, 2018 and this study

$$g = 9,8 \tag{38}$$

$$9,78033 \le g \le 9,83203 \tag{39}$$

$$g = \left(9,780327\left(1 + 0.0053024\sin^2\Phi - 0.0000058\sin^2 2\Phi\right)\right) + \left(-3.086 \times 10^{-6} \times h\right) \tag{40}$$

Net Head (m) (1,5−1900 (a constant value or a function)) based on Saracoglu and de Simon Martin, 2018 and this study

$$H_{net} = 240 \tag{41}$$

$$245 \le H_{net} \le 250 \tag{42}$$

$$1,5 \le H_{net} \le 1900 \tag{43}$$

Total Budget (million €) (alternative functions) based on this study

$$B_{total} = 5.000.000 \ \ \& \ \ C_{total} \le B_{total} \tag{44}$$

$$B_{total} \le 10.000.000 \ \& \ C_{total} \le B_{total} \tag{45}$$

$$5.000.000 \le B_{total} \le 10.000.000 \ \& \ C_{total} \le B_{total} \tag{46}$$

All previously applied and also possible functions will be presented as unselective and selective, unchangeable and changeable manner to the users like presented in above experimental test equations as experimental test standard objective, constraint, and design variables. These main ideas and approaches in this part of the system give some powerful properties in the core modeling and structuring of the system. Billions, trillions or quadrillions of data and information (objective, constraint and design variable) based on several sources will be collected and stored in the proposed MOEAs-KAS-F-REPPs. They will be presented whenever the users call or request them.

The "Standardized SOPs & MOPs Console: SSOPMOPC" includes all renewable power technology modules in its current RD³&D study progress status of the proposed MOEAs-KAS-F-REPPs. These modules are the same as the ones in the SOGCC, SCGCC, SDVGCC. When a renewable energy technology module is called by a user, all standard objectives, constraints and design variables in that renewable energy technology module are presented to the user as an unselective and selective, unchangeable and changeable, unrevisable and revisable manner. The unselective, unchangeable and unrevisable standard objectives and constraints are the direct standardized SOPs and MOPs that are applied in the previous cases (like template cases). The selective standard objectives and constraints can be selected by the user to generate new standardized SOPs and MOPs in the up to date case with tiny adjustments. The changeable and revisable standard objectives and constraints can be selected by the user to generate fully new standardized SOPs and MOPs in the up to date case based on the stored SOPs and MOPs in the proposed MOEAs-KAS-F-REPPs. There will be extensive changes in these new SOPs and MOPs comparing to previous ones. All of these new SOPs and MOPs will be saved, stored and presented in the proposed MOEAs-KAS-F-REPPs. Millions or billions of standardized SOPs and MOPs data and information based on several sources will be collected and stored in the proposed MOEAs-KAS-F-REPPs. They will be presented whenever the users call or request them. Some of the experimental test standard objective, constraint, and design variables have already been researched to present some test standard objective, constraint and design variables to the researchers in the following RD³&D stages. For instance; Hydropower Module > Selective MOPs (Figure 2).

Figure 2 Standardized SOPs & MOPs Console of MOEAs-KAS-F-REPPs.

There are many MOEAs algorithms presented by their developers. The "Standardized MOEA Console: SMOEAC" includes all multiple objective algorithms in its current RD^3&D study approach of the proposed MOEAs-KAS-F-REPPs. The classification of those algorithms is made according to the literature. The current main classification is as Non-Pareto-based MOEAs and Pareto-based MOEAs. The Pareto-based MOEAs has two main groups (elitist, non-elitist). The pseudo codes and algorithms of MOEAs are stored in this console (MOGA Pseudo Code, MOGA Algorithm, Coello et. al.[61] Fonseca and Fleming,[62] NSGA-I Pseudo Code, NSGA-I Algorithm Coello et al.[61] Srinivas & Deb.[63] Srinivas and Deb[64] NSGA-I Pseudo Code, NSGA-II Algorithm Coello et al.[61] Deb et al.[62] Deb et.al.,[63] Moreover, the development process information of MOEAs, the advantages, and disadvantages of those MOEAs, the developers' information of MOEAs, and any other details related to those MOEAs are found, kept and presented with their own reference documents in this console.

For instance, Multi-Objective Genetic Algorithm (MOGA) (1st Generation MOEA) (Carlos et.al. 1993), Niched Sharing Genetic Algorithm/Non-dominated Sorting Genetic Algorithm (NSGA-I) (1st Generation MOEA) (Srinivas and Deb,[63]), and Niched Sharing Genetic Algorithm Version II (NSGA-II) (2nd Generation MOEA).[65]. Moreover, all definitions and notations (e.g. feasible region, Pareto optimal set, Pareto front) related to the MOEAs will be presented in its manuals and documents. Thousands, millions of MOEAs algorithms data and information based on several sources will be collected and stored in the proposed MOEAs-KAS-F-REPPs. They will be presented whenever the users call or request them.

There is some MOEAs commercial off-the-shelf, free and free open source software available in this research field. The "Standardized Tools Console: STC" includes all free and free open source software, platforms, and tools (e.g. Scilab, Scilab Cloud, Python, GNU Octave) in its current RD^3&D study approach of the proposed MOEAs-KAS-F-REPPs. Those tools will be presented in detail. The scripts and codes are collected automatically, semi-automatically, or manually (non-automatic) in a regular periodical manner. The scripts and codes will be automatically, semi-automatically, or manually (non-automatic) converted to each other. The first RD^3&D studies focus on only manual regular periodical conversion activities. There are already some executions of automatic and semi-automatic conversion tools in the software world such as "Matlab to Scilab translator" on Scilab 6.0.1. (Matlab to Scilab Conversion https://help.scilab.org/docs/6.0.1/en_US/section_4801ad3c5ee461a8e0cf7935db6b4b97.html). The main idea behind the conversion tool is represented in Table 4. The users will be able to work with any tool, that they are familiar without any major effort and learning process on the proposed MOEAs-KAS-F-REPPs. Moreover, the users will be able to run the MOPs by multiple MOEAs with serial computing and parallel computing principles.[66,67]

An experimental test multiobjective optimization problem example

The aim of this e-book is to explain the proposed MOEAs-KAS-F-REPPs. It doesn't focus on a MOP solution. Some experimental test MOPs' examples for the proposed MOEAs-KAS-F-REPPs have been studied since 2014. The main aim of these experimental test MOPs is to help developing real-world application MOPs and to start supplying necessary data and information for the consoles and modules (e.g. SOGCC, SCGCC, SDVGCC, SSOPMOPC) of the proposed MOEAs-KAS-F-REPPs. The first studies have been performed in the hydropower plant EDPs (i.e. small hydro power plant designs, pumped hydropower plant designs). Although all data and information are gathered from real-world projects (e.g. discharge (m^3/s) (flow duration curve), total investment cost (million €)), there hasn't any exact and concrete model been built yet, so that the virtual and experimental terms are used in the current RD³&D study status. This terminology is in accordance with the author's Doctor of Philosophy (Ph.D.) thesis that is about an executive support system (ESS).[68] That ESS aims to recommend the best real-world private investment alternative amongst hundreds, thousands, millions, billions, trillions, quadrillions or quintillions private investment options in different real-world sectors to private investors (e.g. agriculture, animal husbandry, logistics, tourism, energy). Those private investment options are generated by MOEAs and selected by Multi-Criteria Decision Making (MCDM) methods. There wasn't any real-world investment intention in several sectors or different investment options of the private investors as presented in the case study. The only real life intention was a new shipbuilding shipyard investment, which was at the end detail/final design stage and at the beginning of construction stage (everything such as layout selected) on those days. Hence a virtual entity was imagined and some private port and ship repair yard private investment options and new shipbuilding shipyard investment options were generated on the same location.[68] The virtual term was preferred for that reason on those days.

Table 4 Conversion tool idea

S. No	Scilab Blocks	Conversion	R Blocks	Conversion	Others
1	Objective Function	↔	Objective Function	↔	Objective Function
2	MOEAs Parameters	↔	MOEAs Parameters	↔	MOEAs Parameters
3	MOEAs Functions	↔	MOEAs Functions	↔	MOEAs Functions
4	Optimization	↔	Optimization	↔	Optimization
5	Visualization	↔	Visualization	↔	Visualization
6	Explication & Interpretation	↔	Explication & Interpretation	↔	Explication & Interpretation

This study also only presents a virtual small hydropower plant design and investment (VSHPDI) with some experimental test MOPs. The basis of this application is related to the applications in.[69] In fact the current applications are some successors of them. Scilab is preferred in the current application like in the previous one. Several versions of Scilab is preferred by many other users too.[70–74] Only the NSGA-II algorithm with the optim nsga2 solver of the Scilab 6.0.1 is used in this study unlike Saracoglu and de Simon Martin,[69] (MOGA, NSGA-I, NSGA-II algorithms with the optim_moga, optim_nsga, optim nsga2 solvers on the Scilab 6.0.0). It is thought that genetic algorithms in Scilab were introduced by Yann Collette (http://ycollette.free.fr) by some optimization solvers with some macros.

Two main optimization function groups are studied in the current application like in Saracoglu and de Simon Martin,[69] These are maximization of energy generation (MWh) and minimization of total investment cost (million €) (No.3 and No.21 in Table 3). The energy generation (MWh) is kept same as the previous application in Saracoglu and de Simon Martin, 2018 (only main function). The inputs (arguments, input variables) of this function are instant or instantaneous power (MW) (P_i) and % percentage of time (P_i). The instant power (MW) (P_i) is a function of the instant efficiency of turbines $(ç_{tr_i})$, the instant efficiency of generators $(ç_{g_i})$, the instant efficiency of transformers $ç_{t_i})$, the instant density of water $(ñ_{w_i})$, the instant gravity of earth $(g$), the instant discharge (flow) (Q_i) the instant net head (H_{net_i}). All these inputs of the instant power have also their own functions. For instance, the instant efficiency of transformers or in general terminology the efficiency of transformers has a function of equation (32) (a turbine manufacturer performance curve). The efficiency of turbines, efficiency of generators, efficiency of transformers, density of water, gravity of earth are assumed constant values respectively as 0,92; 0,955; 0,99; 1000,00 or 1,00 (unit conversion), 9,81 in this application.

The instant discharge (flow) (Q_i) is a function of flow data at % percentage of time (t_i). It is related to the stream flow characteristics and can be generated by some approximations of the stream gauging station data and information or by some stochastic and statistical estimation methods of similar basins. They all have their own functions too. 4 functions are generated for the instant discharge (flow) (Q_i) in this study. They are all experimental test functions (i.e. equations (22), (23), (24)) based on real world stream gauging station data. Those functions are intentionally generated as a linear function (equation (22) R^2: 0,7792), a quadratic function (second degree of polynomial function) (equation (23) R^2: 0,9065), and a polynomial function (equation (24) R^2: 0,9349) (only a third degree of polynomial function, not any others such as fourth, fifth and so on). As a result, the experimental test MOPs are founded on 3 types of functions (i.e. linear, quadratic, polynomial). The instant or instantaneous net head (m) (H_{net_i}) is a function of the instant gross head (m) (H_{net_i}) and the sum of all losses. The net head varies according to all turbine manufacturers possible heads for all turbine types in this study (e.g. low head to high head). Although this constraint is not realistic in practice, it is not any major issue of this publication in the current RD³&D stage. As it is shown in the sentences above, at least 7 functions are necessary to present a realistic case of the energy generation in a small hydropower plant design. The total investment cost (million €) is kept same as the previous application in Saracoglu & de Simon Martin,[69] (only main function), however the functions are very different from it.

The inputs of this function is as same as the previous one. 5 functions are generated for the total investment cost in this study. They are all experimental test functions (i.e. equations (10), (11), (12), (13), (14)) based on real world small hydropower plant investment cost data in a South East European Grid country. Those functions are intentionally generated as a linear function (equation (10) R^2: 0,952), a quadratic function (second degree of polynomial function) (equation (11) R^2: 0,9814), and a polynomial function (equation (12) R^2: 0,9998) (only a third degree of polynomial function, not any others such as fourth, fifth and so on). As it is shown in the sentences above, at least 1 function is necessary to present a realistic case of the total investment cost in a small hydropower plant design. Besides, at least 7 functions are necessary to present a very simple realistic case with 2 objectives (energy generation, cost) in a small hydropower plant design. Finally, the experimental test MOPs are founded on 3 types of functions (i.e. linear, quadratic, polynomial) in this study. As a result, there are 9 alternative experimental test MOPs (Table 5).

Table 5 MOPs alternatives & runtime results (maximization of energy generation, minimization of total investment cost)

Alternative MOPs	Discharge (flow duration) (m3/s)	Total Investment Cost (million €)	Function Type	NSGA-II Algorithm Runtime (seconds)
A	-22	-10	Linear & Linear	32,824
B	-23	-10	Quadratic (2nd)* & Linear	32,542
C	-24	-10	Polynomial (3rd)** & Linear	50,666
D	-22	-11	Linear & Quadratic (2nd)*	32,715
E	-23	-11	Quadratic (2nd)* & Quadratic (2nd)*	31,216
F	-24	-11	Polynomial (3rd)** & Quadratic (2nd)*	31,430
G	-22	-12	Linear & Polynomial (3rd)**	31,533
H	-23	-12	Quadratic (2nd)* & Polynomial (3rd)**	32,165
I	-24	-12	Polynomial (3rd)** & Polynomial (3rd)**	29,489

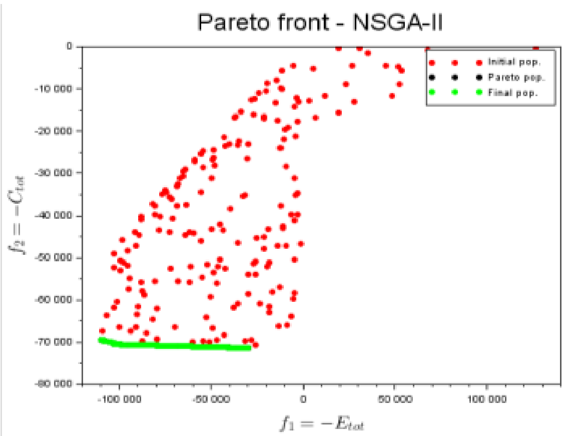
*Quadratic function: second degree of polynomial function, ** Polynomial function: third degree of polynomial function (not any others such as fourth, fifth and so on)

The draft script of the NSGA-II algorithm with the optim nsga2 solver of the Scilab 6.0.1 in this study (script info: total 143 line, total 117 command line, total 26 comments line, total 2 history cleaning line, total 115 command line for application) is a draft script like the one in Saracoglu and de Simon Martin, 2018. The first objective function (energy generation (MWh)) have to be maximized and the second objective function (total investment cost (million €)) have to be minimized by the optim nsga2 solver of the Scilab 6.0.1 like in the previous application. The values of both objective functions cannot be negative so that their signs are changed during the execution by the optim nsga2 solver of the Scilab 6.0.1 like in the previous study (Saracoglu & de Simon Martin,[69]). The major differences between this study and the last one are the discharge function block (previous equations, current equations) and the total investment cost block (previous equations, current equations) (Table 4 and Appendix). Only the script of alternative MOPs (I) is presented in the Appendix (equation (24), equation (12); polynomial & polynomial).

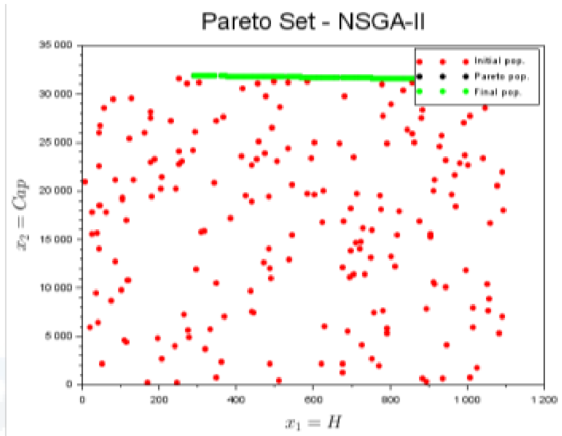
The Pareto-optimal front (Pareto front, Pareto-efficient front, Pareto frontiers, Pareto) (left Figure 3) and the Pareto-optimal set (Pareto set, Pareto-efficient set) (right Figure 3) of the alternative MOPs (i.e. A, B, C, D, E, F, G, H, I) are presented in Figure 3. The Pareto-optimal front graph of each alternative MOP (i.e. A, B, C, D, E, F, G, H, I) presents the solutions of two objective functions scripted as two objective cost functions like the previous study (left graphs in Figure 3), while the Pareto-optimal set graph of each alternative MOP (i.e. A, B, C, D, E, F, G, H, I) presents the values of the net head and the capacity respectively (right graphs in Figure 3). The Pareto-optimal front solutions are shown in the green color (left graphs in Figure 3). They are at the borders of the Pareto optimal set that are the non-dominated (green color) set of the entire feasible decision space (red and green colors) including the dominated set (red color).

It is observed that the alternative MOPs (E, F, G, H, I) have some sort of convex Pareto-optimal front shapes. The alternative MOPs (A, B, C, D) have some sort of non-convex Pareto-optimal front shapes. The alternative MOPs (E, F, G, H, I) have more non-dominated solutions (Pareto-optimal front) than the alternative MOPs (A, B, C, D). It is very difficult to decide, which function types to research more with the current findings, but it may be underlined that the function type of the total investment cost (million €) is more influencing factor than the function type of the discharge (flow duration) (m^3/s), so the energy generation (MWh). The functions types, feasible decision space, infeasible decision space, Pareto-efficient set, Pareto-efficient front, and the shapes of the Pareto-optimal front will be studied with specific attention, interest, and detail in the following research stages of the proposed MOEAs-KAS-F-REPPs.

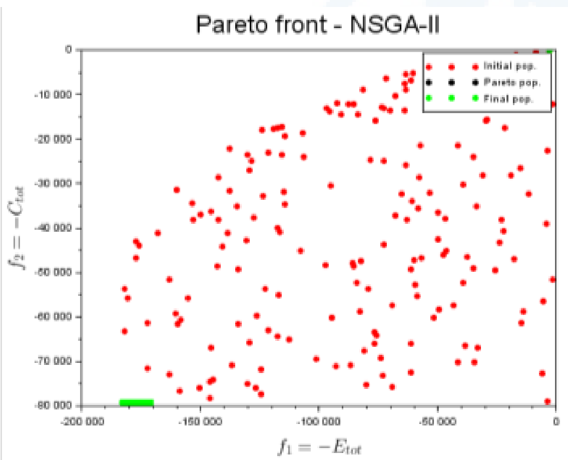
MOP(A) (Energy Generation, Total Investment Cost)



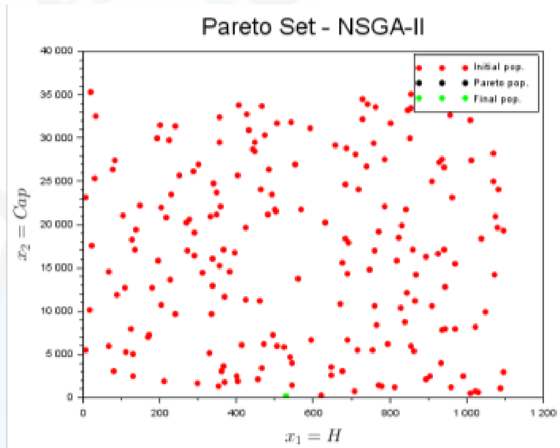
MOP(A) (Capacity, Head)



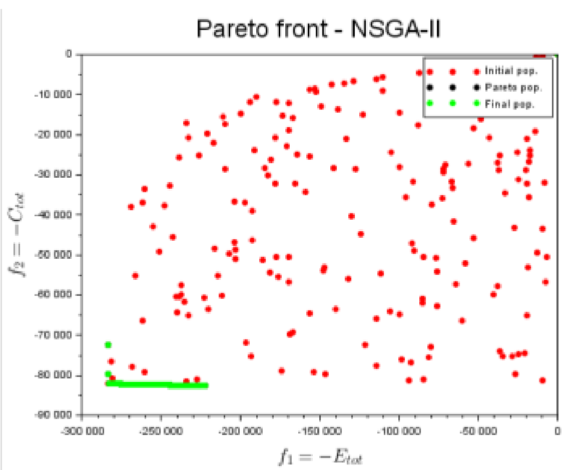
MOP(B) (Energy Generation, Total Investment Cost)



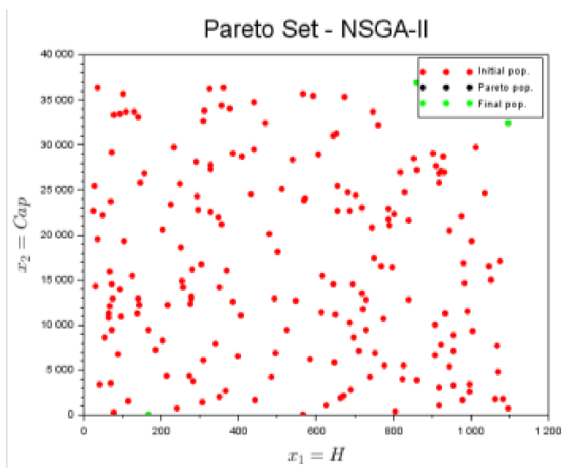
MOP(B) (Capacity, Head)



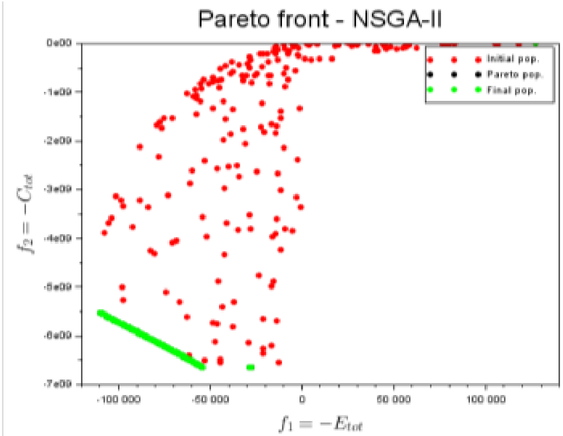
MOP(C) (Energy Generation, Total Investment Cost)



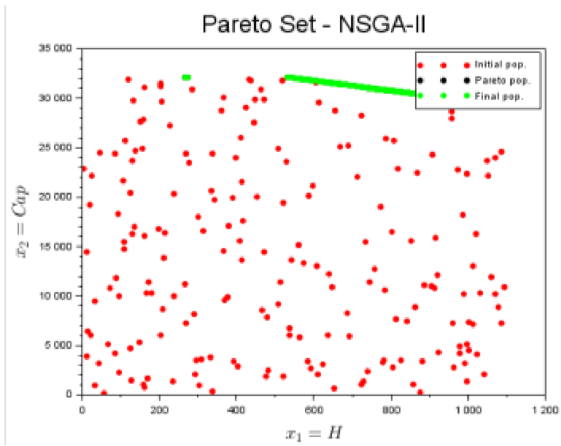
MOP(C) (Capacity, Head)



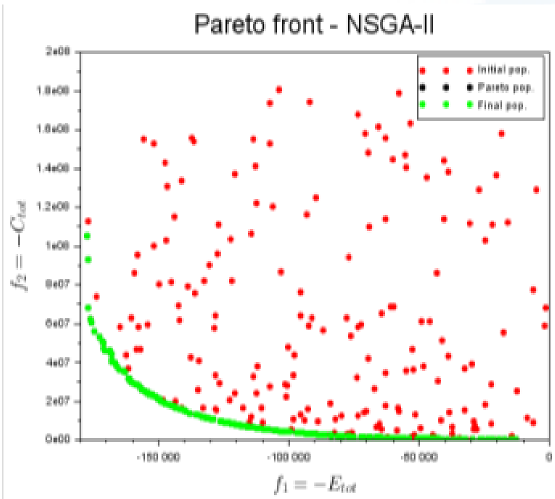
MOP(D) (Energy Generation, Total Investment Cost)



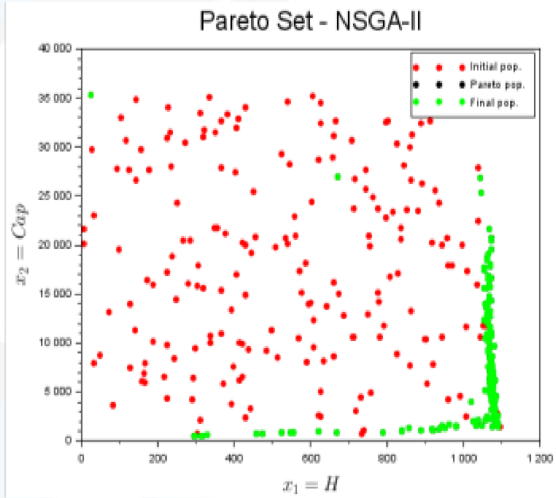
MOP(D) (Capacity, Head)



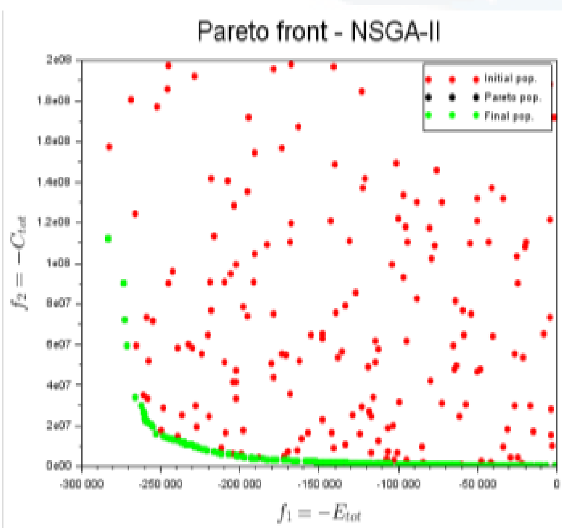
MOP(E) (Energy Generation, Total Investment Cost)



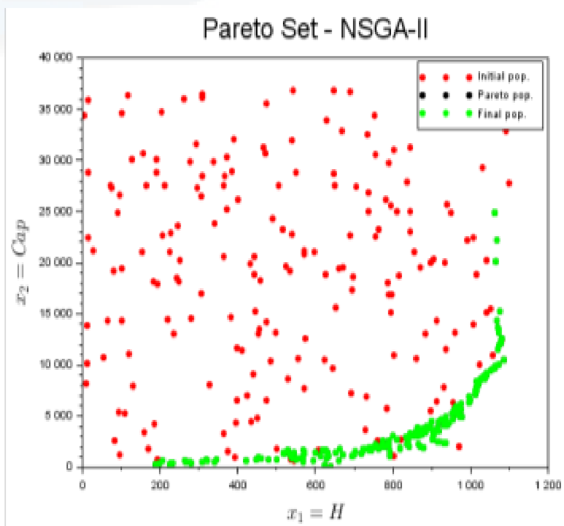
MOP(E) (Capacity, Head)



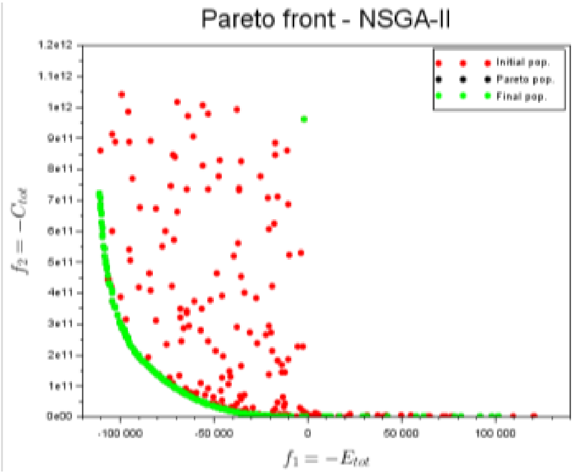
MOP(F) (Energy Generation, Total Investment Cost)



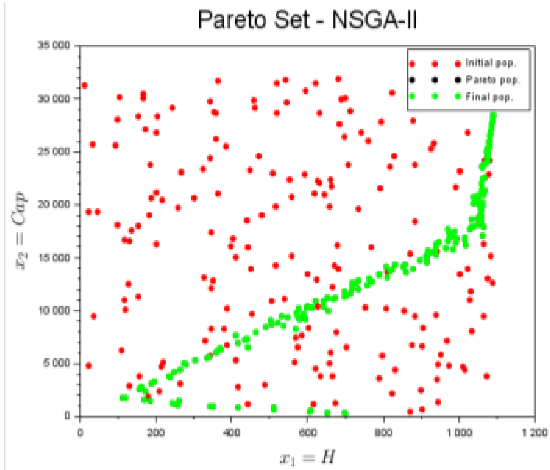
MOP(F) (Capacity, Head)



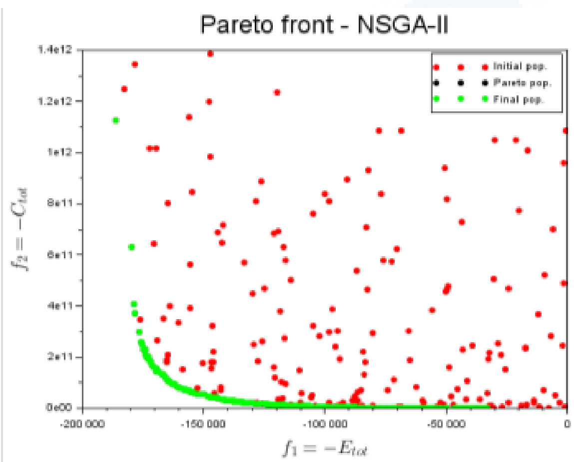
MOP(G) (Energy Generation, Total Investment Cost)



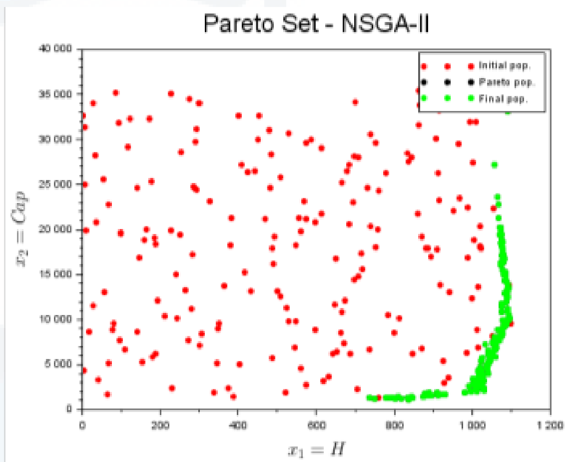
MOP(G) (Capacity, Head)



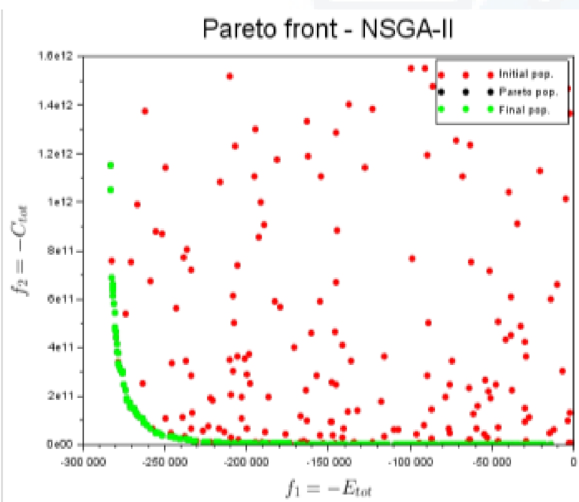
MOP(H) (Energy Generation, Total Investment Cost)



MOP(H) (Capacity, Head)



MOP(I) (Energy Generation, Total Investment Cost)



MOP(I) (Capacity, Head)

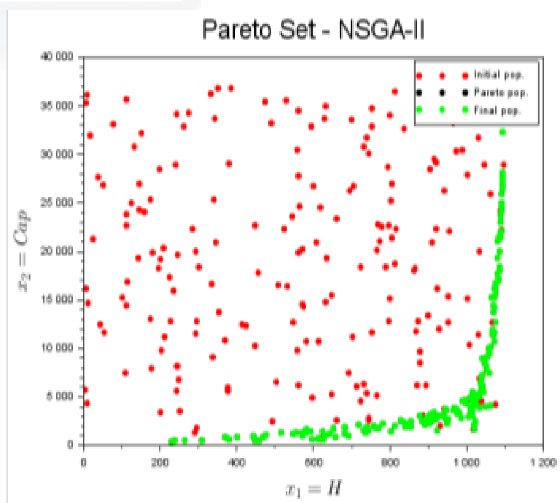
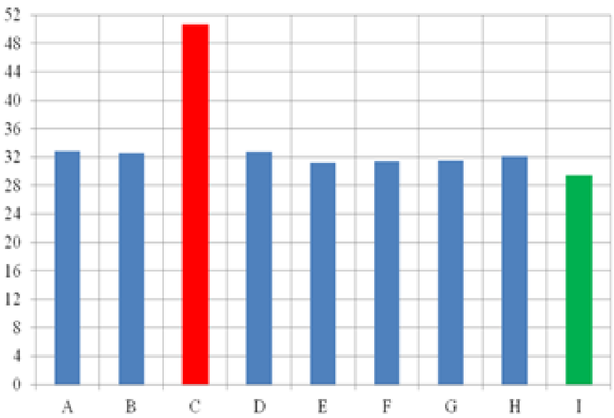


Figure 3 Pareto set & Pareto front of MOPs solutions by NSGA-II algorithm on Scilab 6.0.1.

The comparisons of alternative MOPs' (i.e. A, B, C, D, E, F, G, H, I) solutions by the NSGA-II algorithm with the optim nsga2 solver of the Scilab 6.0.1 on a PC Windows 10 Pro, Intel(R) Core(TM) i5 CPU 650 @ 3.20 GHz, 6,00 GB RAM with internet connection are presented in Table 5, Figures 3 & 4. The author expects that the alternative MOP (I) (Polynomial & Polynomial) takes the longest running time (maximum running time), the alternative MOP (A) (Linear & Linear) takes the shortest running time (minimum running time), and all others take the running time in between of those two values, but this expectation does not become true in the current case.

NSGA-II Algorithm Runtime (seconds)



NSGA-II Algorithm Runtime Relative To Minimum(seconds)

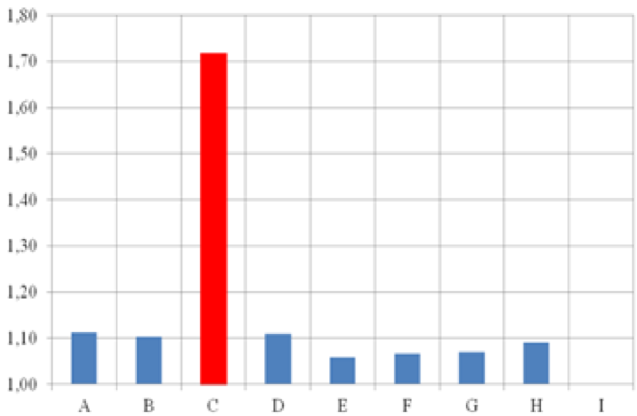


Figure 4 Pareto set & Pareto front of MOPs solutions by NSGA-II algorithms on Scilab 6.0.1.

The shortest running time (minimum running time) is 29,489679 seconds at the alternative MOP (I) (Polynomial & Polynomial), the longest running time (maximum running time) is 50,66671 seconds at the alternative MOP (C) (Polynomial & Linear), and all others take the running time in between of those two values. Moreover, the longest running time (50,66671 seconds at the alternative MOP (C)) is 1,72 times longer than the shortest running time (29,489679 seconds at the alternative MOP (I)). The second shortest running time (31,21694 seconds at the alternative MOP (E)) is 1,06 time longer than the shortest running time (29,489679 seconds at the alternative MOP (I). The second longest running time (32,82429 seconds at the alternative MOP (A)) is 1,11 times longer than the shortest running time (29,489679 seconds at the alternative MOP (I)). The second longest running time (32,82429 seconds at the alternative MOP (A)) is 1,53 times longer than the longest running time (50,66671 seconds at the alternative MOP (C)). These findings are surprising, confusing and shocking for the author because there isn't any clue found in this study how the functions should be generated to get the realistic MOPs solutions in the shortest running time (shortest running time executions goal). For instance, if the shortest realistic MOPs solutions running times may vary between milliseconds to weeks (e.g. 1ms, 1hour, 1day or 1 week), the longest realistic MOPs solutions running times will vary 1,72 times more milliseconds to weeks (e.g. 1,72ms, 1,72hour, 1,72 days or 1,72week). The only clue for the future function generation processing studies is the alternative MOP (I) (Polynomial & Polynomial) has better performed than any others. Any generalization is impossible with these findings. Other performance evaluation metrics (e.g. Inverted Generational Distance (IGD), Epsilon, Hyper volume, Spacing) of the MOEAs such as comparing Pareto-efficient fronts (e.g. closeness to the true Pareto-efficient fronts, diversity of the solutions on the Pareto-efficient fronts, spread of the solutions, amount of non-dominated solution of the Pareto-efficient fronts) aren't analyzed in the current application. The performance evaluation metrics of the MOEAs will be studied with great attention, interest, and detail in the following research stages of the proposed MOEAs-KAS-F-REPPs.

Conclusions

The proposed multiobjective evolutionary algorithms knowledge acquisition system for renewable energy power plants (MOEAs-KAS-F-REPPs) and its RD^3&D studies are briefly explained in this publication. Although this RD^3&D study and its aim is a major challenge, it is thought that the proposed MOEAs-KAS-F-REPPs with its nine consoles "LLC", "EALC", "PALC", "SOGCC", "SCGCC", "SDVGCC", "SSOPMOPC", "SMOEAC" and "STC" on its proposed web-based platform and its "SSOPMOP", "SMOEA", and "ST" on its proposed desktop-based platforms will help engineers, not only to learn and understand single objective optimization and multiobjective optimization topics better, but also to present the best of best renewable power plant solutions amongst the best solutions of engineering problems or engineering design problems in daily routine in next decades.

Moreover, this publication presents the importance of the system integration of G^2PS and its sub-systems G^2EDPS, G^2P^3S, G^3SPS, G^3SEGPS, G^3SP^3S, G^3SCPS, G^2CSPS, G^{2}CSEDPS, G^{2}CSP^{3}S, G^{2}CSP^{2}S (Saracoglu, 2017a-2017f; Saracoglu, 2018a, Saracoglu, 2018b) and 1GOAHIDSM, ACBIDSS.[14–17,75–80] Some of these RD^3&D studies are more difficult than others, but it is presented that all of them are possible, but not impossible. They will sure perform and serve in %100 renewable global power grid very well.

Acknowledgments

None

Conflicts of interest

Author declares there are no conflicts of interest.

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