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A financial approach to renewable energy production in Greece using goal programming

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ABSTRACT

Investing in renewable energy production is a high interest venture considering global energy needs and the environmental impact of fossil fuel consumption. Motivated by the goals set by the European Union towards 2020, this study aims at designing a renewable energy map (installing solar power plants) in Greece. Three aspects are considered, namely, social, financial, and power production aspects. A goal programming model is developed under target and structural constraints, and all possible weight combinations are examined. The solutions derived from each iteration are subjected to a financial meta-analysis, considering different tax and return scenarios aligned to the Greek taxation and banking system. The analysis considers Greece and each region separately, taking net present value (NPV) as an objective measure to assess the solutions. From the results, it is concluded that the internal rate of return is approximately 22.5% – 25% for the overall network. In addition, higher NPV values are obtained when the financial and power production aspects are given greater emphasis. The proposed model provides multi-dimensional information for decision makers; investors can determine the optimal budgeting mix, and policy makers can determine the weight on each aspect that guarantees the success of the venture.

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1. Introduction

The increase in energy demand in combination with the over-exploitation of natural resources and environmental pollution has led countries to shift to renewable energy production investments. Except for cleaner energy production, renewable energy investments are growth drivers and contribute to the development of local societies. Nevertheless, special attention should be given to the financing schemes of such investments to ensure their economic viability. There should also be a special framework and corresponding policies for the optimal planning of investments in renewable energy production in order to achieve maximum efficiency.

Generally, for investments in such production often more than one aspect is considered, such as economic, social, and environmental aspects. The economic aspect concerns all factors connected with the financial appraisal and return of the investment. The social aspect of the investment incorporates macro-economic factors (e.g., GDP and unemployment). Especially in terms of social acceptance, renewable energy plants should comply with local societies' preferences, providing a positive outlook for employment or any other socially equivalent measure that would benefit local economies. As for the environmental aspect, a renewable energy plant should not disturb the ecological homeostasis of flora and fauna. Furthermore, in some cases, the aesthetics of the landscape are harmed [1]. In addition to the potential impact on the environment, renewable energy plants, and solar energy plants in particular, have a direct effect on the agricultural sector because the land used for solar plants is not arable as long as the plant is installed in the area. Therefore, there should be a trade-off between the availability of land for agriculture and the installation of renewable energy production plants.

Regarding renewable energy planning and production at a country level, in addition to the aforementioned aspects, the following technical issues should also be considered: distributed generation, production, integration, and storage. The aggregation of all these aspects is a complex procedure in which conflicting criteria need to be traded off. For example, investing in highly sophisticated renewable energy production technologies that benefit

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the environment and are socially acceptable may not be financially sustainable. Thus, if a renewable energy production investment is socially acceptable, financially viable, and environmentally friendly, then it is considered to be sustainable [2].

In the European Union (EU), a shift towards renewable energy investments has been observed in the last decade and is expressed via the EU goals for 2020 (the EU2020 strategy). The target percentage of renewable energy for Greece is 18% of total energy consumption from renewable sources [3]. The motivation of this study stems from the goals set by the EU for 2020, which set a target of 20% power production from renewable energy sources in conjunction with high solar irradiation in Greece (Fig. 1). The present study examines the financial appraisal of renewable energy investments with emphasis on solar power plants in Greece.

Taking all of the challenges that have been described previously into account, a flexible framework that considers all of the aforementioned factors, providing a holistic view of the nature of the problem, is imperative. The contributions of this methodology are threefold. First, a weighted goal programming (WGP) model is proposed for the allocation of solar power plants in Greece (at the country level) considering the social, financial, and power production aspects. All possible weight combinations for each aspect are examined, providing a set of objective feasible solutions. The weighting procedure was not biased by a panel of experts, and, therefore, the model is holistic and can be generalized and applied to any instance. Second, a combination of forecasting techniques has been applied in order to predict future solar irradiation values for each examined region of Greece. Finally, based on the forecasted solar irradiation values and the WGP solutions, a financial meta-analysis is presented investigating the optimal budgeting mix, which is based on the number of solar plants, the taxation percentage, the return percentage, and the weight combinations.

1.1. Methodologies in the production and planning of renewable energy

Multi-criteria decision analysis (MCDA) methods and multi-objective goal programming (MOGP) techniques have been used for a variety of problems in renewable energy production and planning. More specifically, MCDA methods have been applied to the investigation of problems regarding energy production and consumption, greenhouse gas (GHG) emissions, and economic and social welfare. Several criteria for sustainable energy planning have been suggested in the literature [5], such as technical, economic, environmental, and social criteria. Especially for analyses of subjects that are related to renewable energy sources (RES), the indices that are examined take into account the price of the energy produced, the emissions reduction, the availability and limitations of technology, efficiency, land use, and social impact [6]. Numerous MCDA and MOGP techniques have been used for assessing the sustainability of renewable energy power plants. MCDA methods are used in order to rank alternatives or to help decision makers select the best out of multiple alternatives [7]. Some of the widely used MCDA methods are the analytic hierarchy process (AHP); the analytic network process, which is an extension of AHP; REGIME; PROMETHEE; Electre III; MACBETH; and the ordered weighted average [8]. The selection of the optimal renewable energy technology has been investigated using the AHP and five MCDA tools, and the scores derived from the AHP were used as inputs to the MCDA tools for ranking renewable energy technologies [9]. The AHP has been applied to the selection of various renewable energy technologies ([10–12]). The installation of wind power plants under economic, social, environmental, and technical criteria has been investigated using the REGIME method [13] in the island of Thassos.

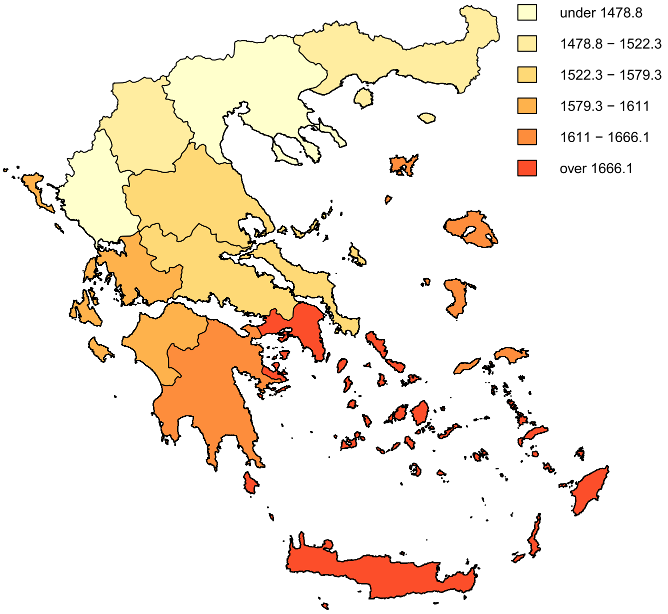

Fig. 1. Solar irradiation distribution in 2016 ($kWh/m^2.mo$) [4].

Similar to MCDA techniques, MOGP techniques examine the nature of the problem by considering more than one objective/goal. Among MOGP techniques, the goal programming (GP) methodology is a flexible type of mathematical formulation that can incorporate many different aspects of the problem and provide a set of feasible solutions that satisfy all constraints. This set of solutions is assumed to belong to the Pareto frontier. When dealing with renewable energy projects, profit maximization and cost minimization are not the only objectives to be taken into account [14]. GP formulations have been used in order to evaluate energy technologies and assess the sustainability of renewable energy projects. More specifically, the sustainable development of renewable energy has been investigated through social, economic, and energy objectives under environmental constraints using GP; solutions were proposed for strategic planning, the allocation of resources, and the implementation of sustainability strategies [15]. The optimal mix of renewable energy technologies in Spain has been examined with a GP formulation. The allocation of different renewable energy plant alternatives (wind, solar, biomass, and hydroelectric) was considered with respect to economic, social, and environmental goals [16]. In the UK, the wind farm offshore selection problem has been modeled with an extended GP formulation taking into account different decision maker philosophies [17]. Using social, environmental, and economic criteria, a multi-objective integer programming model has been examined in order to design and allocate the most appropriate renewable energy plant in Greece [18]. The optimal mix of renewable energy sources and existing fossil fuel facilities has been also examined with respect to environmental (emission minimization) and economic (cost minimization) aspects and applied to the Appalachian mountains region in the eastern United States [19]. Co-evolutionary algorithms have also been used in multi-objective programming for the optimal sizing of distributed energy resources [20]. Several techniques have also been proposed to tackle the problem of multiple solutions derived from GP formulations, including the augmented ε-constraint method [21], and meta-heuristic algorithms ([22,23]).

For the design of the renewable energy technologies mix, GP models are combined with the forecasting of future resource availability. More specifically, a GP model has been examined for the installation of solar panels using an auto-regressive moving average (ARMA) model for the forecasting of solar irradiation in Brazil [24]. Due to renewable resource variability, the need for accurate forecasting in renewable energy generation and distribution has led to sophisticated forecasting models and methods. More specifically, for solar irradiation, many models have been proposed under the assumption of a clear sky; the Solis model, the European Solar Radiation Atlas (ESRA) model, the Kasten model, polynomial fit, regressive models (moving average, ARMA, and Mixed Auto – Regressive Moving Average with exogenous variables (ARMAX)), artificial intelligence techniques (artificial neural networks (ANNs), Threshold Logic Unit (TLU), and Adaptive Linear Neuron (ADALINE), remote sensing modes, and hybrid systems ([25,26]). The forecasting of the energy yield from grid-connected PV systems has been also investigated with the use of ANNs and auto-regressive exogenous models [27]. Forecasting the availability of the renewable energy resource provides valuable insight to decision makers. Uncertainty in power production, as a result of unstable power generation from renewable energy sources, needs to be estimated. In this direction, a day-ahead model for the optimal bidding in an electricity energy market has been proposed using an analog ensemble methodology [28] based on meteorological forecasts and historical forecast data [29].

The optimal planning of renewable energy selection and allocation is not a stand-alone term but rather is examined in the context of distributed generation and integration into the electric grid system. Due to the increasing penetration of solar energy systems, questions arise about the role and integration of PV systems in the grid. Some strategies have been proposed on a country level suggesting that PV systems should have a passive role in power production, whereas other countries have examined their active participation [30]. The role of renewable energy power plants highlights the importance of energy storage systems [31]. Operating strategies of renewable energy source generators have been proposed in building efficient load shifting applications with battery storage systems ([32,33]).

1.2. Financial assessment of renewable energy projects

The risk and the benefits of renewable energy investments in power production are topics of discussion and study, bringing the appraisal of such projects to the center of interest. The information gathered is vital for stakeholders and investors, as the maximization of value is critical in the process of choosing or rejecting a RES project. Along with several social or environmental benefits, economic benefits, such as reduced costs and the provision of improved electrical services, are also important. On the other hand, the risk is also a crucial factor to examine and can include incorrect system sizing due to load uncertainty, challenges related to community integration, equipment compatibility issues, inappropriate business models, and risks associated with geographic isolation [34]. The decision-making in the application and sustainability of RES investments is a complex process, as a combination of economic, environmental, and social aspects should be considered. As found in the literature, the economic approaches to RES investments examine criteria including investment costs, operation and maintenance costs, energy costs, the payback period (PBP), the internal rate of return (IRR), the net present value (NPV), the service life, the equivalent annual cost, life cycle assessment (LCA), and cost-benefit analysis. At the same time, the environmental criteria examined include land use, the impacts on ecosystems, noise, and CO_2, NO_x, and SO_2 emissions. For the social aspect, criteria such as job creation, social acceptability, local development, and income from jobs are examined [35]. In terms of the financial appraisal, the tools of financial and economic analysis are used, such as the NPV and the PBP, and several studies have been conducted over the last decade. Campoccia et al. (2009) [36] examine the effect of different support policies for RES in Europe (feed-in tariffs, green tags, and net-metering) adopted for photovoltaic (PV) and wind systems. The comparison among the different support policies was conducted by calculating the PBP, the NPV, and the IRR for different sized PV and wind systems. The study concludes that in some cases, the implied support policy is not convenient for a certain type of RES investment and that the effects of the same support policies towards a specific RES investment may differ across different countries. Among several tools for evaluating the economic feasibility of solar PV investments, the levelized cost of electricity (LCOE) is presented [37]. This method is based on real data and is a tool that ranks different energy generation technologies in terms of the cost-benefit balance. Even though the use of real data removes biases between different technologies, this method ignores differences in the investment risks and the actual financing tools, implementing the same economic evaluation for different technologies (considering only differences in actual costs, energy production, and the useful period). Dolan et al. (2011) [38] present a financial model in order to calculate cash flows, the NPV, and the IRR for anaerobic digestion (AD) investments for renewable energy production over a 20-year lifetime, and they perform a sensitivity analysis. The study reveals that the financial viability of AD investments depends on economic incentive payments from the public sector and on the cost of waste management fees. Audenert et al. (2010) [39] conduct an economic evaluation of PV grid connected systems (PVGCS) for companies situated in Flanders (Belgium), calculating the cash flows, the NPV, the IRR, the PBP, the discounted payback period (DPBP), the profitability index (PI), the yield unit cost, the yield unit revenue, and the break-even turnkey cost. The model includes the taxation dimension and conducts a sensitivity analysis concentrating on the initial investment cost, the discount rate, and the energy price. The financial viability of investments in RES under recent regulations that promote investing in PV systems for self-consumption by paying lower grid-injected electricity tariffs compared to the regular electricity price is examined by Rodrigues et al. (2016) [40]. In their study, they take into consideration different sizes of solar PV systems (1 kW and 5 kW) and four different consumption scenarios ranging from 100% to 30% self-consumption, and they calculate the NPV, the IRR, the simple payback period, the DPBP, and the PI. They conclude by pointing out that the viability of PV system projects depends on a combination of four variables: the investment cost, the electricity tariff, government incentives, and solar radiation. In terms of small investments in RES, Rahman et al. (2014) [41] conduct a study focusing on the hybrid application of biogas and solar resources in households in order to fulfill energy needs. In their study, they apply the HOMER computer tool, which is suitable for handling small–scale, renewable–based energy systems, they calculate the net present cost and the LCOE, and they quantify the monetary savings from replacing traditional fuels. The profitability of RES investments and more particularly of PV grid-connected systems was examined by Talavera et al. (2010) [42]. In their study, they conduct a sensitivity analysis of the IRR by setting three different scenarios (each of which represent the top three geographic markets for PV: the Euro area, the USA, and Japan) revealing the impact of annual loan interest, the normalized initial investment subsidy, the normalized annual PV electricity yield, the PV electricity unitary price, the normalized initial investment, and taxation. The profitability of grid-connected PV systems in Spain (Zaragoza city) is examined by Bernal and Dufo (2006) [43]. They carry out an economic and environmental study focusing on the profitability of PV solar energy installations by calculating the NPV and the PBP using different values of the interest rate and energy tariffs. In their analysis, they also take into consideration the LCA of the examined systems, calculating the environmental benefits of their installation, the recuperation time of the invested energy, the emissions avoided, the externality costs, and the possible effects of the application of the Kyoto Protocol. In India, Shrimali et al. (2016) [44] study the cost-effectiveness of the federal policies for reaching the country's 2022 renewable targets and provide a mix of governments' budgets towards the fulfillment of these goals. Using cash flow projections based on regression analysis, they calculate the LCOE for wind and solar plants, and they compare it with the marginal cost of fossil fuels, focusing on whether a policy of support for the RES is needed. A sensitivity analysis is also applied in the study in order to examine the effects of changing the cost variables on the results. The economic feasibility of a large–scale PV installation on a small island (Kiribati) is examined by Hsu et al. (2014) [45] by calculating the maximum allowable installation capacity at the proposed installation site, estimating the power generation of PVGCS, and finally executing a cost-benefit analysis based on NPV and payback yield estimations. Supporting investors' needs for IRR values, Talavera et al. (2007) [46] present a set of tables as a basis for estimating the IRR of PV systems. The study and the calculations of the IRR are based on the life-cycle cost of the system and the present worth of cash inflows per kilowatt peak of the PVGCS. Similar to the IRR, the break-even price of energy (BEPE) is proposed by Garcia et al. (2014) [47] as a financial indicator for the appraisal of RES investments. The BEPE is the price that makes the NPV of the project equal to zero, and it can be applied to a range of activities taking into account several factors, such as inflation, the tax rate, the depreciation period, and special features of the investing project. In order to support decision makers in complex questions concerning investing in RES and making trade–offs between financial benefits, social welfare, and environment sustainability,

Table 1
Indices, parameters, and variables of the proposed model.

Index	
$i(i=1,\dots,13)$	Region
$j(j=1,2,3)$	Criteria
$k(k=1,\dots,600)$	Weights
$t(t=1,..,10)$	Years
$p(p=1,\dots,4)$	Tax scenarios
$\lambda(\lambda=1,..,10)$	Return scenarios
Integer variables	
N_i	Number of installed power plants in region i
Binary variables	
ζ_i	1 if additional solar plants are installed in region i, 0 otherwise
Non-negative variables	
$s_i^{-,GDP}$	Slack variable for under–achieving target GDP for region i
$s_i^{+,GDP}$	Slack variable for over–achieving target GDP for region i
$s_i^{-,ER}$	Slack variable for under–achieving target employment rate (ER) for region i
$s_i^{+,ER}$	Slack variable for over–achieving target employment rate (ER) for region i
$s^{-,Inv}$	Slack variable for under–achieving target investment
$s^{+,Inv}$	Slack variable for over–achieving target investment
$s_i^{-,PI}$	Slack variable for under–achieving target power installed for region i
$s_i^{+,PI}$	Slack variable for over–achieving target power installed for region i
$s_i^{-,SI}$	Slack variable for under–achieving target solar irradiation for region i
$s_i^{+,SI}$	Slack variable for over–achieving target solar irradiation for region i
Parameters	
w_j^k	Weight combination k for each criterion j
GDP_i	GDP percentage (%) for region i
ER_i	Employment rate percentage (%) for region i
Inv	Investment for each plant (€$\cdot kWh^{-1}$)
PI	Power installed (kWh)
G_i^{GDP}	Goal for GDP percentage for region i
G_i^{ER}	Goal for employment rate percentage for region i
G^{Inv}	Goal for investment for each plant (€)
G^{SI}	Goal for solar irradiation $kWh\cdot(m^2\cdot mo)^{-1}$
L_i	Available land for solar power plant installation in each region i (ha)
SI_i	Solar irradiation in each region i ($kWh\cdot(m^2\cdot mo)^{-1}$)
PP_i	Power production in each region i (kWh)
$PP_{i,k,t}^f$	Power production in each region i for weight combination k at year t (kWh per year)
Ri,k,t	Revenue of each region i and each weight combination k (€) at year t (€ per year)
Ci,k,t	Cost of each region i and each weight combination k (€) at year t (€ per year)
$\Pi_{i,k,t}$	Profit of each region i and each weight combination k (€) at year t (€ per year)
$CF_{i,k,p,t}$	Cash flows of each region i, each weight combination k, and tax scenario p at year t (€ per year)
$NPV_{i,k,p}$	NPV of each region i, each weight combination k, and tax scenario p (€)
τ_p	Tax (%)
r_λ	Return (%)
Scalars	
γ	Efficiency factor of solar power plant
β	Factor for transforming m^2 to ha
pl	Land per each solar plant installation
Cap	Capacity of potentially installed solar power plant
A	Area that is covered by each solar power plant

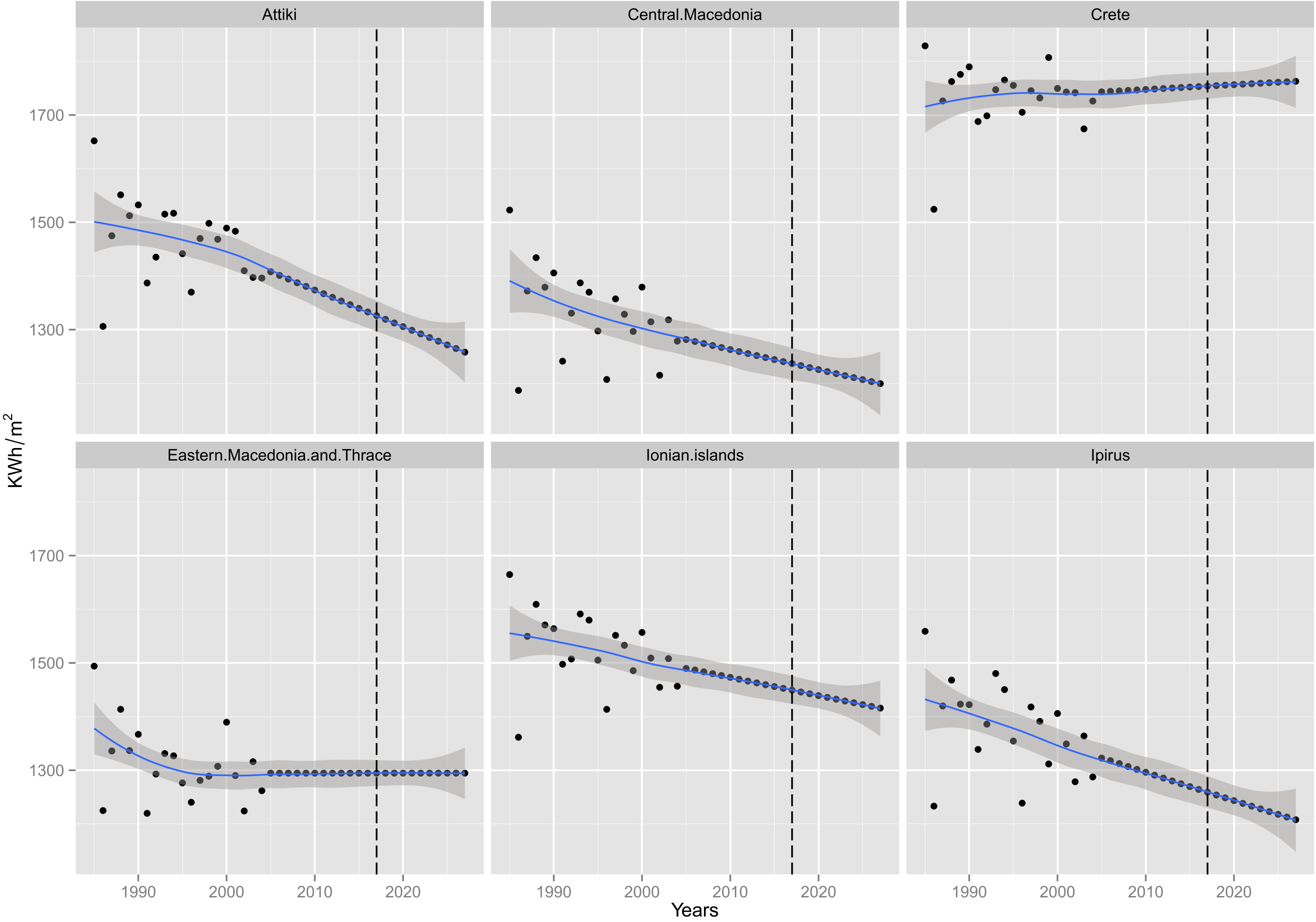

Fig. 2. Forecasted values of solar irradiation ($SI^f_{i,t}$), Attiki, Central Macedonia, Crete, Eastern Macedonia and Thrace, Ionian Islands, and Ipirus.

Petrillo et al. (2016) [48] propose a comprehensive tool based on LCA and the AHP. The tool is applied to a radio base station for mobile telecommunications, proposing a small-scale stand-alone renewable energy power plant (PV power plant) as the suitable technology to satisfy the energy needs of the station. In addition to sensitivity analysis and other traditional methods, the Monte Carlo method (MCM) is also used to estimate the sustainability of renewable energy projects. In their study, Silva Pereira et al. (2014) [49] apply the MCM in order to estimate the behaviors of economic parameters in the risk analysis of a roof-located GCPVS and a stand-alone PV system in the Amazon region. The main feature that makes MCM special is that it considers uncertainties with a probabilistic behavior (i.e., equipment, operating and maintenance costs, market conditions, and policy changes) over the project lifetime rather than following a deterministic pattern. Furthermore, for the evaluation of RES investments under uncertainty, the real options approach is applied. In the literature, the real options approach is used in the energy sector for power generation investments, policy evaluation, and R&D programs [50]. As applied by Monjas-Barroso and Balibrea-Iniesta (2013), the proposed real option method includes the identification of the real options of the regulatory framework (by applying the MCM and the binomial method), the estimation of cash flows and the projects' volatility, and, finally, the calculation of the expanded NPV. The findings of the study reveal the importance of regulatory options on the valuation of RES projects, both for investors and for policy makers, underlying the importance of volatility and uncertainty [51]. Mart?n-Barrera et al. (2016) [52] present a real option valuation model for the analysis of the impact of public R&D financing on renewable energy projects from companies' perspectives. The proposed model includes the calculation of the NPV, the calculation of the return on assets, the estimation of the grants effect on the NPV, calculations of real option values, and a set of varying conditions. Furthermore, the real option approach has been applied to the evaluation of R&D investments in wind power in Korea [53], the appraisal of investments in electrical energy storage systems [54], and the appraisal of wind plants investments in Greece [55].

Other empirical studies, not focusing on the financial appraisal of RES investments, examine citizens' participation in energy production, analyzing the technological and political factors that encourage them to invest in RES ([56]). Other studies focus on investors' responses to government policies, underlying the need for the policies' revision ([57]). Tate et al. (2010) ([58]) examine the drivers influencing farmers' adoption of enterprises associated with renewable energy.

2. Theory and calculations

2.1. Notation

The indices, parameters and variables of the proposed model are shown in Table 1.

2.2. An outline of the theory

In this section, the theory will be analytically described, and the calculations will be demonstrated in order to make the proposed methodology reproducible by other researchers. First, the weighted 0–1 mixed integer programming (MIP) GP model is formulated, assigning weights (w_j) to the three aspects of the study, namely social (w_1), financial (w_2), and power production (w_3), such that $\sum_{j=1}^{3} w_j = 1$. The model allows for decisions concerning the slacks towards each target (s^-, s^+) and the number of solar panels (N_i) to be installed in each region *i*. In the absence of decision makers, all of the combinations of weights have been examined for each aspect, leading to 600 $(k = 1, \ldots, 600)$ different objective function formulations. After solving each weighted 0–1 MIP GP model, the optimal solutions $s^{-,*}, s^{+,*}$, and N_i^* were derived. As a second stage, the decisions regarding the number of solar panel facilities in each region are used to compute the power production (P) of each region, assuming that the network is not intra–connected. Based on those calculations, revenue (R) and cost (C) functions are deployed, and the NPV (NPV) is calculated. Scenarios regarding the tax rate (τ) are examined, providing a projection of NPV in each scenario and drawing conclusions for the financial sustainability of the investment. Furthermore, the IRR (IRR) is calculated. The model has been modeled and compiled in GAMS as a MIP model using CPLEX solver [59], and for the forecasting analysis, RStudio [60] has been used.

2.3. Mathematical formulation

2.3.1. Formulation of the GP model

GP formulation is a multi-criteria decision making type of analysis where certain goals are examined in terms of trade-offs [18]. For example, when considering the renewable energy planning of a region or a country, conflicts among the aspects often arise; e.g., a wind farm may provide clean energy and may contribute to the local economy of the region, but it may affect the normality of ecosystems. In this case, GP models are proposed in order to bridge that gap. The aim of the proposed methodology is to allocate solar plants to each region of Greece, taking into account social, financial, and power production criteria. The model would choose the number of solar panels to be installed $(N_i \in \mathbb{Z}^+)$ in each region *i*. As mentioned in the outline of the methodology for each target, slack variables measure the deviation from each goal. A generalized form of a weighted 0–1 GP model is shown in equation set (1). It can be seen that the objective function penalizes each slack variable according to the direction of the goal. If the goal should not be exceeded, then the left hand side should be less than or equal $(\leq)$ to the right hand side; in this case, s^+ is minimized in the objective function. In the case where the target value should be exceeded, then the left hand side should be greater than or equal $(\geq)$ to the right hand side, and s^- is minimized. Finally, in the case where the left hand side should be equal $(=)$ to the right hand side, both slack variables, $s^- + s^+$, are minimized.

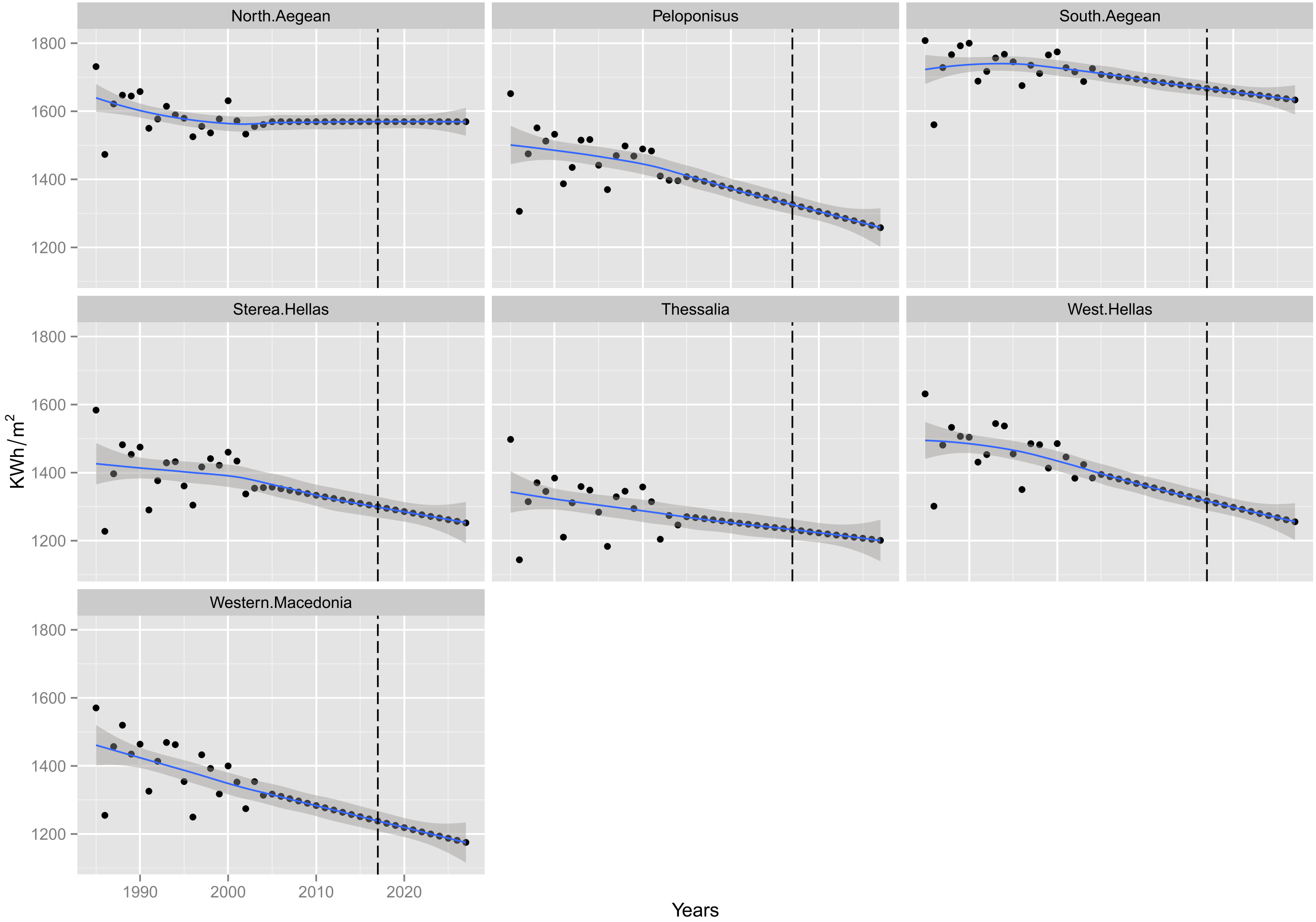

Fig. 3. Forecasted values of solar irradiation $(SI_{i,t}^f)$, North Aegean, Peloponissos, South Aegean, Stere Hellas, Thessalia, West Hellas, and Western Macedonia.

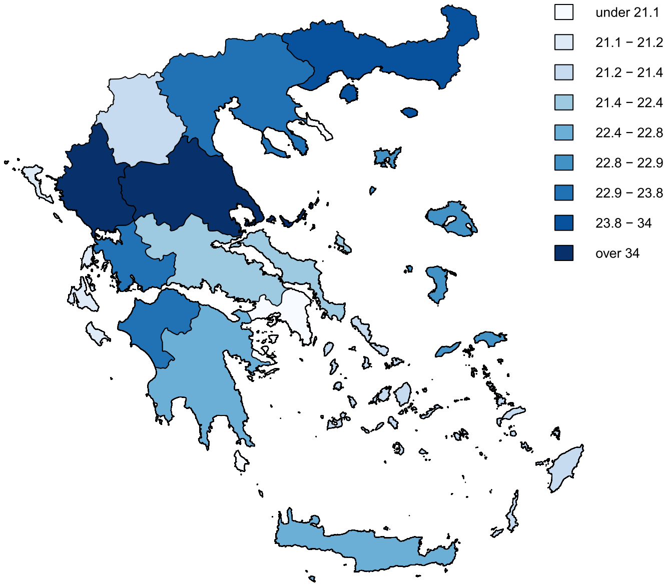

Fig. 4. Average solar power plant units per region i ($\overline{X}_i$).

$$
\begin{aligned}
&\min w_1 \cdot \sum_{p1\in S_1} \frac{s^-_{p1}}{G_{p1}} + w_2 \cdot \sum_{p2\in S_2} \frac{s^+_{p2}}{G_p2} + w_3 \cdot \sum_{p_3\in S_3} \frac{s^-_{p3}+s^+_{p3}}{G_{p3}} \\
&s.t. \\
&a_p \cdot x_p + s^-_p - s^+_p = G_p,\ \forall p\in S \qquad (1)\\
&x_p \geq 0,\ \forall p\in S \\
&s^-_p, s^+ \geq 0,\ \forall p\in S \\
&w_1 + w_2 + w_3 = 1
\end{aligned}
$$

GP formulation (1) is a weighted 0–1 model, as the slacks in the objective function are normalized for each goal; this provides more robust results, as, depending on the data, slack variables may demonstrate extreme values.

The aim of the proposed GP model is to provide solutions to decisions regarding the number of solar plants that would be installed in each region of Greece. There are 13 large regions in Greece, with special land morphology and extreme socio-economic differences. The major criteria that are examined are the following:

1. Social
2. Financial
3. Power production.

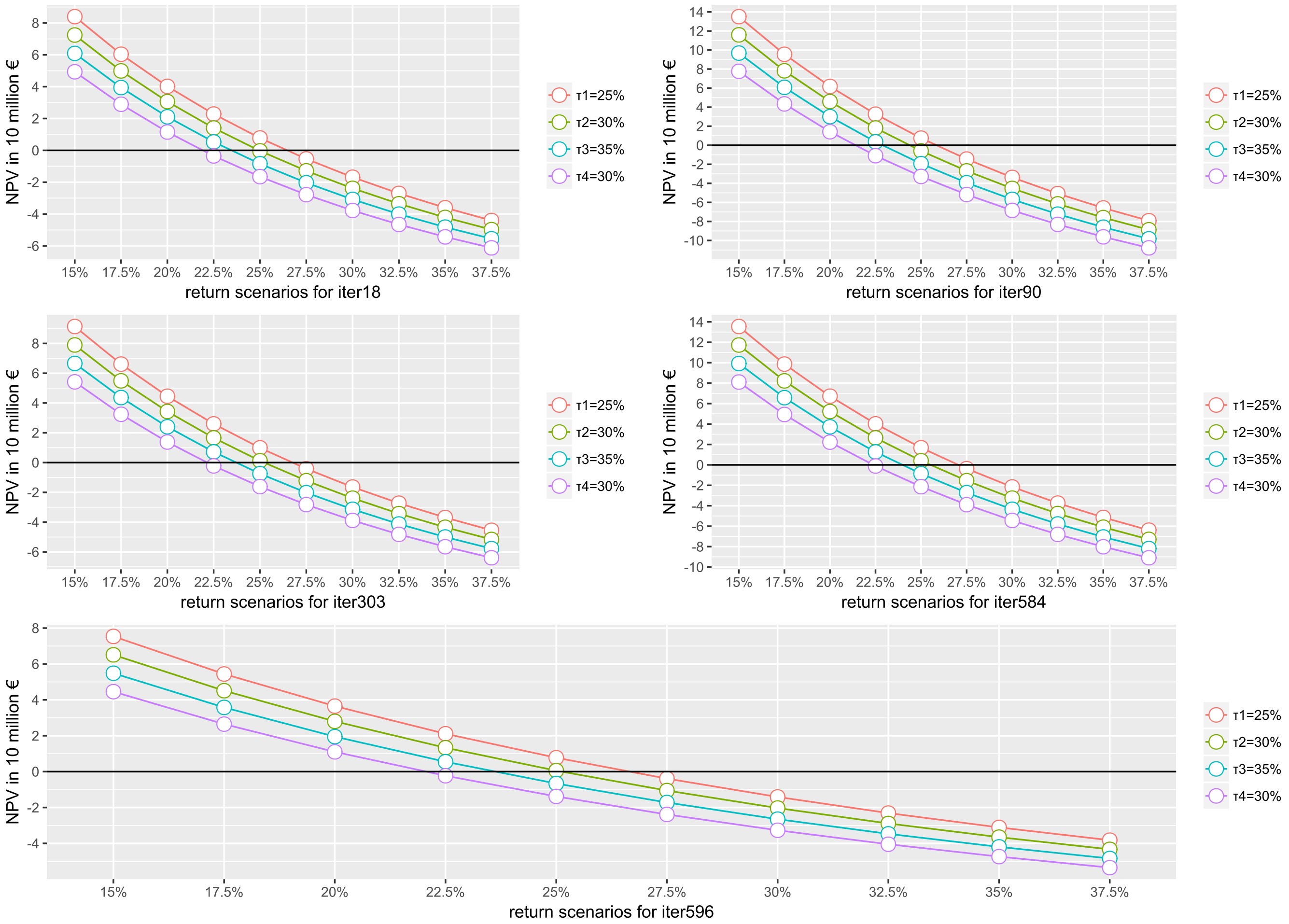

Fig. 5. The total NPV values of all regions for taxation categories $\tau_1 = 25\%$, $\tau_2 = 30\%$, $\tau_3 = 35\%$, and $\tau_4 = 40\%$; for different return scenarios (λ); and for weight representations $k = 18$, $k = 90$, $k = 303$, and $k = 584$.

Following the aforementioned criteria, corresponding GP constraints are formulated. The first set of constraints reflects the social aspect of the study. The data for the study have been retrieved from annual statistical authorities and relevant works [4]. The first goal constraint (2) is a surrogate measure of the welfare of each region, setting a target for GDP. The goal for GDP per capita is set equal to 16436.45 €.

$$GDP_i \cdot N_i + s_i^{-,GDP} - s_i^{+,GDP} = G_i^{GDP}, i = 1, \ldots, 13 \tag{2}$$

In this case, the regions with a high GDP are penalized, as the aim of the study is to allocate power plants with priority to poorer regions. The second goal constraint (3) models the employment rate; data regarding the employment rate percentage have been retrieved for each region. In this case, regions with higher employment rates are penalized, and the rationale is the same as for the GDP goal constraint. The employment rate goal is set equal to 52.07%.

$$ER_i \cdot N_i + s_i^{-,ER} - s_i^{+,ER} = G_i^{ER}, i = 1, \ldots, 13 \tag{3}$$

Regarding the financial aspect of the study, a goal constraint is introduced stating that the budget of all of the ventures should be equal to the total budget available. The mathematical formulation of the goal constraint is shown in the next equation (4). The goal for investment is defined as the capital for installing solar power plants (500.000 € per 100 kWh) multiplied by the kilowatt hours to be installed in order to reach the EU goal (213 kWh).

$$\sum_{i=1}^{13} (pl \cdot Inv_i \cdot N_i) + s^{-,Inv} - s^{+,Inv} = G^{Inv} \tag{4}$$

Based on the European Directives, a target is set for energy installed by 2020. However, the target should incorporate the already installed power from solar plants in each region i. Therefore, the installed power set by the directive would count toward the installed power in each region and is subtracted from the already installed power ($G^{PI} = 213$ Kwh).

$$\sum_{i=1}^{13} \left(PI_i - Cap \cdot N_i + s_i^{-,PI} - s_i^{+,PI} \right) = G^{PI} \tag{5}$$

In order to take advantage of the solar irradiation of certain regions, a goal is set ($G^{SI} = 1600$ kWh $\cdot (m^2 \cdot mo)^{-1}$).

$$SI_i \cdot \zeta_i + s_i^{-,SI} - s_i^{+,SI} = G_i^{SI}, i = 1, \ldots, 13 \tag{6}$$

Based on the following formulation, a binary variable ζ_i is introduced so that if more weight is given to the corresponding deviational variable of the goal constraint (6), then the binary variable is triggered, activating the constraint (7). As the aim of this goal is to take advantage of the solar irradiation of certain regions, the slack variable that underestimates the goal is minimized in the objective function ($s_i^{-,SI}$). The extra solar power plants that will be installed in this situation are denoted by $N^U = 25$.

$$N_i \geq N^U \cdot \zeta_i, i = 1, \ldots, 13 \tag{7}$$

The design of such ventures should take into account functional constraints regarding land availability and power consumption. The solar power plants are installed in a certain area in order to produce a fixed amount of power (100 kWh). In addition, the land that is covered by solar power plants is not arable, and, therefore, a specific area of land should be available for this purpose. In each region i, the number of selected solar plants should not exceed the available land, as in constraint (8).

$$A \cdot N_i \leq L_i, i = 1, .., 13 \tag{8}$$

In order to guarantee that at least 20 solar and a minimum number of 50 power plants will be selected in each region, constraints (10) and (9) are introduced. A maximum of 200 and a minimum of 100 plants are assumed to be installed in all regions, modeled by constraints (12) and (11).

$$N_i \geq 20, i = 1, .., 13 \tag{9}$$

$$N_i \leq 50, i = 1, .., 13 \tag{10}$$

$$\sum_{i=1}^{13} N_i \geq 100 \tag{11}$$

$$\sum_{i=1}^{13} N_i \leq 200 \tag{12}$$

2.3.2. *The proposed 0–1 weighted MIP GP formulation*

The objective function is defined as the weighted sum of the deviational slack variables assigned to each goal constraint and is minimized. The mathematical formulation of the 0–1 weighted MIP GP model is shown in (13).

$$\begin{aligned}
& for\ k = 1, .., 600 \\
& min \sum_{i=1}^{13} \left[w_1^k \cdot \frac{s_i^{+,GDP}}{G_i^{GDP}} + w_2^k \cdot \frac{s^{-,Inv} + s^{+,Inv}}{G^{Inv}} + w_3^k \cdot \left(\frac{s_i^{+,PI}}{G_i^{PI}} + \frac{s_i^{-,PI}}{G^{SI}} \right) \right] \\
& s.t \\
& GDP_i \cdot N_i + s_i^{-,GDP} - s_i^{+,GDP} = G_i^{GDP}, i = 1, \ldots, 13 \\
& ER_i \cdot N_i + s_i^{-,ER} - s_i^{+,ER} = G_i^{ER}, i = 1, \ldots, 13 \\
& \sum_{i=1}^{13} (pl \cdot Inv_i \cdot N_i) + s^{-,Inv} - s^{+,Inv} = G^{Inv} \\
& \sum_{i=1}^{13} \left(PI_i - Cap \cdot N_i + s_i^{-,PI} - s_i^{+,PI} \right) = G^{PI} \\
& SI_i \cdot \zeta_i + s_i^{-,SI} - s_i^{+,SI} = G_i^{SI}, i = 1, \ldots, 13 \\
& A \cdot N_i \leq L_i, i = 1, .., 13 \\
& N_i \geq 20, i = 1, .., 13 \\
& N_i \leq 50, i = 1, .., 13 \\
& \sum_{i=1}^{13} N_i \leq 200 \\
& \sum_{i=1}^{13} N_i \geq 100 \\
& N_i \geq 25 \cdot \zeta_i, i = 1, \ldots, 13 \\
& \zeta_i \in \{0, 1\}, N_i \in \mathbb{Z}^+, s_i^-, s_+^- \geq 0, i = 1, .., 13 \\
& end\ for
\end{aligned} \tag{13}$$

Model (13) is solved for each of the 600 weight combinations, and after each iteration, the optimal solutions are extracted. Decision levels for the optimal number of solar power plants ($N_i^\star$) are extracted after solving (13) for each region (i) and for each weight

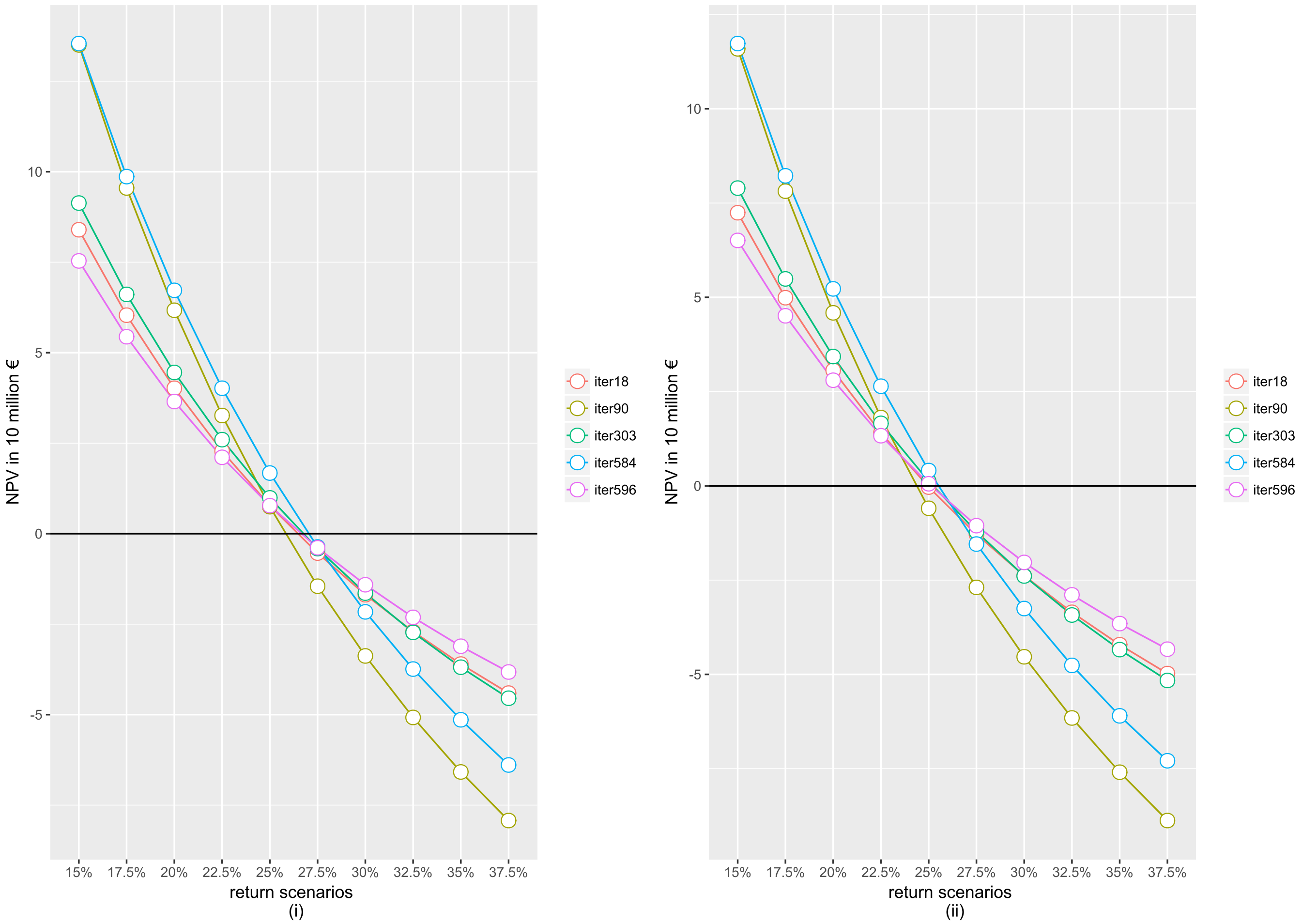

Fig. 6. NPV curves for tax scenarios: (i) $\tau_1 = 25\%$, (ii) $\tau_2 = 30\%$; weight representations $k = 18, k = 90, k = 303, k = 584$, and $k = 596$; and return scenarios (λ).

combination (k), leading to the matrix ($X_{i,k}$) with dimensions 600×13.

2.3.3. Formulation of the financial analysis

After solving model (13), the financial analysis is implemented based on the optimal values for each weight combination ($X_{k,i}$). The first step of the proposed analysis is to forecast the power production for each region i, based on which the cash flows will be calculated. The starting year of the analysis is considered to be 2016, and the projection is conducted for the years 2017 – 2025. The basic notion of the analysis is to set each region i as a separate entity and, based on the financial analysis, to determine the optimal mix of the tax scenario and the weights on the financial, social, and power production criteria so that the venture will be financially sustainable in the long run.

2.3.4. Forecasting solar irradiation

In Figs. 2 and 3, the solar irradiation (kWh/m^2) for each region i is presented.[1] The horizon of the forecasted values spans from 1985 – 2025, and a dashed vertical line is drawn for each region i at year 2017; this line indicates that after this year, forecasted values are derived using the following forecasting techniques:

1. Dynamic level linear regression
2. Dynamic trend linear regression
3. Exponential smoothing (Holt-Winters)
4. Box-Cox transformation, ARMA errors, trend, and seasonal components (BATS).

The dynamic level linear regression differs from the usual linear model, as the coefficient varies over time. This variation enables the model to forecast the actual data accurately, assuming that the solar irradiation ($SI^f_{i,t}$) is a stochastic random-walk (observation equation) and the update equation includes a time-dependent constant coefficient. For simplicity reasons, dimension i has been removed from the $SI^f_{i,t}$. Assuming that the errors are normally independent and identically distributed, the dynamic level linear regression can be expressed as follows [61]:

$$\textit{Observation equation}: SI^f_t = \alpha_t + \varepsilon_t, \varepsilon_t \sim N\left(0, \sigma^2_\varepsilon\right) \tag{14}$$

$$\textit{Update equation}: \alpha_t = \alpha_{t-1} + u_t, u_t \sim N\left(0, \sigma^2_u\right) \tag{15}$$

By including an additional parameter (a slope coefficient except for the constant term), the aforementioned model becomes a dynamic trend linear regression model [62]. These models tend to perform more accurate forecasts than the dynamic level linear regression. The observation equation and the update equations for

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[1] http://www.soda-is.com/eng/services/services_radiation_free_eng.php.

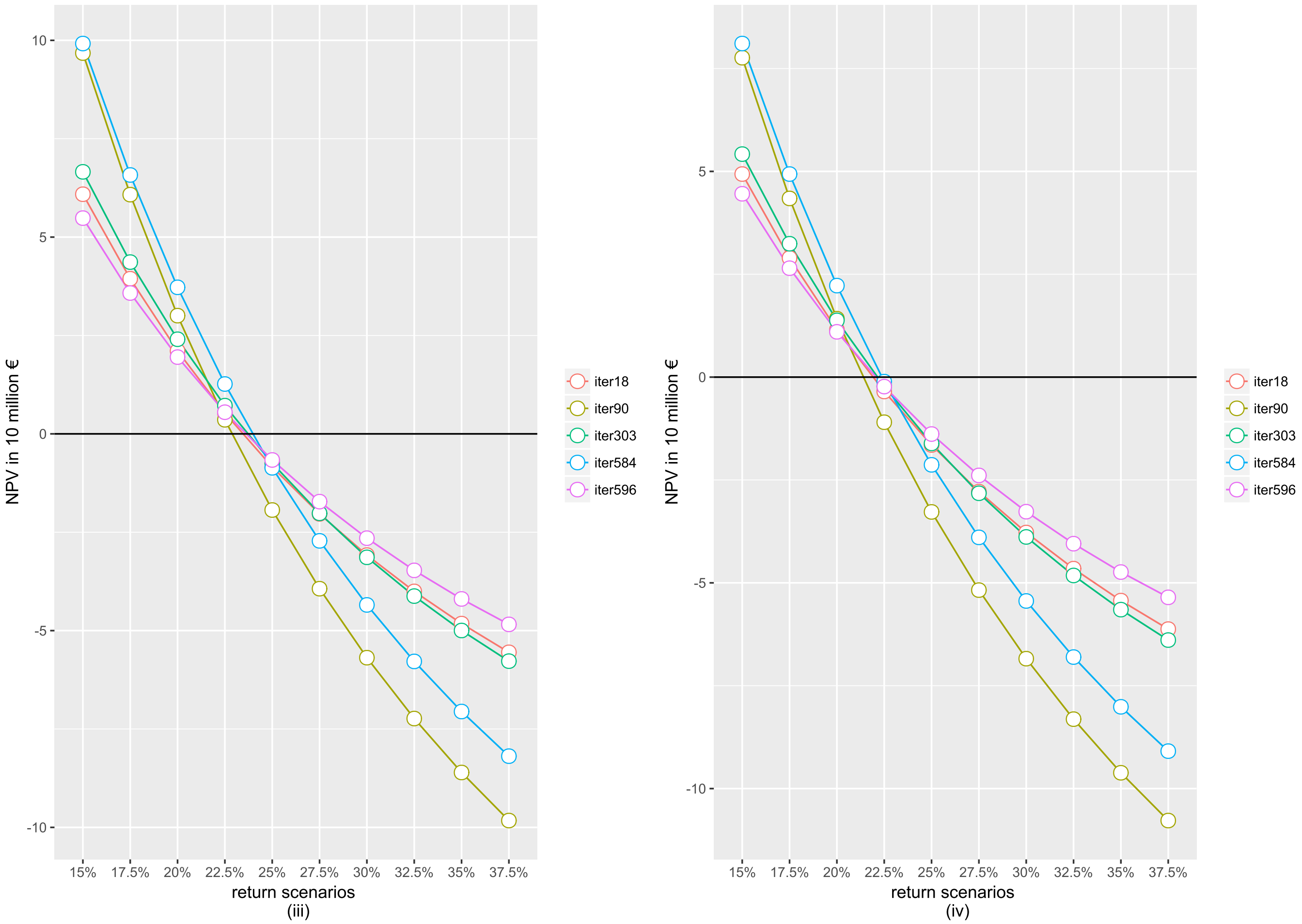

Fig. 7. NPV curves for tax scenarios: (iii) $\tau_3 = 35\%$, (iv) $\tau_4 = 40\%$; weight representations $k = 18, k = 90, k = 303, k = 584$, and $k = 596$; and return scenarios (λ).

each coefficient are given by the following:

$$\text{Observation equation}: SI_t^f = \alpha_t + \beta_t + \varepsilon_t, \varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right) \tag{16}$$

$$\text{Update equation}: \alpha_t = \alpha_{t-1} + u_t, u_t \sim N\left(0, \sigma_u^2\right) \tag{17}$$

$$\text{Update equation}: \beta_t = \beta_{t-1} + \xi_t, \xi_t \sim N\left(0, \sigma_\xi^2\right) \tag{18}$$

The usual method to estimate coefficients in either the dynamic level or dynamic trend linear regressions is the maximum likelihood method. Holt-Winters models of exponential smoothing are commonly used in time series analysis and are flexible alternatives to dynamic models. Their advantage lies in the fact that they may be specified in various ways, assuming multiplicative or additive errors or seasonal components. However, due to a lack of data used for estimation, not all models assume a specification for the seasonal component. The models that have been used are the Holt-Winters model with an additive trend and error component, that with a multiplicative trend and error component, and that with a multiplicative trend but an additive error component. In state space notation, the different Holt-Winters specifications that were used in this study are demonstrated in equations [63]:

$$\text{Observation equation}: mu_t = l_{t-1} + b_t \tag{19}$$

$$\text{Update equation}: l_t = l_{t-1} + b_{t-1} + \alpha \cdot \varepsilon_t \tag{20}$$

$$\text{Update equation}: b_t = b_{t-1} + \alpha \cdot \beta \cdot \varepsilon_t \tag{21}$$

$$\text{Observation equation}: mu_t = l_{t-1} \cdot b_t \tag{22}$$

$$\text{Update equation}: l_t = l_{t-1} \cdot b_{t-1} + \alpha \cdot \mu_t \cdot \varepsilon_t \tag{23}$$

$$\text{Update equation}: b_t = b_{t-1} + \frac{\alpha \cdot \beta \cdot \mu_t \cdot \varepsilon_t}{l_{t-1}} \tag{24}$$

$$\text{Observation equation}: mu_t = l_{t-1} \cdot b_t \tag{25}$$

$$\text{Update equation}: l_t = l_{t-1} \cdot b_{t-1} + \alpha \cdot \varepsilon_t \tag{26}$$

$$\text{Update equation}: b_t = b_{t-1} + \frac{\alpha \cdot \beta \cdot \varepsilon_t}{l_{t-1}} \tag{27}$$

Lastly, the BATS models are used in order to produce accurate predictions for solar irradiation. The model, in state space format, is formulated as [64]:

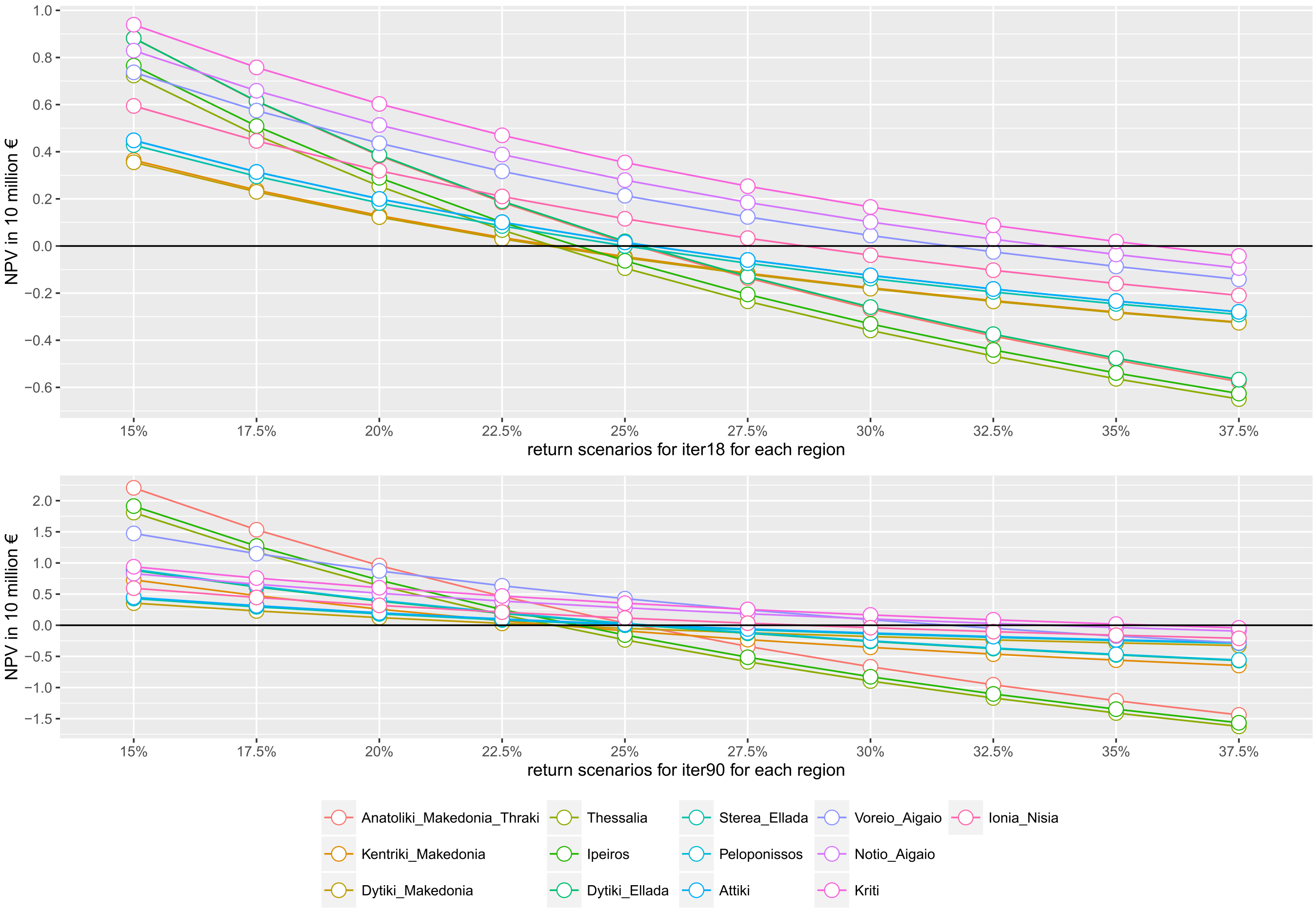

Fig. 8. NPV per region for $\tau_1 = 25\%$ and weight representations $k = 18$ and $k = 90$.

$$SI_t^f = \begin{cases} \dfrac{SI_t^{f\lambda-1}}{\lambda}, \lambda \neq 0 \\ log\left(SI_t^f\right), \lambda = 0 \end{cases}$$

$$SI_t^f = l_{t-1} + \phi \cdot b_{t-1} + \sum_{i=1}^{T} s_{t-m}^i + d_t \tag{28}$$

$$l_t = l_{t-1} + \phi \cdot b_{t-1} + \alpha \cdot d_t \tag{29}$$

$$b_t = (1 - \phi \cdot \beta) + \phi \cdot b_{t-1} + \beta \cdot d_t \tag{30}$$

$$s_t = s_{t-m} + \gamma \cdot d_t \tag{31}$$

$$d_t = \sum_{i=1}^{p} \phi_i \cdot d_{t-i} + \sum_{i=1}^{q} \theta_i \cdot \varepsilon_{t-i} + \varepsilon_t \tag{32}$$

2.3.5. *Financial meta-frontier assessment of solutions*

The power production for each region i is demonstrated in (33). Formula (33) resembles the formula presented in constraint, but parameter $SI_{i,t}^f$ has been simulated based on the values of solar irradiation for each region i.

$$PP_{i,k,t}^f = \gamma \cdot A \cdot SI_{i,t}^f \cdot X_{i,k}, i = 1, .., 13, k = 1, .., 600, t = 1, .., 10 \tag{33}$$

Based on the power production for the planning horizon 2017 – 2025 ($PP_{i,k,t}^f$), the revenue and cost functions are constructed as in (34) and (35). In equations (34)–(37), the revenue ($R_{i,k,t}$), cost ($C_{i,k,t}$), profit, and cash flow ($CF_{i,k,t,p}$) functions are presented. It can be seen that the revenue function is the product of the selling price [65] and the power production per each region i, weight scenario k, and forecasted year t.

$$R_{i,k,t} = price_t \cdot PP_{i,k,t}^f, i = 1, .., 13, k = 1, .., 600, t = 1, .., 10 \tag{34}$$

Based on the revenue function and the investment (Inv) of each plant, the cost function is constructed. According to the literature, the cost function [66] entails operating and maintenance cost ($c^{O\&M}$), insurance cost (c^{Ins}) [65], depreciation of the investment (D), and income loss (I^{loss}); the depreciation of the investment is the annual depreciation and is defined as $D = \frac{1}{T} \cdot Inv$.

$$C_{i,k,t} = \left(c^{O\&M} + c^{Ins} + D\right) \cdot Inv \cdot X_{i,k} + I^{loss} \cdot R_{i,k,t} \\ i = 1, .., 13, k = 1, .., 600, t = 1, .., 10 \tag{35}$$

The profit function is defined as the difference between revenue

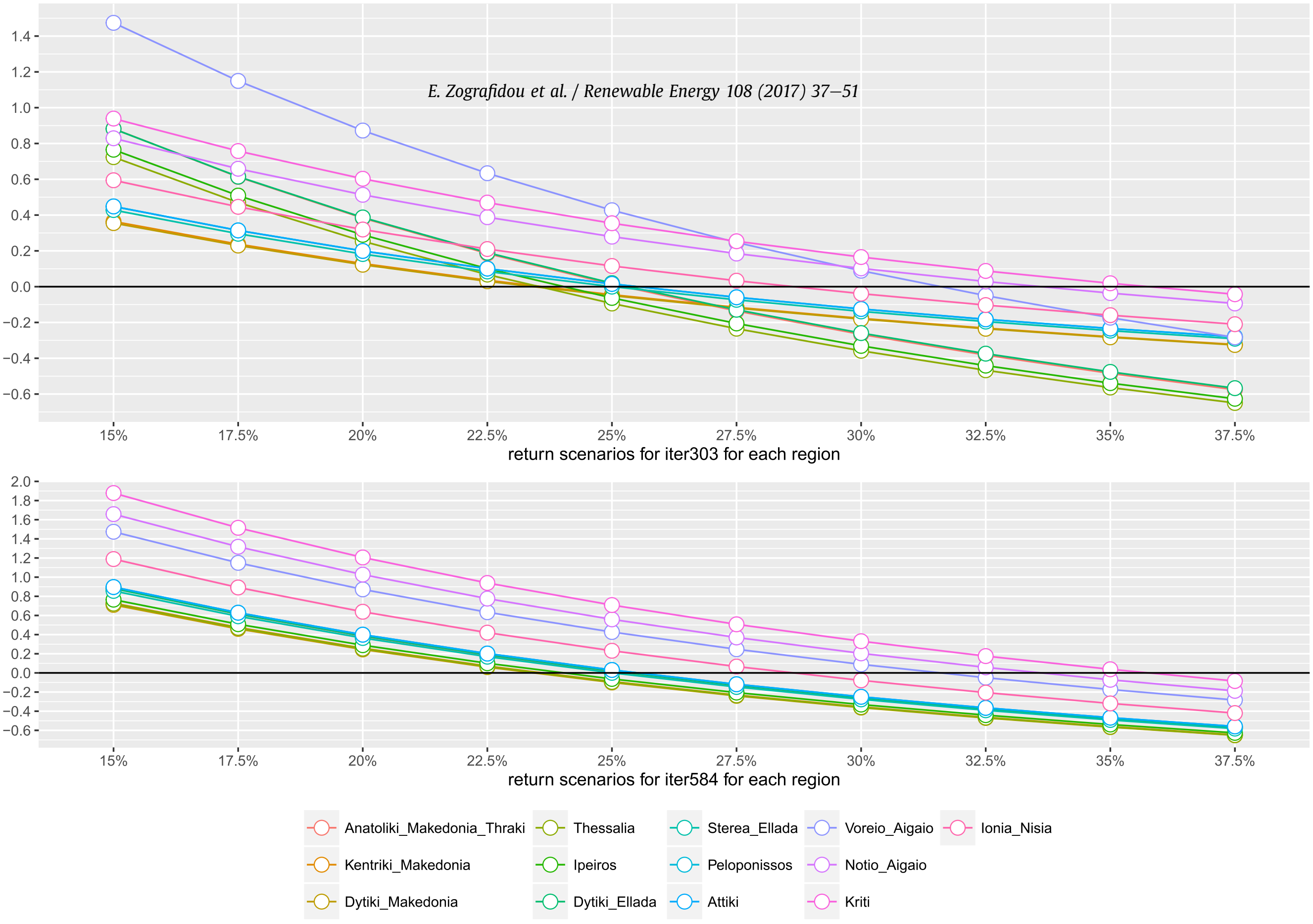

Fig. 9. NPV per region for $\tau_1 = 25\%$ and weight representations $k = 303$ and $k = 584$.

and cost for each region *i*, weight scenario *k*, and forecasted year *t*, as in (36). Similarly, the cash flow function ($CF_{i,k,t,p}$) is constructed by integrating different tax scenarios, providing a holistic view of the possible changes that may occur in the future.

$$\Pi_{i,k,t} = R_{i,k,t} - C_{i,k,t}, i = 1, .., 13, k = 1, .., 600 \\ t = 1, .., 10 \tag{36}$$

$$CF_{i,k,t,p} = \Pi_{i,k,t} \cdot (1 - \tau_p) + D \cdot Inv \cdot X_{i,k} \\ i = 1, .., 13, k = 1, .., 600, t = 1, .., 10, p = 1, .., 4 \tag{37}$$

NPV ($NPV_{i,k,p,}$) is constructed taking into account the cash flow function and the investment for each region *i*, each weight *k*, and each tax scenario *p*. In this analysis, different discount ratios are assumed, leading to the following formula (38).

$$NPV_{i,k,t,p,\lambda} = \sum_{t=1}^{11} \frac{CF_{i,k,t,p}}{(1 + r_\lambda)^t} - Inv \cdot X_{i,k} \\ i = 1, .., 13, k = 1, .., 600, p = 1, .., 4, \lambda = 1, .., 10 \tag{38}$$

3. Results

In this section, the results of the analysis are demonstrated in two parts. First, a network analysis is shown, where the results of the number of solar plants that will be installed in each region *i* are presented for each weight scenario *k* ($X_{i,k} = N_i^\star$, as discussed in the previous section). Each solution corresponding to scenario *k* is subjected to a financial meta-analysis that takes into account financial indices like NPV under different tax scenarios.

In Fig. 4, the average number of solar plant units per each region *i* is shown. The average number has been calculated as per the examined scenarios using the following formula: $\overline{X}_i = \frac{1}{600} \cdot \sum_{k=1}^{600} X_{i,k}$. As the proposed model takes into account multiple factors, a dispersion of the resulting average numbers of solar plants installed per each region is demonstrated. For example, it would be expected that regions with higher solar irradiation would attract most of the solar power plants, but this analysis would eliminate the social factor, as it would boost the power production and would aim socially at certain regions irrespective of the GDP and the employment rate of the region.

In Fig. 5, the results for NPV for selected tax scenarios and weight representations are presented. More specifically, NPV curves for the $\tau_1 = 25\%$, $\tau_2 = 30\%$, $\tau_3 = 35\%$, and $\tau_4 = 40\%$ tax scenarios and for the weight representations $k = 18, k = 90$, $k = 303, k = 584$, and $k = 596$ are demonstrated, showing the point at which the NPV turns negative. The specific tax scenarios were selected after iteratively investigating the point at which the NPV becomes zero (or close to zero) and taking into account the Greek taxation system and laws. From Fig. 5, the weight representation $k = 18$, which corresponds to weights on each aspect of $w_1 = 0.02$, $w_2 = 0.04$, and $w_3 = 0.94$, for tax equal to 30%, seems to have an IRR of 25%. When examining the NPV curve of a scenario or a region, the slope of the curve indicates the sensitivity to return rates; the steepest NPV curves have a low IRR, and the smoothest have a high IRR. In the previous weight representation, more emphasis is given to the power production aspect. Similarly, for weight representation $k = 90$, which corresponds to $w_1 = 0.007$, $w_2 = 0.983$, and $w_3 = 0.01$, the IRR equals 25% and is achieved for tax scenario 25%. However, it can be seen that the curves in this instance ($k = 90$) correspond to higher NPV values in comparison to weight representation $k = 18$. The latter weight representation ($k = 18$) emphasizes the financial aspect. High NPV values are reported for $k = 584$, with the weights of $w_1 = 0.019$, $w_2 = 0.196$, and $w_3 = 0.766$, which emphasize the power production aspect.

In Figs. 6 and 7, the aggregated NPV curves for all regions and for selected weight representations and tax scenarios are demonstrated and compared with each other. An obvious outcome from the figures is that as taxation increases, the IRR decreases. In addition, different scenarios lead to different NPV values, leading to the fact that the weights in each aspect lead to better or worse solutions. Through this meta-analysis, the determination of the best solution will be conducted based on financial analysis, taking into account the IRR and taxation.

In Fig. 8, the results for NPV for each region i and selected weight representations for tax scenario $\tau_1 = 25\%$ are presented. It can be seen that in weight representation $k = 18$, a higher NPV is reported for the region of Kriti, and a higher IRR is reached (approximately 35%). The steepest NPV curve is reported for Ipirus, and the lowest IRR value is reported for Thessalia. Similarly, for weight representation $k = 90$, the highest NPV value is reported for Anatoliki Makedonia and Thraki, but the slope of the NPV curve for this region is very steep, leading to IRR= 25%. The NPV curves of Ionia Nisia and Kriti are parallel, reporting IRRs approximately equal to 34%. For weight representation $k = 303$, as can be seen in Fig. 9, the Voreio Aigaio region has the highest NPV, with an IRR of approximately 32%, and the regions of Kriti and Notio Aigaio report higher IRR values at 33% and 36%, respectively. For weight representation $k = 584$, all NPV curves are shown to be parallel, with the NPV curve of Kriti to be the highest of all; the highest IRR is reported to be approximately 36%. Finally, in Fig. 10, the highest NPV value is reported for region of Ipirus, but the NPV curves of the other regions are quite smooth and not so steep. Different weight representations lead to different NPV values, NPV curve slopes, and IRR points for each region. The highest IRR is reported when more emphasis is given to the financial and power production aspects, whereas a lower IRR is reported for the weight representations that place more emphasis on the social aspect. Similarly, higher IRR values are reported when the financial aspect is emphasized, whereas the lowest IRR is reported when the social aspect is emphasized.

4. Conclusions

Investing in renewable energy is challenging, as many different factors should be taken into account and aggregated. The success of such a venture is not solely dependent on economic and financial outcomes but also depends on unobservable macro-economic factors. The proposed approach provides a unified framework for analyzing the factors, based on which the renewable energy network can be constructed. Three aspects have been taken into account (namely, social, financial, and power production). In order to design the renewable energy network and install solar power plants in Greece, several targets were assumed. Most of them were derived from EU directives, local laws on renewable energy

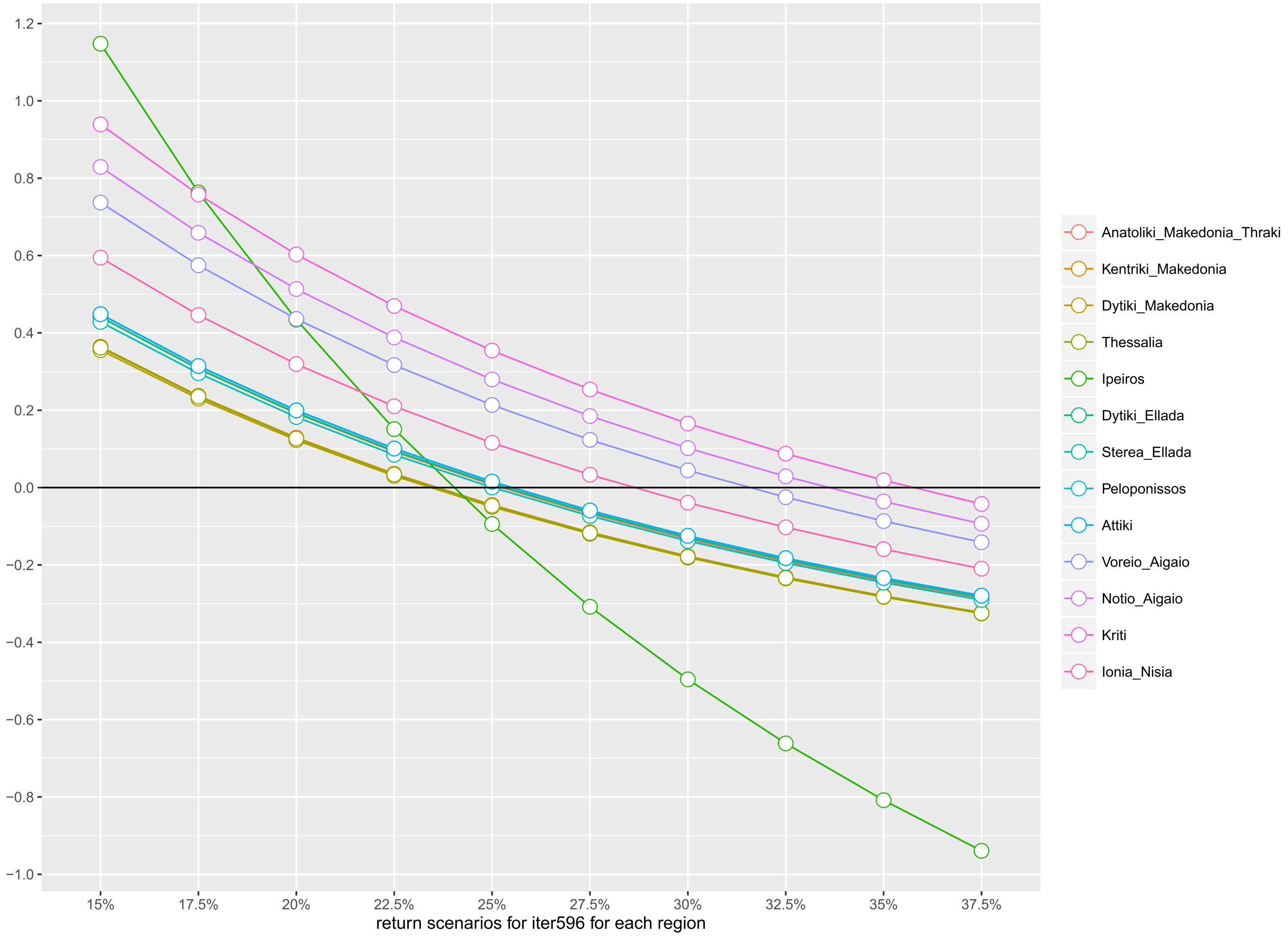

Fig. 10. NPV per region for $\tau_1 = 25\%$ and weight representation $k = 596$.

production, and taxation. The first step of the proposed approach was to develop a GP model providing levels of decisions regarding the number of solar power plants that would be installed in each region of Greece under several target and land constraints. In the objective function, each of the targets was given a weight, and all weight combinations were examined. For each weight combination (or weight representation), a solution was assigned, leading to an equal number of solutions and weight representations.

In the second stage, a financial meta-analysis was applied to filter all the solutions based on NPV criteria. Taking into consideration that the proposed model integrates social, economic, and financial factors, the results are a set of optimal solutions that can be used by decision makers towards their final decisions in investing in RES in Greece. The results reveal that different combinations of weight representations result in different NPVs. Based on the objective of NPV maximization, the model's outcome may influence decision makers to adjust the undertaken policy in terms of RES investments in Greece. Furthermore, the differences in the NPVs of the examined scenarios can be used as a tool in the process of releasing licenses in the different regions, considering the objectives of the decision makers. As the model provides information regarding the IRR of each region, the investors can choose a mixture of budgeting taking into consideration the available bank loan rates and the willing investor's return. For the above analysis, the optimal mix of the number of solar power plants that will be installed in each region under selected tax and return scenarios has been investigated. The results show that after solving the GP model for all weight representations, the maximum average number of solar power plants will be selected in Ipirus and Thessalia. From the financial analysis, it has been determined that the investments' IRR is approximately 22.5% – 25%, as has been demonstrated for the overall network. Each region reports a different IRR, depending on the weight representations. Emphasizing financial and power production leads to the highest IRR, whereas emphasizing the social aspect leads to a lower IRR.

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