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ANEXO 28
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Modelling of efficient distributed generation porfolios using a multiobjective optimization approach

Jonas von Haebler,
Fabian Erlemeyer, Christian Rehtanz
TU Dortmund University
Dortmund, Germany
jonas.von-haebler@tu-dortmund.de

Gerardo Blanco
National University of Asunción,
San Lorenzo, Paraguay
gblanco@pol.una.py

***Abstract*—In course of the German power system transition to a higher share of renewable energy sources decentralized activities constitute a major driving force for the growth of renewable energy capacity. In this context plural activities and initiatives on the local and regional level are followed to develop concepts for an efficient and sustainable regional energy supply. To achieve these goals various objectives has to be simultaneously accomplished. Generally, these objectives contradict to each other and cannot be handled by a single optimization technique. This paper proposes a multiobjective (MO) optimization approach for identifying efficient DG generation portfolios regarding multiple objectives. The methodology presented allows the planner to decide the best trade-off between the self-supply degree, environmental impact and electricity generation cost. The proposal applies, in a study case, a MO genetic algorithm that allows identifying a set of non-inferior Pareto-optimal solutions.**

***Index Terms*—Distributed generation, portfolio analysis, multiobjective programming, genetic algorithms.**

I. Introduction

The German electric energy system face remarkable changes in the past decade. The German energy transition process to a carbon free and sustainable energy supply leads to an increasing share of decentralized and renewable energy resources (DER resp. RES) in the energy mix. The German government announced an official target to increase the share of renewable energies in the electricity mix to reach 40-45% by 2025 and 55-60% by 2035. RES have already become a dominant energy source in the German electricity market, providing 30% of the total electricity production in 2015 [1]. Thus, decentralized activities have been a major driving force for the growth of renewable energy capacity in Germany, based on a plurality of several activities and initiatives on the local and regional level. Growing environmental concerns is an additional drive to more efficient local energy generation with less CO_2-emissions.

For achieving the state's climate and energy goals local and regional governments have actively driven the expansion of renewable energy capacity and foster activities for planning and investments in efficient and sustainable RES-generation technologies. Many regions pursue a local supply from 100% renewable energy sources [2]. This concept involves generating the same amount of regional sourced renewable energies as the considered region consumes annually. Additionally, important motivations for pursuing a locally growth of RES projects by local and regional governments are additional tax revenues, regional added value and positive employment effects. In this context, local and regional authorities develop regional energy concepts as a basis for planning concepts that can be used as strategic tools in regional planning processes. Initially it is necessary to define locally and regionally feasible potentials of eligible technologies that are necessary for estimating and developing strategies to a decentralized energy supply. The potential analysis constitutes the fundament for the definition of future scenarios as well as the derivation of specific measures that should be pursued by certain actors. The definition of suitable and efficient scenarios with respect to different goals as sustainability, economic efficiency and a high degree of self-supply by RES as well as preferences of all affected stakeholders constitute a complex decision making problem.

If the regional potential of installable capacity is known site- and technology-specific, a portfolio of distributed generation (DG) projects composed of several generation units allows developing DG-integration strategies involving any number of units from any DG technology resulting in any supply level of RES. Consequently, the search for an optimal integration strategy consists of an optimization problem.

Since the goal of many regions is to maximize their share of RES-supplied electric energy demand, this criterion is taken into account to the planning model. Furthermore, the sustainability represents an important criterion for the development of efficient DG portfolio, especially in the context of fulfilling the goals of CO_2-emissions reduction by the German government. Hence, the environmental impact of DG portfolios represented by the CO_2-equivalent and the affected land use will be considered in the planning model. Moreover DG integration strategies lead to an investment problem. Thus, the economic aspects of DG portfolios expressed by minimizing costs are addressed into the planning model.

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These economic, environmental and technical aspects are distinct measure units that lead to the requirement of a multi-objective model and solution method for answering the DG planning problem. Consequently, in this paper a multiobjective optimization algorithm (MOA) based on a genetic algorithm (NSGA-II) is applied that allows setting a Pareto-optimal set of DG integration strategies, that faces on maximizing the degree of local RES-supply and minimizing the economic and environmental impacts of each solution.

II. Literature Review

The MO approach for identifying DG portfolios have been addressed in several works in the literature. Different aspects concerning both technical and economical characteristics, and different solution methods are involved. Several works in the literature are focused on the subject of reducing system losses with optimal siting and sizing of DG, taking the perspective of system reliability and improving grid robustness [3]-[6]. In [7] the optimal siting of DG is examined to provide relief for overloaded grid components and therefore defer grid expansion costs. Under consideration of grid constraints and investment budget constraints the proposed algorithm utilizes the concept of successive backward method. Starting from an overbuilt system, the algorithm removes the expansion option with its least system benefit relative to its investment. Aiming to find the optimal size and location of distributed generation resources in power distribution systems, [8] combines both the minimization of investment costs and active power losses. The number of DG units is predefined and the optimal location and size is evaluated by the solver. Pursuing the same goal of finding the optimal size and location of DG units, [9]-[11] take into account the operation and maintenance costs, the costs of energy buying from transmission grid and the costs of energy not supplied. The environmental impact of DG is considered by [12] using CO_2 emission factors.

Different techniques and methods were used to determine optimal siting and sizing of DG portfolios, analytical approaches applied [13] [14], different kind of genetic algorithms (GA) [9]-[12], ant colony optimization method [10], a combination of a GA and ε-constrained technique [11], particle swarm algorithm combined with a Maximin metric [12]. Comparison among approaches were also performed, for instance, both a nonlinear optimization algorithm and a genetic algorithm is applied and consequently compared in [8]-[15]. As a result [8] states that with an increasing number of DG units the genetic algorithm outperforms the nonlinear algorithm. Particularly, NSGA-II is used in [9], being a commonly approved and widely utilized method for solving MO problems.

Despite these existing works for identifying DG portfolios with MO, it is not used on determining strategies for regional energy concepts pursuing the raise of RES-share at the local supply to contribute the superordinate transition of the electrical energy system. Considering the background of increasing numbers of local authorities and the transition of the energy system, the respective parameters are examined and the trade-off is evaluated. In this context, the main contribution of this work is the formulation and solution of a MO problem providing a fundament for the decision making process of regional energy concepts. In this context, for solving the planning problem, the NSGA-II algorithm is applied in this paper.

III. Multiobjective Programming

The identification of efficient generation portfolios involves different objectives generally conflicting. Hence, selecting a portfolio amongst all feasible portfolios implies a trade-off between these objectives. The solution approaches can be distinguished between a single optimization methods and MO methods. The transformation of multiple objectives to a single objective optimization problem provides only one solution using a form of weighting technique a priori. Such an approach is applicable if the weights for each objective can be defined a priori. Mostly it is difficult for the decision maker to define weights a priori. However, utilizing the non-dominancy concept of MO optimization provides the opportunity to obtain a Pareto-optimal set of non-inferior solutions [16]. Accordingly, the latter method empowers the decision makers according to their preferences. The following is the mathematical formulation of MO optimization problems.

$$\begin{gathered} \min f(\boldsymbol{x}) = \min(f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \dots, f_i(\boldsymbol{x})) \\ \boldsymbol{x} \in X \\ c_i(\boldsymbol{x}) = 0 \quad j = 1 \dots m \\ g_k(\boldsymbol{x}) \leq 0 \quad k = 1 \dots p \end{gathered} \tag{1}$$

where f_i is the i-th objective function, $\boldsymbol{x}$ is a decision vector belonging to the decision space X, whereas c_i and g_k are equality respectively inequality constraints restricting the objective space. Since maximize $f(\boldsymbol{x})$ is the same as minimize $f(\boldsymbol{x})$ with respect to different optimization problems there is no loss of generality in (1). Evaluating MO optimization problems evolutionary and genetic algorithms are popular und widely proved [17].

The proposed algorithm used in this work is a modified variation of the second version of the *nondominated sorting based multiobjective evolutionary algorithm* (NSGA-II) introduced in [16]. This algorithm utilizes a spacing metric and a limitation of the individuals on the first Pareto-optimal front. Both methods ensure the convergence of the Pareto-optimal set and maintain the diversity of the population. Additionally, the distribution of individuals with lower fitness level is ensured by limiting the fraction of individuals on the first Pareto-optimal front. Although the method potentially limits the number of solutions on the first Pareto-optimal front it identifies local minima and ensures the convergence of the obtained solution to an optimal Pareto-front.

IV. MO Problem Formulation

To assess the potential trade-offs of different DG-Portfolios and to obtain information which portfolio can be further pursued to either formulate or follow local and regional goals for an efficient and sustainable energy supply, the following MO problem is proposed. The electrical energy demand of the analyzed region is depicted as the basis for the optimization algorithm. It is modeled as time series represented by standard load profiles that are parameterized by the annual energy demand of the considered region.

A. The Portfolio sources

For the location and sizing algorithm the different considered DG-technologies for the portfolio has to be specified. Each DG unit n is defined by its rated power P_N^{DG}. The power output $P_{n,t}^{DG}$ of each DG unit n at every time step t is calculated by power infeed factors $pf_{n,t}$ corresponding to the regional weather characteristics or technology's operation strategy multiplied by the rated power $P_{N,n}^{DG}$ of each DG unit:

$$P_{n,t}^{DG} = pf_{n,t} \cdot P_N^{DG} \tag{2}$$

B. Objective Functions

The aim of the proposed planning algorithm is to determine efficient DG-portfolios by minimizing different objective functions related to the regional residual load, the portfolio cost, expressed by the levelized costs of electricity (LCOE), and the environmental impact, expressed by the CO_2-equivalent and the local land use of a given portfolio.

1) DG-penetration level

The DG-penetration level is included as an objective to attain all tradeoffs across all DG-levels of the solution space. In this work the DG-penetration level is defined as the share of locally generated electricity at the local electrical energy demand. The goal is to maximize the share of RES-supply in the examined region. Therefore, an annual time series analysis with an hourly resolution is done. The residual load P_t^{RL} at time step t is defined as the difference between the load demand P_t^L and the generation of the DG-Portfolio:

$$P_t^{RL} = P_t^L - \sum^N x_n \cdot P_{n,t}^{DG} \tag{3}$$

with x_n DG units of technology n. The minimization of the residual load represents equivalently the aim of a high DG-penetration level. Applying the least squares method on the residual load allows considering higher expressions of P_t^{RL} with a higher impact on the objective function. Consequently, the aggregated residuals are defined as

$$R_{PF}^{AR} = \sum^T (P_t^{RL})^2 \tag{4}$$

and taken into account as the objective function corresponding the DG-penetration level.

2) Portfolio Costs

Since the DG integration study is an investment problem, economic criteria, such as costs, should be considered into the planning model. The portfolio costs are taken into account to represent the economic efficiency from the cost perspective of different DG-portfolios in the proposed planning algorithm. The objective function to be minimized is thus represented by the portfolio's levelized costs of electricity $LCOE_{PF}$, that indicates the economic efficiency regarding the production costs of each portfolio solution. The LCOE is defined as the net present value of the unit-cost of electricity over the life time of a generating asset. The portfolio's $LCOE_{PF}$ is calculated by the sum of the weighted $LCOE_n$ of each technology n in the depicted generation portfolio and the average import cost c_{imp} that is needed for supplying the positive residual load by the general electricity mix, which is evaluated by the spot market price. As the approach focusses on the portfolio's cost efficiency, potential revenues for exported electricity surplus are not considered. The general expression is the following:

$$LCOE_{PF} = \sum^N w_n \cdot LCOE_n + w_{imp} \cdot c_{imp} \tag{5}$$

where w_n is the share of the n-th technology of the portfolio's electricity generation. The weights w represent the share of each technology resp. the imported energy at the entire generated electricity in the portfolio.

The LCOE can be calculated as the sum of costs over lifetime (T) over the sum of electric energy produced over T. The electricity generation of renewable technologies depends on the power in-feed characteristics at the precise siting location. Additionally technology specific investment costs I_0, operation and maintenance costs $c_{O\&M}$ as well as fixed costs c_{fix} affect the LCOE. Moreover the yield expectations of investors – expressed by the weighted average cost of capital $WACC$ – have a notably impact on the LCOE. Following [22] the $LCOE_n$ of each technology n is given by:

$$LCOE_n = \frac{I_{n,0} + \sum^T \frac{c_{O\&M,t} + c_{fix,t}}{(1+WACC)^t}}{\sum^T E_{n,t}} \tag{6}$$

with the electrical energy generation $E_{n,t}$ of technology n. The LCOE can be interpreted as the earnings per unit that has to be achieved for realizing a profitable project.

3) Environmental Impact

Regarding the portfolio's sustainability has a high significance. The generation of electrical energy as a social need causes an environmental impact which represents external costs on the society that can be internalized into the portfolio's electricity generation. Integrating RES into the portfolio enables more efficient use of energy concerning the reduction of environmental impacts as pollutant emissions and greenhouse gas (GHG) emissions.

To consider the environmental impact of electricity generation two criteria are regarded for the planning problem. On the one hand the CO_2-equivalent is taken into account representing the GHG-emissions. On the other hand the land use of each technology is considered. The absolute values of both indicators are normalized to the import alternative given by the general German electricity mix. The normalization enables to summarize both criteria to one environmental index to be minimized as objective function.

In order to assess GHG-emissions from energy sources used in electricity generation, in this work the methodology applied in [18] will be used. Thus the CO_2-equivalents represent the GHG-emissions of the entire process chain along the technology's life cycle. This methodology assumes that there is a linear relationship between the electricity generation E_n (kWh) and the GHG-emissions em^{CO_2} (g_{CO2}) referred to technology n expressed by the CO_2-equivalent factor $f_n^{CO_2}$ (g_{CO2}/kWh). Thus, the CO_2- equivalent of each technology is:

$$em^{CO_2} = f_n^{CO_2} \cdot E_n \tag{7}$$

The impact on the land use criteria is represented by the land use factor f_n^A, that expresses the specific landuse (m²) per electricity production unit (kWh) for each DG unit. According to [18] the land use is defined as the sealed area that is necessary for the operation of the dedicated production unit. To combine both variables to one representative factor for the environmental impact both factors are normalized to the appropriate factors f_{imp}^* of the general German electricity mix as the reference alternative of the electrical energy system:

$$f_n^{*CO_2} = \frac{f_n^{CO_2}}{f_{imp}^{CO_2}}\ ,\ f_n^{*A} = \frac{f_n^A}{f_{imp}^A} \quad \forall\, n \in N \tag{8}$$

where $f_n^{*CO_2}$ resp. f_n^{*A} represent the normalized CO_2-equivalent factor resp. land use factor. The specific environmental factor f_n^{env} for each technology of the portfolio is given by

$$f_n^{env} = \frac{f_n^{*CO_2} + f_n^{*A}}{f_{imp}^{env}} \quad \forall\, n \in N \tag{9}$$

with $$f_{imp}^{env} = f_{imp}^{*CO_2} + f_{imp}^{*A} = 2. \tag{10}$$

Finally the environmental index EI_{PF} of a DG-portfolio is:

$$EI_{PF} = \sum^T \sum^N \left(f_n^{env} \cdot w_n \cdot x_n \cdot P_{n,t}^{DG}\right) + \frac{f_{imp}^{env} \cdot P_{imp,t}}{\sum^T P_{imp,t}} \tag{11}$$

where x_n is the number of DG units of technology n.

4) MO Optimization Task

Consequently, the MO model in this work consists of three objective functions that are supposed to be minimized:

$$\min OF(\vec{x}) = \min[R_{PF}^{AR}(\vec{x}), LCOE_{PF}(\vec{x}), EI_{PF}(\vec{x})] \tag{12}$$

The constraints of the problem adopted in this work that has to be fulfilled by each portfolio realization of the Genetic Algorithm refer to the following conditions:

$$\vec{x}_n^{lb} \leq \vec{x}_n \leq \vec{x}_n^{ub}\ \forall\, n \in N \tag{13}$$

The decision variable x_n states the quantity of DG units for each technology n. The quantity of DG units is constrained at the lower bound $\vec{x}_n^{lb}$ by the already installed capacity in the considered region and at the upper bound $\vec{x}_n^{ub}$ by the maximum feasible installation potential for each technology.

V. Algorithm Outline

An important aspect for a correct setup of the genetic algorithm is a suitable coding of the solution space. For improving the algorithms efficiency the calculation processes during the optimization should be kept as simple as possible. The characteristics of the MO problem are given by the specifications of the considered region. The delimitation of the underlying region can be done by administrative boundaries such as counties or municipalities or technical boundaries such as specified grid areas. In both cases the structure of the region that should be supplied by the investigated portfolio is clearly defined. Either the administrative boundaries or the nodes of the investigated grid area can define the structure of the DG-integration study.

In this work the DG-integration study is applied on the administrative level. Therefore, the delimitation of the underlying region is a county level comprising several municipalities. The goal of the MOA is to find a Pareto-optimal set of DG-Portfolios supplying the counties load demand. The expansion potential of DG-technologies whereas is specified for each municipality. Furthermore the technologies' infeed characteristics are specified for each municipality. Hence, every solution can be constituted as a binary MxN-matrix containing information about the existence of DG-units for N technologies in M municipalities.

To solve the dimensioning problem of the portfolio it is necessary to determine typical installed capacities for each technological DG-unit. This information allow calculating every technology- and location- specific time series in advance of the optimization procedure. As there is no application of dynamic analysis regarding different operation strategies that change the infeed characteristics during the optimization procedure in this work all input data as well as the fitness functions of the MOA can be formulated based on the quantity of DG-units in each municipality. Hence, the MOA only has to vary the quantity of standard DG-units for each municipality. Thus, the solution contains the following information for each technology and municipality:

$0 \ldots x_{n,m}$ quantity of DG-units of technology n in municipality m

To find the non-inferior solutions of the MO problem a MATLAB-integrated multiobjective GA function based on the NSGA-II is applied. The MOA starts by randomly generating an initial population of possible solutions following a uniform distributed creation function. The MOA chooses randomly a quantity of each technology within the lower and upper boundaries. In order to avoid missing the solutions at the edges of the boundaries the vectors of both realizations are integrated as individuals of the Initial Population. In each generation, the fitness functions are evaluated for all individuals regarding the locally specified time series profiles. These profiles contain hourly time series for the power infeed of all generation technologies, the electric energy demand and spot market prices.

The algorithm stops when the maximum number of generations is reached or when the difference between the fitness function value of the best and worst individuals becomes smaller than a specific value. Finally, the MOA supplies a Pareto-optimal solution containing all non-inferior DG-portfolios represented by the realized quantity of DG units of each technology. The Pareto-optimal solution constitutes the basis for a following decision making process. Subject to the decision maker's preferences efficient portfolios can be chosen to be pursued in regional energy policy processes.

VI. Application Study and Results

In order to present the applicability of the proposed methodology a German rural county consisting of 74 municipalities located in the northern part of Rhineland-Palatinate is examined. The county has 128.000 inhabitants and comprises an area of 786 km². The year 2013 is applied as the base year for the application study. All time-dependent input data originate from that year. The counties annual electric energy demand is assumed to be 575 GWh [19]. The current state of the county with respect to the installed capacity is given in Table I.

A. Simulation Setting

The potential of further installable capacity resp. quantity of generation units for each technology is estimated according to [19]. For defining the potential of wind power and ground mounted photovoltaic generation units (PV_{gm}) spatial, legal and environmental restrictions are taken into account in the potential analysis to regard the approvability of the determined potential.

The standard generation units for each technology used in this work are described in the following paragraph. The wind power potential is given by the quantity of potentially available wind power sites. The rated power of wind power generation units is determined by P_n^W =3 MW corresponding to the state of the art. For Biogas generation units mainly fired by manure are taken into account, represented by a unit size of P_n^{Bio} = 75 kW. The potential of PV generation units is given by the installable capacity on approvable areas. The unit size of PV_{gm} is set to $P_n^{PV_{gm}}$ = 250 kW representing the modularity. For roof mounted PV generation units (PV_{rm}) there is no specific unit size determined following the assumption that the roof-mounted potential can be realized continuously. The installed capacity as well as the further potential representing the lower (lb) resp. the upper boundaries (ub) of the optimization problem are depicted in Table I.

TABLE I. STANDARD UNIT SIZES AND OPTIMIZATION BOUNDARIES

DG type	**Rated power P_n^{DG} [kW]**	**Lower Boundary**		**Upper Boundary**	
		u.	**P_{lb}**	**u.**	**P_{ub}**
Wind	3,000	6	15,100	121	359,100
PV_{gm}	250	-	3750	242	63,550
$PV_{rm.}$	1	-	28,359	-	372,474
Biogas	75	4	2,484	68	5,100

Weather data of the power infeed factors are taken from the weather model data base COSMO-EU from the German Meteorological Service DWD [20]. The spot market prices for electrical energy are based on the EPEX Spot Auction data [21]. The applied data (Table II) for evaluating the economic properties of the portfolio is based on [22].

TABLE II. COST DATA

DG type	**I_0 [€/kW]**	**$c_{O\&M}$ [€/kWh]**	**c_{fix} [€/kWa]**	**WACC [%]**	**T [a]**
Wind	1,600	0.018	0	3.8 %	20
PV_{gm}	1,200	0	35	2.8 %	25
PV_{rm}f	1,400	0	35	2.6 %	25
Biogas	4,000	0.025	0	4.1 %	20

Environmental data for evaluating the environmental index is depicted in Table III. The CO_2-equivalents are based on [18]. The land use data for wind power units is based on [23], data for PV_{gm} is based on [24] and data for the import alternative and Biogas units is based on [18]. The land use of PV_{rm} units is assumed to be zero, because its realization does not cause additional land use. The raw data for land use is given in m²/kW. As the land use per generated electrical energy unit depends on the specific site conditions Table III shows the median for all 74 municipalities. Similarly the environmental index of each technology is represented by the median over all municipalities.

TABLE III. ENVIRONMENTAL DATA

DG type	**$f_n^{CO_2}$ [g/kWh]**	**$f_{n,med}^{A}$ [m²/kWh]**	**$f_{n,med}^{*A}$**	**$f_n^{*CO_2}$**	**$f_{n,med}^{env}$**
Wind	8.86	0.0165	0.76	0.017	0.39
PV_{gm}	55.19	0.0175	0.81	0.106	0.46
PV_{rm}	55.19	0	0	0.106	0.05
Biogas	216	0.0037	0.17	0.415	0.3
Import	520.15	0.0216	1	1	1

B. Simulation Results

Applying the proposed algorithm to the previously described use case a set of 145 solutions is obtained on the final Pareto-optimal front. The MOA terminates after 3,800 generations due to less average changes in the spread of Pareto solutions less than 1e-5. In Fig. 1 the resulting portfolios are presented with respect to the values of the objective functions.

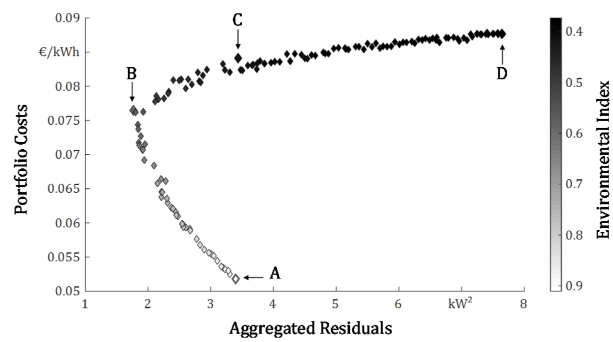

Fig 1. Obtained Pareto-front with respect to the objectives

There are four significant portfolios highlighted representing plausible scenarios. Table IV presents the composition of these portfolios and moreover the electrical energy supply provided by RES, that is distinguished as follows:

i. Annual energy balance: The annual share of RES at the local electricity demand.
ii. Timely power balance: The share of time accurate supplied electricity to the local demand by RES.

Scenario A represents the base case with the lowest portfolio cost as well as the lowest annual energy balance resp. timely power balance. In that scenario no further potential is realized corresponding to the region's current state (lb). It can be observed that a moderate DG penetration (PF B) leads to optimal energy autonomy with respect to the minimal residual load. Moreover, PF B allows the region to overachieve the average German target of a RES-share of 55-60% by 2035.

TABLE IV. PORTFOLIO COMPOSITION

Portfolio	**A**	**B**	**C**	**D**
x_{Wind}	6	31	47	92
x_{PV-gm}	20	40	39	94
x_{PV-rm}	28.4T	160T	352T	371T
x_{Biogas}	4	68	67	68
Annual energy balance	12,6 %	58 %	100 %	143 %
Timely power balance	12,6 %	50 %	63 %	71 %
Portfolio costs (€-Ct./kWh)	5,17	7,65	8,41	8,67
Environmental index	0,91	0,59	0,42	0,376

Increasing DG-penetration levels cause a higher amount of energy exports and therefore increasing the residual load of the region. For portfolios with a higher share of RES the portfolio costs are rising caused by a higher local degree of RES at electrical energy supply. Furthermore portfolios with a rising share of RES show an increasing environmental index that can be interpreted as a rising contribution for reducing the environmental impact by the considered region. As can be seen a higher annual energy balance does not result in proportionally higher timely power balance, caused by the specific not controllable infeed characteristics of the RES-technologies.

Finally, the decision making process is important to constitute one or more representative scenario(s) that are defined as a guideline for regional energy policy processes contributing the superordinate energy transition process. Various preferences of involved stakeholders signify a main challenge for the decision making process that are addressed in further works.

Conclusion

The paper presents a MO optimization methodology for obtaining Pareto-efficient DG-portfolios in a regional context. Moreover it shows that the proposed MOA can contribute decision making processes on defining strategies for the decentral contribution to the superordinate transition of the energy system regarding conflicting objectives. Thus, the proposed model allows the decision makers to derive a fundament for finding strategies concerning their individual preferences.

For that issue the decision making process of choosing a specific Pareto-optimal solution, that fulfills the decision makers' preferences, becomes very important. The analysis and application of suitable decision making methods regarding multiple criteria should be addressed in further research. Furthermore, the integrability of the Pareto-efficient solutions to the distribution system and its interrelated consequences on the system planning process are going to be investigated in further research.

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