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RESEARCH ARTICLE

Optimizing Incentive Plans for Renewable Energy Growth in the Electricity Market

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ABSTRACT The competitive edge of renewable energy depends on financial support from central planners. An effective intervention with reasonable burden on taxpayers requires anticipating the choice of profit maximizing investors regarding capacity installation and electricity generation from certain locations for solar, wind and fossil-based power plants in response to technology, cost, price and incentive parameters. A 10-year generation expansion planning horizon is favored, during which capacity factors, cost projections, and electricity prices remain reasonably predictable. Investment costs within the horizon are accounted for using a depreciation model. Scenarios are considered for technology, costs, demand, wholesale prices and depreciation rates for investigating outcomes of intervention by investment subsidies and generation incentives. A mixed-integer model is devised for optimal investor decisions. Pareto analysis is conducted for each scenario setting over the optimal solutions at different incentive and subsidy rates for wind and solar plants considering three criteria: cost of intervention, renewable shares in installed capacity and overall energy generation. Under a moderate scenario, sharing 20% of the commissioning and operation costs, the central planner elicits nearly 30% increase in the shares of renewable plants in installed capacity to 72%, and electricity generation to 80%. An overall optimistic scenario achieves 75% renewables with similar interventions, while an overall pessimistic scenario attains 60%. Most of this variability is accountable to the depreciation scheme, scenarios on renewable technology and cost are partially effective, while fluctuations in demand, wholesale prices, technology and cost of the natural gas alternative are shown to have negligible impact on outcomes of the intervention.

INDEX TERMS Generation expansion planning, incentive policies, mixed-integer programming, multicriteria, Pareto optimal, renewable energy.

I. INTRODUCTION

Growth in energy output is one of the core requirements for economic development and social progress [1]. Electricity is used in almost every daily activity and industrial application, leading to a significant increase in energy demand driven by increasing population, urbanization, industrialization, technological advances, and improved welfare. However, the adoption of renewable energy sources to meet this escalating demand has been slower in comparison. In 2015, 90% of the energy demand was met by the production from fossil fuels such as coal, petroleum, and natural gas (NG) [2]. This reliance on fossil-based resources raises concerns about depletion, population outgrowth, and, most importantly, the environmental and health risks associated with them.

Renewable energy sources have the potential to meet two-thirds of the global energy demand and contribute to reducing greenhouse gas emissions, aiming to limit global warming to 1°C [3]. In alignment with this potential, there has been a steady increase in the installed capacity of renewable energy modalities, particularly wind and solar energy. According to the International Renewable Energy Agency (IRENA, see Table 1 for a list of acronyms, abbreviations and notation used), renewable energy resources accounted for a quarter of worldwide electricity production in 2017 [4]. Unfortunately, this proportion falls short of what is required to effectively address global warming and environmental degradation. Despite three years of constant levels

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TABLE 1. Acronym, index, parameter and variables of the mixed-integer programming problem, and their definitions.

Acronym	Definition
IRENA	International Renewable Energy Agency
NG	Natural Gas
PV	Photovoltaics
FIT	Feed-in tariff
FIP	Feed-in premium
GEP	Generation expansion planning
RPS	Renewable portfolio standards
O&M	Operation and maintenance
VAR	Vector autoregression
MIP/MILP	Mixed-integer (linear) programming
MINLP	Mixed-integer nonlinear programming
MW	Megawatt
MWh	Megawatt-hour
CF	Capacity factor
SYD	Sum-of-the-years digits accounting scheme
Index	**Definition**
$1, \ldots, n$	Indices of locations for power plant capacity installations
$1, \ldots, \mathrm{m}$	Indices of modes for electricity generation
$1, \ldots, H$	Indices of periods (stages) within the planning horizon of H periods
Parameter	**Definition**
a_i	Availability factor of plant i
C_i^t	Maximum capacity of facility i that can be installed in stage (period, interchangeably used) t in MWs
r_i^t	Effective variable investment cost of facility i in stage t after subsidy in TL/MW
$\hat{r}_i^t$	Pre-subsidy variable investment cost of facility i in stage t in TL/MW
r_i^t	Effective variable investment cost of facility i in stage t after subsidy in TL/MW
$\hat{f}_i^t$	Pre-subsidy fixed investment cost of facility i in stage t in Turkish Liras in TL/MW
f_i^t	Effective fixed investment cost of facility i in stage t after subsidy in TL
Δ^{t}	The ratio of the investment that deprecates during the planning horizon under the adopted accounting scheme
q_i^t	Unit production cost of facility i in stage t including variable O&M costs, in TL/MWh
d_j^t	Demand for electricity in mode j during stage t in MWh
p_j^t	Electricity retail price in mode j during stage t in TL

TABLE 1. ***(Continued.)*** **Acronym, index, parameter and variables of the mixed-integer programming problem, and their definitions.**

π_{ij}^t	Electricity retail price effective in plant *i* in mode *j* during stage *t* after wholesale incentive in TL
o_i^t	Fixed O&M cost of installed capacity at plant *i* during stage *t* in TL/MW/year
β	$\beta = (a_i, o_i^t, \hat{f}_i^t, \hat{r}_i^t, d_j^t, p_j^t, \Delta^t)$ an overall scenario combining settings for parameters according to their respective scenarios
Σ	The set of all scenarios $\beta = (a_i, o_i^t, \hat{f}_i^t, \hat{r}_i^t, d_j^t, p_j^t, \Delta^t)$ as described in Table V
Variable	**Definition**
v_i^t	Binary variable with value 1 if there is an installation at location *i* in stage *t*, 0 otherwise
x_i^t	Capacity installed in facility *i* in stage *t* in MW
w_i^t	Existing generation capacity of facility *i* in stage *t* in MW
y_{ij}^t	Electricity generated at facility *i* in mode *j* during stage *t*
Hyperparameters	**Definition**
α_k	Electricity wholesale price incentive rate for generation modality $k \in \{PV, Wind\}$
σ_k	Investment subsidy rate for generation modality $k \in \{PV, Wind\}$
I_k	Levels of electricity wholesale price incentive rates α_k for generation modality $k \in \{PV, Wind\}$
S_k	Levels of investment subsidy rates σ_k for generation modality $k \in \{PV, Wind\}$
Π	$\Pi = I_W \times S_W \times I_{PV} \times S_{PV}$, the set of possible incentive policies investigated for governmental intervention
α	$\alpha = (\alpha_W, \sigma_W, \alpha_{PV}, \sigma_{PV}) \in \Pi$, one specific setting of hyperparameters investigated as an incentive policy

from 2014 to 2016, CO_2 emissions due to energy production increased by 1.4% in 2017. A critical barrier to this transition is the high initial commissioning and capacity installation costs for renewable power plants [5].

Numerous studies have analyzed policies and programs for the development of renewable energy, discussing the effectiveness of these programs and optimizing incentive policies. Aquila et al. [6] compares various incentive policies, including price guarantees and net meters, in the context of Brazil, discussing the advantages and disadvantages of each. Zhao et al. [7] systematically analyze incentive policies that have contributed to the massive growth of renewable energy in China, considering modalities such as wind, photovoltaic (PV), small hydroelectric, biomass, and geothermal. The study highlights the role of research and development support, financial/taxation, tariff, and other incentive programs in ensuring the growth of renewable energy production. Sheikhhoseini et al. [8] devise a tariff supportive scheme for the growth of residential PV energy usage, pointing out the increase in photovoltaics with increasing support. Yılmaz and Öziç [9] emphasize the importance of exclusive renewable energy incentives that should accompany geographic circumstances of the location.

Wiser and Pickle [10] provide insights to policymakers on the important nexus between renewables policy design and finance. Gifford et. al. [11] present recommendations on the optimal characteristics of a model to calculate rates for cost-based incentives and feed-in tariffs (FITs). Yılmaz Balaman et. al. [12] focus on the three main financial incentive schemes to promote renewable energy sector in the United Kingdom for electricity, heat and fuel production from renewables, namely FIT, renewable heat incentive and renewables obligation certificate, considering the fact that optimal policy design depends on effective analyses of the impacts of incentives on the performance of renewable energy systems. Marcantonini and Ellerman [13] analyze the German experience in promoting renewable energy over the past decade to identify the ex-post cost of reducing CO_2 emissions in the power sector through the promotion of renewable energy, specifically, wind and solar.

In addition to the policies aimed at transitioning to renewables, several studies examine the measurement of the effects of increasing renewable energy investments on the environment and the economy. Zheng et al. [14] analyze the reduction in CO_2 emissions resulting from renewables using quantile regression and pathway analysis. The results indicate that each 1% increase in the share of renewables reduces CO_2 emissions by 0.028-0.043%. Li et al. [15] focus on economic growth, applying a fixed effect test and panel vector error correction model on South Asian Association for Regional Cooperation countries covering the years 1995-2018. The study compares geothermal, hydroelectric, and wind energy modalities, highlighting hydroelectricity as the most promising renewable resource for promoting economic growth. Inglesi-Lots [16] takes a combined perspective on welfare and growth. The analysis in this study, based on panel data, indicates that renewable energy has a significantly positive effect on economic growth, emphasizing the importance of renewable energy incentives not only for environmental concerns but also for economic growth. Zhao et al. [17] additionally consider social acceptance and commercialization factors alongside economic and environmental aspects, comparing geothermal, wind, biomass, and solar modalities. The study suggests that hydrogen is the most effective energy resource, with its production based on wind energy effectively meeting demand and replacing fossil resources.

Bekar [18] takes a geopolitical perspective on the effects of investments in renewables and notes that geopolitical risks involved slow down the transition. Marks-Bielska et al. [19] investigate views of the society on renewable energy and find that the high initial costs of equipment purchase and installation are major barriers for transitioning to renewables. The authors suggest incentives on investment and tax subsidies as a remedy.

There are several models that approach renewable investments from firm dynamics, microeconomic analyses and financing aspects. Nie et al. [20] approach promotion of renewables by an investigation of bank loans accompanying government subsidies under a microeconomics model. Castillo-Ramirez and Mejía-Giraldo [21] devise a mixed-integer programming (MIP) model for optimizing the generation portfolio of a company including renewables to minimize the income tax that the company incurs. Shrimali and Baker [22] model firm dynamics in a multiperiod setting where myopic investors base their decisions on the levelized cost of energy. They model investor behavior and technology change for the reduction of greenhouse gas emissions under dynamics of learning-by-doing and economies-of-scale. Garcia et al. [23] formulate dynamics for FITs and renewable portfolio standards (RPS). While FITs aim to incentivize, RPS encourage or directly mandate certain levels of renewable share in generation. The study points out that RPS and incentives should be well tailored to specific modalities and target sites in order to promote renewable without hindering certain sites of social value and conventional modalities.

The spectrum on the design of policies for increasing installed capacity and generation from renewable energy modalities, along with their regulation in the energy markets, involves governmental interventions for facilitating efficiency and viability of renewables in the energy market with trading mechanisms, aiding investors to cope with risks involved in renewables, or increasing profitability of renewables with FITs [24]. Where FITs may cause overcompensation due to drift of market prices beyond expectations, particularly causing inefficiencies when prices are low [20], variable compensation mechanisms such as feed-in-premiums (FIP) are considered. It is not uncommon that incentives such as FIT and FIP are also referred to as production or generation subsidies, that is, compensated by the government based on the amount produced (often in megawatt-hours -MWh). The other kind, subsidies paid with respect to the capacity installations (in megawatts -MW, or megawatts-peak) can be called capacity subsidies. These subsidies can be used for direct effect: The former can be used for a direct effect on aims regarding externalities of generation, such as reducing greenhouse gas emissions, and increasing market share of renewables in the electricity supply and the latter can be used for aims involving capacity installation related externalities, such as learning spillovers or learning-by-doing, that is, improvement of technology with increasing installations and hence reducing costs [25], [26]. While, generation subsidies are more effective in increasing renewable shares in the market output, Ying et al. [27] discuss that taxation of non-renewables for subsidizing renewables is important for renewable transformation, however it is important to keep the renewable energy generating companies within a competitive setting for energy efficiency and lower prices for consumers. A good policy design should differentiate with respect to modalities, with specific subsidy rates for PV and wind, in order to avoid overproduction in one modality. This, achieves efficiency with reducing intermittency problems and reduces dependency on storage systems that compensate for overproduction [28].

Various studies suggest optimal plans for energy investment, management, and production. Zhou et al. [29] undertake the problem of "generation expansion planning" (GEP) with a bilevel model. The lower-level program involves a cost minimizing agent planning capacity expansions on coal power plants, wind power plants, alongside considering capacities of the coal transportation and electricity transmission networks, in order to meet electricity demands on nodes. The higher-level program minimizes the cost of the intervention program, which involves taxes on variable operation and maintenance (O&M) costs for existing and new coal plants along with subsidies on variable O&M and fixed O&M costs for existing and new wind plants. Additionally, taxes for new coal plant installations and subsidies for new wind plant installations are considered. Dang et al. [30] include constraints on emissions and share of renewables in energy portfolio in their GEP model, consider subsidy/penalties on investment, operating costs of installed capacities and electricity generation costs. The cost minimizing investor is directed to renewables by policy intervention, and heuristic approaches are used to tackle the problem with a large number of integer variables. Huang et al. [31] consider optimal electricity production portfolios under demand uncertainty with the aim of minimizing costs. Niknam et al. [32] jointly minimize costs and emissions by modeling output, demand, and prices under a stochastic programming framework. Shiina and Birge [33] also devise a stochastic model for scenario-based optimal solutions under uncertainty, with a focus on cost minimization. Their model seeks investment and capacity installation plans to meet increasing electricity demand while minimizing costs. Karimi et. al. [34]

discuss production tax credit alternatives, incentives that are functions of plant capacity and the biomass cofiring ratio. Ko et. al. [35] evaluate the effect of imposing a renewable energy certificate incentive in off-peak periods on mitigating wind power fluctuations. Here, batteries are utilized with the purpose of improving reliability and increase profits from the sales of energy. Saeidpour Parizy et. al. [36] propose a co-optimization algorithm to find the minimum incentives that result in the desired level of renewable energy source penetration in energy supply chain and optimal distribution of power sources in the electric power grid.

A problem receiving attention in renewable energy incentive analysis has been the coping with intermittency problem and curtailment, when solved renders renewables more efficient and increases their penetration. Regulation of and incentives for reducing intermittency is critical [37], which requires modeling the energy retail dynamics at a higher temporal resolution. Choi and Lee [38] consider PV and wind technologies and their impacts, in a setting where production subsidies are used to plan the generation expansion in Jiangsu, China for 2020-2050, which also considers flexibility requirements for handling variability and intermittency of PV and wind renewable sources. Several studies address the problem of variability, intermittency and uncertainty involved in renewable energy plants with integration of energy storage systems [39], electric vehicle systems [40], aspects that can be incorporated into the generation expansion context. When the penetration level of renewables is high, fluctuations in renewable energy generation are dealt with by operation constraints, which increase utilization of renewables in the grid [41]. The curtailment problem is solved within a GEP setting adding regulation capacity and speed constraints that assures expanding generation meets regulation requirements within generation and demand variations [42]. Another power system operation is unit commitment, hourly planned and integrated into cost minimizing GEP involving fossil fuel/thermal, hydroelectric and wind modalities resolution, CO_2 emission charges and allowances, and reserve margin constraints [43]. One cost-oriented study considers investment and operations of thermal, wind and PV plants incorporating construction, share and utilization constraints for renewables, and pointing out optimal capacities of considered modalities [44].

The motivation behind this study is to foster the growth of renewable energy, providing incentives using limited financial resources, particularly under the auspices of a competitive setting with profit-seeking electricity generation companies. Our primary goal is to promote renewable energy utilization through strategic deployment of the central incentive program. However, certain limitations must be acknowledged, including the absence of a stochastic model for parameters, attributed partly to the discrete nature of available data presented in extreme and moderate scenarios. Another assumption in line with the data at hand is nationwide wholesale electricity pricing. With local electricity pricing and incorporation of transmission networks to the model, an extension applying location specific incentives, possibly incorporating transmission expansion planning (cf. [45]), becomes feasible. Further constraints include the lack of degradation models for generation equipment, as well as limited temporal resolution aspects in unit commitment and dispatching problems. We address these by assuming reasonable average measures pertaining to the aggregate level of planning undertaken in this study, presenting scenarios that explore incentive program prognoses under a broad representation of outcomes covering for fluctuations in aggregate level parameters and details not incorporated. These scenarios encompass extreme pessimistic and optimistic scenarios, and combine multiple conservative/advanced ends of mathematical program parameters.

Existing studies that employ GEP with strategies for promoting renewables have been closely examined, as presented in Table 2. These studies vary in their incorporation of modeling aspects, approaches to promoting renewables, solution methodologies, and the use of real or synthetic data in case studies. While common aspects such as the presence of wind and solar modalities; MIP tools; multi-level modeling of agency; and a combination of strategies such as FIT, FIP, RPS, carbon tax, green certificate trading are evident; our study stands out by profit-oriented considerations incorporating both production and investment subsidies. In contrast to the prevalent cost minimization orientation, our approach includes a multi-objective analysis, emphasizing cost of the intervention, end-of-planning horizon installed capacity, and the share of generation from renewables.

In contrast to findings presented in Table 2, our study makes a distinctive contribution by integrating profit-oriented considerations encompassing both production and investment subsidies to facilitate renewable energy growth. We stand apart by incorporating future electricity prices within a competitive market framework, scrutinizing profit-oriented investment and generation decisions, and adjusting production incentives according to electricity wholesale prices. Our multi-objective analysis focuses on program cost, installed capacity, and the share of generation from renewables, further emphasizing the uniqueness of our approach.

Central to our study is the incorporation of scenario-based data, predictions of the future of energy technologies across conservative, moderate, and advanced scenarios. This approach addresses uncertainties inherent in the renewable energy landscape, providing a comprehensive understanding of potential outcomes under different technological advancements and settings for evolution of the electricity market.

Our study recognizes the pivotal role of profitability in attracting necessary finances for renewable energy investment, especially in developing countries. Given the challenges posed by uncertain energy market prices and high initial investment costs, we emphasize the role of governments in facilitating investment through direct financial support in the form of subsidies for capacity installations and electricity purchase price incentives. Our objective is to devise an effective program that promotes significant growth

TABLE 2. A table of related studies involving multiobjective GEP, renewable promotion or electricity market price modeling.

Author	Year	Renewable Modalities	Policies for Renewables	Mathematical Model	Objective	Additional Aspects	Retail Electricity Price Model	Retail Price Dependent Incentive	Case study
Zhou *et al.*	2011	Wind	Renewable portfolio standards, production tax, production incentive	Bilevel programming, inverse optimization	Upper: Min. Policy cost. Inner: Lower: installation, O&M and coal transportation costs	Central planning investor, coal transportation, transmission networks	-	MWh scaled tax and subsidies	U.S.A.
Zhang *et al.*	2017	Solar	Investment subsidy based on total project value, CO_2 emission trading scheme	Real options model, least squares Monte Carlo simulation	Estimation of the optimal subsidy level	Stochastic process model of electricity price, CO_2 price and investment cost	Stochastic model of price uncertainty	-	China
Gitizadeh *et al.*	2013	Onshore and offshore wind, solar, others	Carbon tax, FIT, CO_2 emission trading, quota obligations	Multiobjective, MILP, modified normal boundary intersection	Max. Lifetime economic return, min. CO_2, min. conventional generation fuel prices		Deterministic estimates	-	Hypothetical
Nguyen and Felder	2020	Wind, solar, other	Renewable energy credits to meet RPS	Bilevel programming	Min. İnstallation, shutdown, O&M and generation costs	Dynamics of renewable energy credit markets	Variable model under auctions with renewable energy credits	REC offering prices separate	U.S.A.
Kim *et al.*	2021	Wind, solar	RPS, production and generation incentives	MILP, trilevel optimization, Policy maker, generation companies and market analyzed in three levels	Upper: max. consumer surplus, utility profit minus investment, O&M and incentive program costs; mid: max. utility profit; low: max. social profit	Column and cut generation	Considered as variable set by central planner policy	-	8 zone ISO New England
Pineda *et al.*	2018	Wind,	FIT, FIP, green certificate trading	Two stage stochastic quadratic program	Total expected social welfare minus investment and O&M costs		-	FIT, FIP and green certificate quanty based	Denmark
Lv *et al.*	2020	Wind, solar	Production subsidy	Mixed-integer linear program	Min. total installation, O&M, generation, subsidy and demand side investment costs in the planning horizon	Flexibility constraints	Cost based model	Quanity based subsidy	Jiangsu, China
Das *et al.*	2014	Onshore and offshore wind, solar, biomass	Regulated price based and production incentives	Mixed-integer non-linear program linearized to MILP	Minimize total system cost and	Energy conservation targets. Indirect profit by payback periods	Predicted based on fixed annual growth rates	-	Ontario, Canada
Chen *et al.*	2018	Wind, solar	RPS, carbon tax	Simulation, linear program	Min. overall system cost: amortized investment, O&M, fuel and policy costs	Hourly power balancing, flexibility constraints, storage technology	-	-	Northwest China

in installed renewable capacity while concurrently incentivizing profit-maximizing energy companies to favor renewable energy in their production.

The multiperiod GEP model developed in this study distinguishes itself through its emphasis on profit maximization. This focus underscores the significance of devised electricity purchase price incentives in augmenting fixed and variable investment subsidies. Unlike the common approach in existing GEP models focusing on costs or restricting incentive calculations to the amount of electricity generated, this study integrates revenue generated from sales and incorporates associated future price estimates, providing a more nuanced perspective on the dynamics of renewable energy investments. Notably, the devised model exploits revenue-based generation incentives, considering the drift in electricity wholesale prices, rather than the quantity-based generation subsidy factors employed in the existing literature.

A distinctive feature of this study is the relatively short planning horizon of 10 years, requiring meticulous consideration of depreciation rates for capital investment costs in profit calculations. This approach acknowledges the dynamic nature of technology and market conditions, making long-term planning challenging. However, despite the shorter time span, the analysis still accounts for capital investment costs using a reasonable depreciation model that reflects investor attitudes toward risk in project returns and the recovery of investment costs. We explore this risk aversion aspect under various scenarios by incorporating a flexible depreciation model.

Additionally, the investigation includes a comprehensive case study on GEP with renewable incentive optimization in the Turkish market. This dimension has not been explored in the existing literature up to the knowledge and investigation of the authors. The case exemplifies mid-latitude regions abundant in high irradiation locations suitable for PV installations but having limited spots with intense wind. In such cases, renewable transformation resorts to PV along with the wind plant installations. This poses a challenge, given current economic advantage of wind and the more costly endeavor of incentivizing PV, necessitating a careful allocation of financial resources.

Moreover, the Pareto analysis of incentive and subsidy policies introduces a novel dimension, evaluating their effectiveness based on the total cost of the incentive program, the share of renewables at the end of the planning horizon, and the share of renewables in total electricity generation output. This approach ensures a balanced consideration between cost-effectiveness and the achievement of renewable energy targets, embodying a forward-looking strategy against emissions and environmental burdens associated with increasing energy demand.

The remaining of the article is organized as follows. Section II provides a definition of the GEP and elaborates on the various aspects involved. Section III introduces the MIP model formulated for the GEP, outlining the key parameters, variables, and constraints. Section IV focuses on the data collection and analysis process, including formation of scenarios for investment and O&M costs, capacity factors (CFs) for potential power plant project locations, electricity demand and pricing. This section also presents computational results for the Pareto analysis of optimal solutions for different levels of incentive and subsidies applied to wind and PV power plants. The MIP model presented in Section III is used within the framework of Section IV, starting with data collection and analysis for forming scenarios, deriving optimal investor behavior under each scenario and different incentive settings, and analyzing Pareto optimal incentive policies for the decision making of the central planner. The workflow of this framework is presented in Fig. 1. The paper concludes with Section V, summarizing the findings and highlighting the key implications of the study.

II. PROBLEM DEFINITION

In the GEP, the government has the role of a central planner, aside from planning the incentive (incentive and subsidy are used interchangeably and together are often referred to as incentive(s)) program. Sites for the installation of energy generation capacities for different modalities, including wind, PV, and the combustion turbine natural gas plant, are determined by the government, acting as a central planner. The government also investigates and determines limits for maximum yearly capacity installation for each plant location. Investors -who are actually represented by a single profit maximizing agent- assess the cost components for capacity installations and operation throughout the planning horizon, along with the output and revenue potential to plan the capacity installations for each modality and location. In the planning horizon, spanning H years, the central decision maker determines the subsidies for capacity installations, fixed O&M expenses, and the electricity purchase price incentives, expressed as a percentage of the respective transaction. Wind and PV power plants do not have variable O&M expenses [46], as the periodic maintenance and cleaning operations depend on their peak capacities (in ₺(Turkish Liras)/MW/year), i.e., they are accounted as fixed O&M costs.

The investor in the energy sector is treated as a single agent who invests in renewable power plants and/or the conventional natural gas power plant to meet the projected and increasing demand while maximizing profit. A mixed-integer programming model is formulated to analyze the investor choice. The model investigates how specific levels of subsidies and incentives in wind and solar energy impact capacity installations in these modalities compared to fossil fuel-based production throughout the planning horizon. It also examines the effect incentives on the share of renewable modalities in the electricity generation throughout the planning horizon.

The costs of electricity generation consist of three components. Upon construction or capacity installation, fixed and variable costs are incurred. Fixed costs (f_i^t, for location i, period t– Table 1 includes a list of parameter and variables) cover administrative, design,

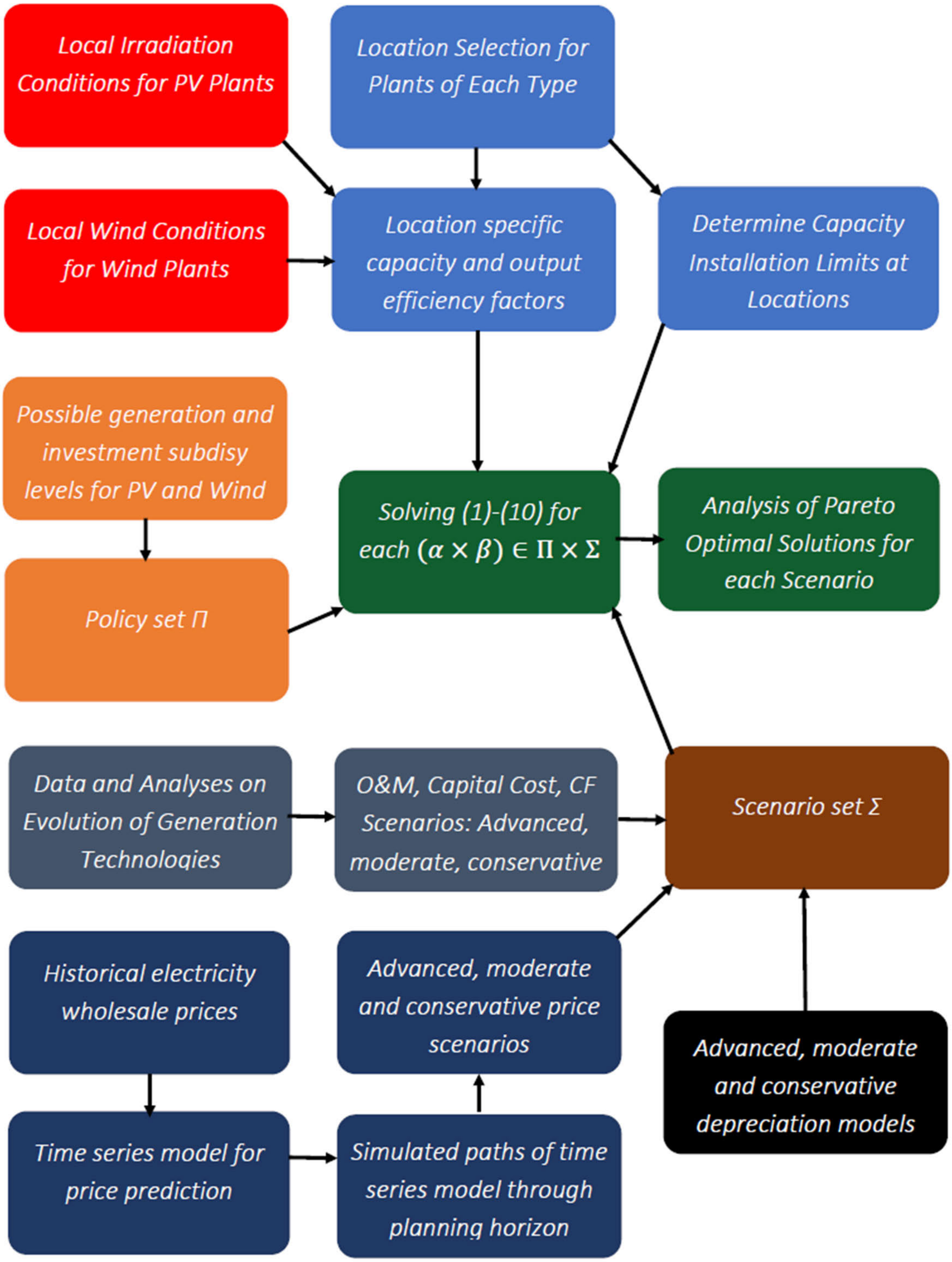

FIGURE 1. The workflow for data collection, analysis, optimization, computation of Pareto efficient frontier and interpretation of results. The optimization model is run for each combination of hyperparameters and scenario in the policy and scenario sets, and for each scenario, Pareto optimal solutions in terms of incentive program cost, end-of-horizon installed renewable capacity and share of renewables in overall electricity generation are found (green). Policy set consists of hyperparameter combinations, where each hyperparameter takes value from sets of levels for generation incentive and investment subsidy rates specific to PV and wind, set by the central planner (orange). The scenario set (brown) combines conservative, moderate and advanced scenarios for evolution of costs -fixed O&M, fixed and variable investment, technology -capacity factors (gray), electricity prices (navy), and depreciation model (black). Data available on costs and technology are readily available in such a scenario format, however, to derive scenarios for evolution of wholesale electricity market prices, a time series model is fit on historical prices, simulated paths are generated, and 10, 50, 90 percentiles of path values in each period are taken for conservative, moderate and advanced scenarios. Scenarios on technology and costs represent evolution of parameter values through the planning horizon, and apply as factors on the plant specific capacity factor and cost values. The central planner sets a specific capacity installation limit to each location, and for each location, specific O&M, investment cost and capacity factor parameters are determined (blue), which require information on local irradiation levels for PV and wind profiles for wind plants (red).

planning, and structural expenses that are independent of the capacity installation size. Variable costs (r_i^t, for location i, period t), per MW of installed capacity, primarily include equipment such as turbines, generators, PV panels, inverters, mounting systems, and cabling costs, which scale with the installed capacity. The third cost component is based on the existing installed capacity in a year, the fixed O&M cost (o_i^t, for location i, period t), per MW per year, which includes maintenance or cleaning of the equipment such as wind or combustion turbines, PV panels, inverters, and plant infrastructure. Variable O&M costs (q_i^t, for location i, period t,) are accounted for per units of electricity produced at the plant (per MWh generated), which are negligible for PV and wind plants. For the natural gas plant, unit electricity generation cost includes the variable O&M cost besides the fuel cost. Electricity purchase prices are specific to mode of the day, where modes different demand levels and the pricing scheme (p_j^t, for mode j, period t) is the main motivator of accounting for electricity demand in modes. Additionally, it is possible that different renewable energy modalities (wind and PV) receive different incentives, therefore the retail price π_{ij}^t in period t is specific to both the plant i and mode j.

Under this cost and price structure, the investor decides each year on how much new capacity to install for each energy production modality at each available location, represented by the variable x_i^t, for location i, period t,in MWs of installed capacity. The expense for increasing installed capacity is the variable cost scaled to the size in MWs of the installation ($r_i^t x_i^t$), in addition to the fixed cost,$f_i^t v_i^t$ (v_i^t is a binary variable indicating whether there is a capacity installation in location i in period t), which varies based on the modality-location pair. The investor also decides how much electricity to produce from each plant in each mode throughout the year to meet the demand, as represented by the variable y_{ij}^t, for location i, mode j, period t,in MWhs of electricity generated. All modality and locations have specific accessibility factors, i.e., the rate of electricity energy output that can be yielded from the installed capacity of the plant during the specific mode. Only the natural gas plant has a positive production cost per unit electricity generated (q_i^t). In the energy market considered in the computational analysis section, there are three modes: day (06:00-17:00), peak (17:00-22:00) and night (22:00-06:00).

The energy retail price is a critical parameter for the profitability of the energy investor. It is taken as a yearly average for each mode, regardless of the plant type or location of usage. It is possible to apply different incentive and subsidy levels to wind and PV, thus by modality specific electricity price incentives, price becomes specific to plant types. A 10% incentive corresponds to an incentive multiplier of 1.1, which might be applied to one or both of wind and PV modalities over electricity purchase prices throughout the planning horizon. The central planner sets the yearly subsidy rate, which multiplies the variable capacity installation cost. A subsidy rate of 5% would reimburse the investor 5% of the variable cost incurred in capacity installation, resulting in an effective variable installation cost rate of 95% of the original market price. Incentives and subsidies apply to renewables but not to the conventional method of electricity generation.

The demand parameters for the investment horizon consider the additional demand that arises with and after the initial year of planning. Therefore, the investor builds new plants and installs generation capacity to meet the growing demand. The projected demand for each year must be satisfied by production from the capacity installed during the previous years of the planning horizon.

In this research, our primary focus is directed towards understanding how the equilibrium between investment subsidies and wholesale price incentives influences the extended investment strategies of power generation companies. We specifically delve into the interplay between incentives and anticipated wholesale prices, investigating their impact on long-term decision-making. Decisions made at an hourly or sub-hourly resolution, such as unit commitment, addressing flexibility constraints, and mitigating issues like curtailment, may not have a direct bearing on overarching, long-term planning. This holds true as long as the parameters governing long-term planning accurately capture system behavior, preferably optimized concerning these short-term challenges. Consequently, we make the assumption that plant capacity factors encapsulate the average behavior in plant output. Similarly, our consideration of wholesale prices revolves around predicting yearly averages, aligning with the temporal scope of long-term planning, rather than daily fluctuations in the electricity market. To account for uncertainty, our model incorporates scenarios. We establish conservative, moderate, and advanced scenarios for electricity price predictions, aligning with available data on investment costs, O&M costs, and capacity factor predictions for various generation technologies. These aspects are also available under corresponding conservative, moderate, and advanced scenarios [46], which provides an opportunity for a comprehensive analysis of prospects of incentive programs under different scenarios.

Hereby, we define the key aspects of our problem and formulate it as a mixed integer programming model in the following section.

III. THE MIXED-INTEGER PROGRAMMING MODEL

In the literature, various capacity expansion models have been proposed. One such model is the multiperiod stochastic programming model by Shiina and Birge [33], which aims to meet expanding demand through new installations and production at different plant locations while minimizing costs. However, in this study, the focus is on a profit-maximizing investor rather than a cost minimizer as in the referred study. While the capacity installation and electricity generation plan is still constrained to meet the demand, cost minimization is not the only choice for an objective, and in this case, profit maximization is more plausible with private sector investors. The government plays a role in regulating capacity installations by planning and approving plants to be commissioned at different locations, ensuring that profit-maximizing decisions driven by incentive plans effectively meet the projected demand.

Choosing a deterministic counterpart instead of analyzing plans in a multistage stochastic setting has several reasons. Firstly, a deterministic decision tool allows for analysis under a non-probabilistic discrete set of scenarios. In this case, the data for generation technologies, including cost and capacity factor (efficiency) predictions, are available under such set of pessimistic/optimistic extremes and a moderate scenario. Where assigning probabilities to scenarios and analyzing probabilistic dependence of parameters might become challenging, it is possible to use the data at hand to analyze comprehensive scenarios. For instance, a comprehensively optimistic scenario is when market prices and CFs follow the optimistic scenario on the high end while investment and O&M costs follow their corresponding advanced scenarios on the low end. Analyzing multicriteria incentive program performance under such comprehensive pessimistic, moderate and optimistic scenarios is a very practical approach, and allows for the interpretation of risks and opportunities on the two ends. Thus, we derive scenarios from the time series models fit onto historical electricity wholesale market data [47], in accordance with the cost and technology data [46]. Additionally, the availability of data points for estimation is a crucial factor. In cases where the number of historical data points is small, volatility in the short data span can result in a highly dispersed simulation tree. Consequently, we primarily employ a vector autoregressive VAR(p=5) time series model that captures the pattern in the data, while converging to the average in the long run. Summing up, we employ a deterministic mixed-integer program to model investor behavior under different levels of incentives and subsidies, analyzing possible scenarios in a case-by-case basis using the model devised. By adopting this approach, we can effectively examine investor decision-making process and its implications on capacity expansion, thus elucidating the performance of the incentive program with respect to the share of renewables in the final installed capacity, share in overall electricity generation, and total incentive program cost.

Table 1 summarizes the index, parameter and variables of the mixed-integer programming model devised in this study. Accordingly, the mixed integer programming model for optimal investment and production at a specific level of incentive and subsidy is:

$$max \ \sum_{t=1}^{H}\sum_{i=1}^{n}\sum_{j=1}^{m}(\pi_{ij}^{t}-q_{i}^{t})y_{ij}^{t}-\sum_{t=1}^{H}\Delta^{t} \times\sum_{i=1}^{n}\left(f_{i}^{t}v_{i}^{t}+r_{i}^{t}x_{i}^{t}\right)-\sum_{t=1}^{H}\sum_{i=1}^{n}o_{i}^{t}w_{i}^{t} \tag{1}$$

$$s.t. \quad x_{i}^{t}\leq C_{i}^{t}v_{i}^{t} \quad i=1,\ldots,n,\ t=1,\ldots,H \tag{2}$$

$$w_{i}^{1}=x_{i}^{1} \quad i=1,\ldots,n \tag{3}$$

$$w_{i}^{t}=w_{i}^{t-1}+x_{i}^{t} \quad i=1,\ldots,n\ t=2,\ldots,H \tag{4}$$

$$y_{ij}^{t}\leq a_{i}^{j}w_{i}^{t} \quad i=1,\ldots,n\ j=1,\ldots m\ t=1,\ldots,H \tag{5}$$

$$\sum_{i=1}^{n}y_{ij}^{t}=d_{j}^{t} \quad j=1,\ldots,m\ t=1,\ldots,H \tag{6}$$

$$v_{i}^{t}\in\{0,1\} \quad i=1,\ldots,n\ t=1,\ldots,H \tag{7}$$

$$w_{i}^{t}\geq 0 \quad i=1,\ldots,n\ t=1,\ldots,H \tag{8}$$

$$x_{i}^{t}\geq 0 \quad i=1,\ldots,n\ t=1,\ldots,H \tag{9}$$

$$y_{ij}^{t}\geq 0 \quad i=1,\ldots,n\ j=1,\ldots,m\ t=1,\ldots,H \tag{10}$$

(1) is the objective function maximizing the profit composed of one income and three cost terms. Generation cost per unit energy is specific to natural gas and does not vary by mode. q_i^t includes variable energy generation costs including fuel and variable O&M costs. However, renewable O&M costs considered here are accounted as fixed O&M costs per active capacity, represented by the rate o_i^t. Installation cost has two terms, the fixed cost $f_i^t v_i^t$, positive if any installation is made in plant i, and the variable installation cost $r_i^t x_i^t$ dependent on the capacity installed, x_i^t. Note that a company accounts for investment costs based on depreciation rates. Here, Δ^t indicates the ratio of the investment in year t that deprecates during the planning horizon and under the accounting scheme adopted by the company. Thus Δ^t is decreasing in years, later years being lightly accounted for by the company within the project scope. However, the specific accounting scheme is specific to setting and is analyzed under scenarios, to be further detailed in the next section. (2) assures that yearly capacity installation limit is respected, and that the fixed cost for capacity installation is accounted for, setting v_i^t to 1 if there is any positive capacity installation ($x_i^t > 0$) at the facility. There is a window for initial capacity installation, thus an installation with period index t is in service in the same period; this is indicated by both the initial capacity equation (3) and capacity update equation (4). Installation x_i^t in a later stage t augments previous capacity in *t-1* and becomes active in production during stage t due to (4). Plants have an overall accessibility factor a_i, representing the yearly output potential from installed capacity (or the respective period length) accounting for system efficiency, related wind or insolation conditions. Accessibility factor is distributed to modes by mode length, as represented by the mode dependent accessibility parameters a_i^j in (5). For instance, the 8 hours night mode has $a_i^3 = 0.33\times a_i\times 365\times 24$. Note that the output from installed capacity in MWs is in terms of MWh per year, thus accounting for number of hours in a year. For the NG plant, this duration-based distribution is reasonable, as generation capacity can be assumed independent of the hour of the day. For wind plants, this is applicable and preferred here, yet data and analysis on hourly wind profiles of locations can alleviate the need for this assumption, possibly providing a more accurate distribution of capacity accessibility to modes. However, for PV plants, 99.2% of irradiation is in the day mode, as a yearly average for the region considered. Thus, capacity accessibility is confined to the day mode, $a_i^1 = a_i \times 365 \times 24$, with no PV output in peak and night modes, $a_i^j = 0$, $j = 2, 3$. Then, (5) poses that the maximum energy that can be generated from a plant in a specific mode of the day is the active peak capacity installed times the accessibility factor of the plant in that mode. (6) states that the

demand for each mode in each period should be met by the overall electricity output of all plants in that mode and period. Finally, v_i^t is a binary variable by (7), as indicating existence of installation activity at plant i in period t, and plant capacity, capacity installations, and electricity generation outputs are nonnegative by (8)-(10).

The notation introduced in Table 1 reveals that some parameters in (1), (5) and (6) are scenario specific, and effective investment costs and electricity prices applicable to the investor possibly differ from market values due to incentive and subsidies. The fixed (variable) investment cost $\hat{f}_i^t(\hat{r}_i^t)$ applies to the investor as $f_i^t(r_i^t)$ after subsidies, and market electricity wholesale prices p_j^t apply as π_{ij}^t after incentives. Both incentive and subsidies are restricted to renewables and specific to plant types, thus wholesale price is effectively plant type specific. The subsidy and incentives determining effective cost and prices, as well as availability factors, demand and accounting scheme is analyzed under scenarios, as discussed in the next section after the problem case data is introduced.

IV. COMPUTATIONAL RESULTS

A. THE NUMERICAL CASE AND DATA ANALYSIS

In the numerical experiments, 21 candidate power plant locations and a 10-year horizon is analyzed (n=20, H=10). Potential plant locations are chosen in Türkiye, where the variation in wind and irradiation conditions represent those that can be attained in many Central European and Mediterranean Countries, along with many global regions of medium latitude. Turkish energy market retail price data is used accordingly, which provides an example for central pricing throughout electricity demand points. Data collected has four components: retail prices, investment and production costs, technology related factors such as development in CFs affecting accessibility rates and future prices. Common periodic range for data collection is up to 2020, thus we assume that the planning horizon begins in 2020 and covers until the end of 2029.

For the installation locations, Southern Anatolia, Aegean and Mediterranean shore in Türkiye is chosen for ten PV plants (approximately 1700 kWh/kWp/year output efficiency on average); mostly Aegean region is chosen for ten wind plants; and an additional natural gas plant location exists. Accessibility factors are analyzed based on the location and global information regarding PV [48] and wind energy [49] (Table 3 presents a summary of yearly installable capacity limits, fixed investment costs, variable investment costs and accessibility factors of plant locations). Despite the high volatility in fuel prices, natural gas plants appear as a more cost-effective generation modality compared to coal as of 2020, and is the dominant choice for new fossil-based power plant installations, thus the alternative modality to renewables that the profit seeking investor can choose is a fictive natural gas plant. As the cost scheme for natural gas capacity installations do not involve a fixed component [46], mathematically

TABLE 3. For each energy generation modality and location, yearly installable capacities, fixed investment costs, variable investment costs and accessibility factors.

		Installable (C_i^t, in MW)	Fixed Investment Cost (f_i^t, in TL)	Variable Investment Cost (r_i^t, in TL/MW)	Accessibility Factor (a_i)
Solar		20	21597090	9431758	0.222
		20	16751680	7675991	0.219
		35	22135695	9281011	0.216
		40	20403036	8195319	0.224
		40	22077449	8057947	0.211
		80	21604230	8720911	0.219
		90	26098973	8421855	0.213
		100	20197547	9192773	0.227
		280	18741625	9132084	0.222
		250	22221993	9679369	0.222
	$\bar{X}$	95.5	21182931.7	8778901.9	0.220
	s	93.9	2460335.0	666066.9	0.005
Wind		70	98486313	9358685	0.342
		75	112091439	11077412	0.366
		75	103503657	11182152	0.339
		85	97265828	10595089	0.351
		87	147674212	7800577	0.351
		88	114138113	7064156	0.421
		93	113796592	10600519	0.336
		95	128083589	9340982	0.475
		225	141425410	9550475	0.385
		250	137442148	11251744	0.320
	$\bar{X}$	114.3	119390730.1	9782179.1	0.369
	s	65.7	18190263.1	1447977.9	0.047
NG		500	0	7526400	0.80

there is no difference between one fictive plant with high installation capacity compared to several locations with lower capacities.

For investment costs, installation costs for PV module and wind turbine prices in the global market are considered. The fixed and variable investment cost scheme and parameters in Table 3 is in line with project cost and size data for PV and wind projects in [48] and [49], respectively. We consider prices in 2020 Turkish Liras (1\$ = 6.72 ₺) in our analysis.

For the investment cost and CF of the (combustion turbine) natural gas plant, we refer to the Annual Technology Baseline database of United States of America National Renewable Energy Laboratory [46]. Estimates for future trends in investment costs are also adopted from this database, and conservative, moderate and advanced scenarios for these parameters are adopted as presented in this resource.

Periodic operation and maintenance for PV plants involve surface cleaning, which is done by washing the panels once

TABLE 4. Additional electricity demand projected, in day, peak and night modes that should be met by newly installed capacity during years 2020-2029.

MWh	Day	Peak	Night
2020	4044300	4282200	3568500
2021	8246300	8731400	7276200
2022	12612200	13354100	11128400
2023	17148400	18157100	15131000
2024	21861500	23147500	19289600
2025	26758400	28332400	23610400
2026	31846300	33719600	28099700
2027	37132600	39316800	32764000
2028	42625100	45132400	37610300
2029	48331700	51174800	42645600

a year [50]. The operation and maintenance costs for wind plants continue with a negative trend since 1984 until 2020 [49], and is again accounted for as fixed O&M costs per kW of installation per year. The natural gas plant incurs a fuel cost for each kWh produced. The study refrains from delving into the intricate econometric modeling of the heightened volatility in natural gas prices post-2020. To streamline scenario presentation and reduce complexity, NG prices and conversion efficiency are maintained at their most advantageous positions. The wholesale prices for energy generators in 2020 are assumed to be 131.5 £/MWh [51], with a recent high conversion efficiency of 0.61, resulting in a cost of 215.7 £/MWh. Accessibility, captured by the CF, is also presumed to be at a high 80% level, aligning with the 2035 reference [46]. Notably, NG carries typical conservative, moderate, advanced investment and O&M cost scenarios. While these figures may be subject to errors due to significant Turkish Lira inflation post-2020, the study acknowledges the omission of detailed econometric modeling for precise estimation. The framework allows for the application of more refined point estimates, if desired.

Electricity demand is projected to increase rapidly in 2020-2040 in Türkiye [52], and moderate estimates of additional generation demand through 2000-2009 is in Table 4. The incentive project is considered to cover a fraction of this arising demand, and coverage is considered to be 20%.

For parameter estimation, we use a deterministic approach in this study, deriving pessimistic, moderate and optimistic scenarios from the selected time series model. This is a practical choice, as mean installed capacity share, production share and utilization results are informative at the aggregate and central level of planning. In addition, particularly for a new technology for which the data is recently being collected, or a country/localization for which data collection has started recently, point estimates are more reliable relative to error estimates. Autoregressive models of low orders can be applied on such data to obtain point estimates, and short-term volatility can render simulation trees overly dispersed. Consider the VAR (p=5) model presented in (Fig. 2), applied on the day, peak and night mode electricity price time series (after checking for stationarity: Augmented Dickey-Fuller test p-values 0.52, 0.44 and 0.55, respectively). There are 31 data points, for estimating the 120-month planning horizon. On a yearly basis, the number of available data points would be even smaller. Fig. 2 demonstrates the simulation paths generated using the VAR(p=5) model for day, peak and night mode prices, where the degree of lags is selected considering the Akaike Information Criterion. In this case, simulation paths have a reasonable dispersion, and estimations converge to a mean after demonstrating a fluctuation pattern for 25 months. However, in line with the scenarios for capacity factor and investment costs, we derive scenarios for electricity prices using the VAR model simulations as follows. At each period, 10%, median and 90% values of simulated path values at the period are computed. Percentile values are a subjective choice, however, in this case, the scenario range is sufficiently covered and distinct scenario representations are obtained by this approach (Fig. 2, right).

The accounting scheme used is also considered under three scenarios, adjusting the number of years in the sum-of-the-years digits (SYD) depreciation model. A more risk averse investor would require returns to quickly pay off capital investment, thus accounting by a 10-year SYD model. A more risk prone investor accounts for the depreciation according to the entire project life, which is commonly 30 years for a PV or wind plant, thus using a 30-year SYD scheme. The moderate scenario in investor attitude towards risk assumes a 20-year SYD depreciation scheme. Under each depreciation model, an investment made in year 1 depreciates according to the total of the rates in the first 10 years of the model used, an investment in year 2 depreciates according to the total of rates for the first 9 years, and the depreciation within the planning horizon for an investment in year 10 is only the rate indicated for the first year of the SYD model used. Fig. 3 displays the fraction of depreciation within the planning horizon for investments in years 1-10 under the three scenarios for depreciation models.

Overall scenario settings are constructed from various combinations of scenarios for individual parameters of (1)-(10), and the MIP is run for each scenario and incentive setting to find optimal investor choice in each case. Pareto optimal solutions for each scenario setting are determined and analyzed for decision making of the central planner, as explained in the next subsection.

B. PARETO ANALYSIS OF INCENTIVE POLICIES UNDER SCENARIO SETTINGS

Most parameters of (1)-(10), including CFs, investment and O&M costs [46], and demand [52] are presented under conservative, moderate and advanced scenarios in the resources for the respective data, and a similar scenario triplet is devised for electricity wholesale prices and depreciation models, as discussed in Subsection IV-A. These scenarios for individual parameters are combined into 18 overall scenarios constituting settings for (1)-(10) for an analysis and

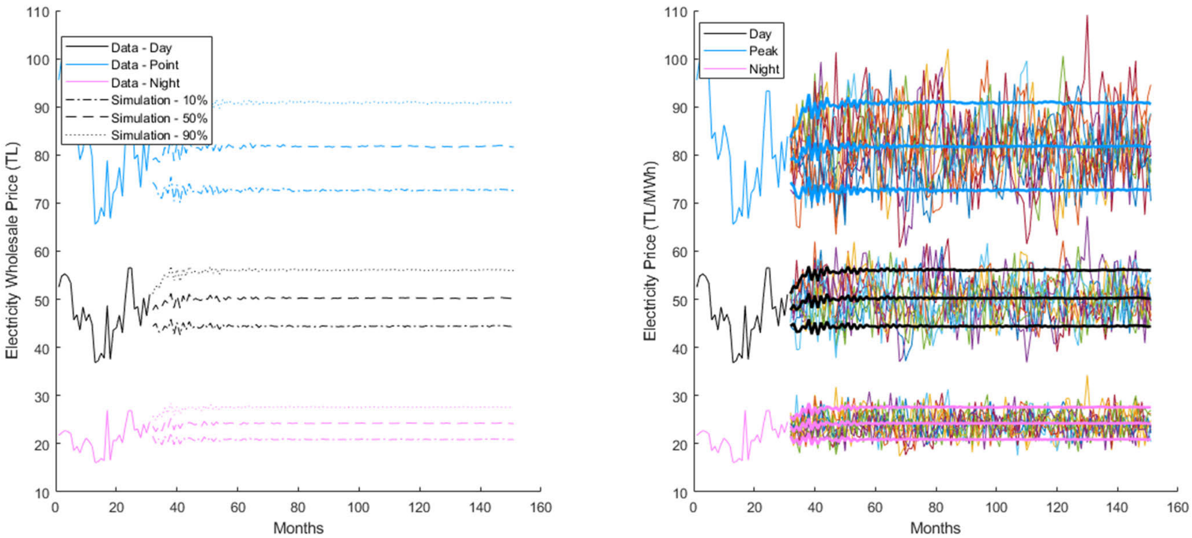

FIGURE 2. Estimates for monthly day, peak and night mode electricity prices in the planning horizon of 10 years, 120 months, using a VAR(p=5) time series model. Estimates are obtained under conservative, moderate and advanced scenarios (left), which correspond to 10, 50, and 90 percentiles of values of paths simulated from the VAR(p=5) model at each time period (right). Estimation is conducted in months, as the past data available spans a restricted 31 months. Yearly averages are computed from estimates to be used as parameters in the mixed-integer programming model.

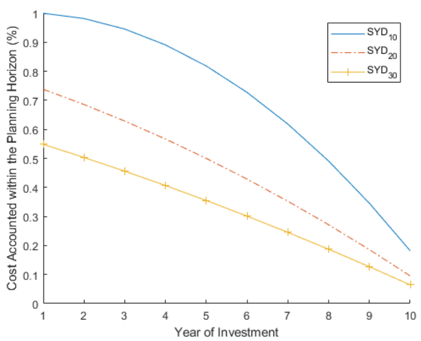

FIGURE 3. The ratio of an investment that depreciates within the 10-year planning horizon with respect to the year that the investment is made. Analyzed under three scenarios with respect to investor attitude, represented by sum-of-the-year-digits depreciation scheme with 10 (SYD_{10}), 20 (SYD_{20}) and 30-year (SYD_{30}) investment spans.

interpretation of investor behavior, program cost and performance in terms of renewable transformation. In sum, each solution of (1)-(10) depends on an overall scenario $\beta\in\Sigma$ where parameters assume a level as defined by their respective scenarios $\beta = (a_i, o_i^t, \hat{f}_i^t, \hat{r}_i^t, d_j^t, p_j^t, \Delta^t)$. Table 5 presents the set of scenarios Σ and the settings for the parameters of (1)-(10) under these scenarios.

In addition to parameters β set by the scenario implementation in a specific run of (1)-(10), final values of parameters $\pi_{\text{ij}}^{\text{t}} = (1+\alpha_k)p_j^t$, $f_i^t = (1-\sigma_k)\hat{f}_i^t$, $r_i^t = (1-\sigma_k)\hat{r}_i^t$ are determined by the generation incentive rate α_k and investment subsidy rate σ_k decided upon by the central planner for modalities $k\in\{PV, \ Wind, \ NG\}(\alpha_{NG} = \sigma_{NG} = 0)$. Thus, an optimal solution of (1)-(10) provides the answer for performance attainable under these settings regarding the criteria of interest besides the objective value, which is the overall profit of the profit seeking energy companies.

The intervention program providing incentive and subsidies on renewable energy installations can have three merits: low cost implies the ability to plan for a project with higher coverage given a fixed budget, high share of renewable energy installations at the end of the planning horizon means effective replacement of fossil-based capacity during the planning horizon, and a high share in the total electricity generation throughout the process equals to immediate action for the environment early on in the planning horizon.

To compare incentive policies regarding the three criteria, we conduct Pareto analysis on possible choices of incentive and subsidy levels for wind and PV plants, where the joint policy choice $\alpha = (\alpha_W, \sigma_W, \ \alpha_{PV}, \sigma_{PV})$ takes a value from:

$$\Pi = I_W \times S_W \times I_{PV} \times S_{PV}. \tag{11}$$

Here, $I_W = S_W = \{0, \ 0.005, \ 0.01, \ 0.015, \ 0.02, \ 0.03, \ 0.04, \ 0.05, \ 0.075, \ 0.1, \ 0.125, \ 0.15, \ 0.2, \ 0.3\}$, and $I_{PV} = S_{PV} = \{0.3, \ 0.35, \ 0.4, \ 0.45, \ 0.5, \ 0.6, \ 0.7\}$. Since wind has capacity per cost advantage, in addition to accessibility throughout the day, some wind plants are more profitable relative to natural gas even before incentives. However, the range of incentive and subsidy rates stimulating PV investments is above the range for wind. The policy choice set Π is explored and compared via (1)-(10). For $\alpha = (\alpha_W, \sigma_W, \ \alpha_{PV}, \sigma_{PV})\in\Pi$, let an optimal solution for (1)-(10) with policy hyperparameter setting α and scenario setting β be $X^*(\alpha, \beta) = (\bar{x}, \bar{v}, \bar{w}, \bar{y},)$, and $g_1(\alpha, \beta)$, $g_2(\alpha, \beta)$, and $g_3(\alpha, \beta)$ be the values of the three criteria for the optimal solution, i.e., the total cost of the intervention program

$$g_1(\alpha, \beta) = \sum_{t=1}^{H} \sum_{j=1}^{m} \Big(\sum_{i\in W} \alpha_W p_j^t \overline{y_{ij}^t} + \sum_{i\in PV} \alpha_{PV} p_j^t \overline{y_{ij}^t}\Big) + \sum_{t=0}^{H} \Big(\sum_{i\in W} \sigma_W f_i^t \overline{v_i^t} + \sum_{i\in PV} \sigma_{PV} f_i^t \overline{v_i^t}\Big)$$

TABLE 5. Computationally explored scenarios, combining conservative (Con), moderate (Mod) and advanced (Adv) scenarios for evolution of parameters such as PV/Wind capacity factors, PV, wind and NG O&M, fixed/variable investment costs, electricity demand, wholesale prices and the accounting model (SYD_X where X indicates length in years) adopted by the investor.

Scenario	PV CF (a_i)	PV Cost ($o_i^t, \hat{f}_i^t, \hat{r}_i^t$)	Wind CF (a_i)	Wind Cost ($o_i^t, \hat{f}_i^t, \hat{r}_i^t$)	NG Cost ($o_i^t, \hat{f}_i^t, \hat{r}_i^t$)	Demand (d_j^t)	Accounting (Δ^t)	Electricity Prices (p_j^t)
1	Mod	Mod	Mod	Mod	Mod	Mod	SYD_{10}	Mod
2	Mod	Mod	Mod	Mod	Mod	Mod	SYD_{20}	Adv
3	Mod	Mod	Mod	Mod	Mod	Mod	SYD_{20}	Mod
4	Mod	Mod	Mod	Mod	Mod	Mod	SYD_{20}	Con
5	Mod	Mod	Mod	Mod	Mod	Mod	SYD_{30}	Mod
6	Con	Con	Con	Con	Adv	High	SYD_{10}	Adv
7	Con	Adv	Con	Adv	Adv	Mod	SYD_{20}	Mod
8	Adv	Con	Adv	Con	Adv	Mod	SYD_{20}	Mod
9	Con	Adv	Con	Adv	Adv	High	SYD_{20}	Mod
10	Adv	Con	Adv	Con	Adv	High	SYD_{20}	Mod
11	Con	Adv	Con	Adv	Con	Mod	SYD_{20}	Mod
12	Adv	Con	Adv	Con	Con	Mod	SYD_{20}	Mod
13	Adv	Adv	Adv	Adv	Con	Low	SYD_{30}	Con
14	Con	Con	Con	Con	Mod	Mod	SYD_{20}	Mod
15	Adv	Adv	Adv	Adv	Mod	Mod	SYD_{20}	Mod
16	Adv	Adv	Con	Con	Mod	Mod	SYD_{20}	Mod
17	Con	Con	Adv	Adv	Mod	Mod	SYD_{20}	Mod
18	Adv	Adv	Con	Con	Mod	Mod	SYD_{10}	Mod

$$+\sum_{t=0}^{H}\left(\sum_{i\in W}\sigma_W r_i^t\overline{x_i^t}+\sum_{i\in PV}\sigma_{PV} r_i^t\overline{x_i^t}\right), \tag{12}$$

the share of renewables in the end of horizon installed capacity

$$g_2(\alpha,\beta)=\frac{\sum_{i\in W\cup PV}\overline{w}_i^H}{\sum_{i=1}^{n}\overline{w}_i^H}, \tag{13}$$

and the share of renewables in the overall electricity generation

$$g_3(\alpha,\beta)=\frac{\sum_{t=1}^{H}\sum_{j=1}^{m}\sum_{i\in W\cup PV}\overline{y}_{ij}^t}{\sum_{t=1}^{H}\sum_{j=1}^{m}\sum_{i=1}^{n}\overline{y}_{ij}^t}. \tag{14}$$

We evaluate solutions in $\Pi\times\Sigma$ and select Pareto optimal solutions within each scenario $\beta\in\Sigma$. We seek $\epsilon-$ dominance prioritizing share of renewables in installed capacity. An incentive choice $\alpha = (\alpha_W, \sigma_W, \alpha_{PV}, \sigma_{PV})$ is Pareto dominated by $\bar{\alpha} = (\bar{\alpha}_W, \bar{\sigma}_W, \bar{\alpha}_{PV}, \bar{\sigma}_{PV})$ if the latter is better in one but is not worse in any of the three criteria,

$$g_1(\bar{\alpha},\beta)\le g_1(\alpha,\beta) \text{ and } g_l(\bar{\alpha},\beta)\ge g_l(\alpha,\beta) \text{ for } l=2,3 \tag{15}$$

or is better in share of renewables in installed capacity,

$$g_2(\overline{\alpha},\beta) > g_2(\alpha,\beta), \tag{16}$$

while having shares in generation from renewables no less than α, considering the tolerance level,

$$g_3(\overline{\alpha},\beta) > (1-\epsilon)g_3(\alpha,\beta), \tag{17}$$

and having a total program cost not more than α, up to the tolerance level:

$$(1-\epsilon)g_1(\overline{\alpha},\beta) < g_1(\alpha,\beta). \tag{18}$$

Instances covering all 18 scenarios and policy settings are run as a randomly ordered batch on an AMD Ryzen Threadripper 3960X 24-Core CPU, 48 GBs of RAM. The solution time is 16069 seconds for 172872 problem instance solutions.

The computational analysis investigates various scenarios to shed light on the diverse outcomes resulting from optimistic, pessimistic, and moderate perspectives in an incentive program for renewable energy. Displaying the Pareto optimal solutions in the spectrum of total incentive program cost for each scenario, possible achievements and risks involved are presented, especially when parameters evolve favorably or otherwise. These scenarios not only support the decision-maker regarding the dynamics at different budget levels but also underscore the challenges and opportunities inherent in each scenario.

Scenarios 6, and 13, representing overall optimistic/advanced and overall pessimistic/conservative scenarios, distinctly differ from the overall moderate scenario, Scenario 3 (Fig. 4). These three scenarios demonstrate the spectrum of achievement to the decision maker at different levels of expense in the incentive program, while pointing out the extent of risk and opportunities when all parameters jointly evolve in a favorable way, or in the other direction -even if such cases are rather unlikely. With low expense programs, the range for renewable installation shares are 55-65%, where achievements in the moderate case are close to the pessimistic case, Scenario 6. However, on the generation side, moderate achieves rather similar to the optimistic scenario, while the range is 60-80%. As program expense reaches 50 billion £, 60% renewable installation shares are exceeded in Scenario 6, while Scenario 3 and Scenario 13 exceed 75%. Renewable shares in generation follow along, but rates are higher, approaching 90% for the optimistic scenario, as generation from NG gets confined to the peak mode with high demand (Fig. 5). With higher wholesale price projections and higher incentive awards, more ambitious programs reaching 70 billion £ expense and 85% renewable installation and generation shares are possible in the optimistic case. This roughly 1 billion \$/7 billion £ yearly incentive program expense can be considered burdensome by the central decision maker, as it exceeds one third of the entailed economy including the total of installation, O&M and fuel costs. However, it is possible to attain a reasonable boost in performance criteria with a program cost of less than half of this. A program

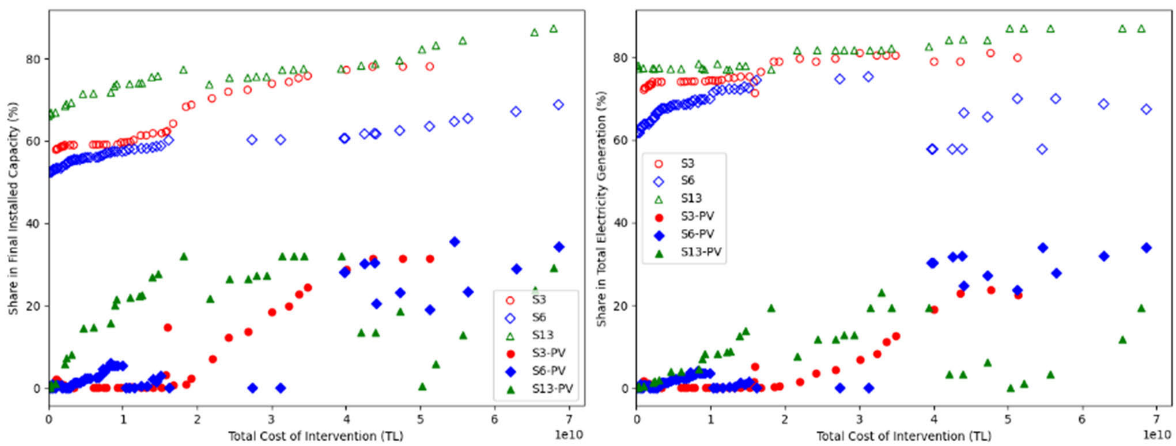

FIGURE 4. For the Pareto optimal solutions of overall pessimistic, optimistic and moderate scenarios (Scenarios 6, 13 and 3, respectively, marked as S6, S13 and S3) the share of renewables (wind+PV) and PV in the end-of-horizon installed generation capacity against the total intervention program expense for generation incentives and investment subsidies (left). The corresponding share of renewables and PV only in total energy generation throughout the planning horizon (right).

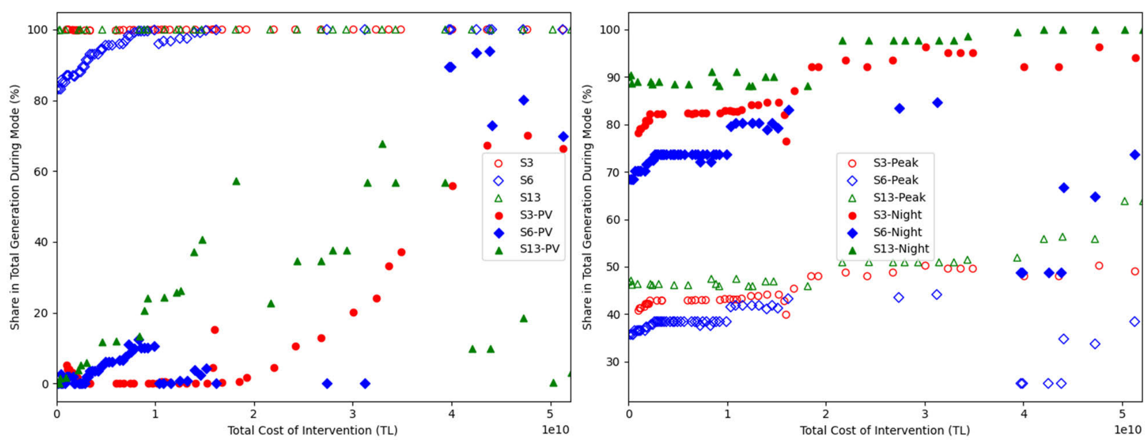

FIGURE 5. For the Pareto optimal solutions of overall pessimistic, optimistic and moderate scenarios (Scenarios 6, 13 and 3, respectively, marked as S6, S13 and S3) the share of renewables (wind+PV) and PV in day mode electricity generation throughout the planning horizon against the total intervention program expense for generation incentives and investment subsidies (left). PV has no share in generation during peak and night modes, wind dominating the night mode with low budget interventions, while peak mode requires a large contribution from the natural gas plant (right).

expense of 27 billion £ in total corresponds to roughly 20% of overall cost of commissioning and running the plants within the scope of the program, renewable installations reach above 75% and renewable share in generation reaches 82% for the optimistic scenario, while moderate scenario lags by a 3% in these criteria (for the pessimistic scenario, government shares 22.5% of the costs, renewable installations are increased by more than 10% and renewable shares in generation approaches 75% with more than 20% increase). By presenting the spectrum of Pareto optimal solutions to (1)-(10), the central decision maker is informed on the risks associated with different scenarios and opportunities attainable at different budget allocations for the incentive program.

During the day mode, minimal incentive program expenditure leads to 100% renewables, but as program expenses increase, PV takes over the day mode, and the share of wind increases during peak and nighttime (Fig. 5). Wind has the capacity per cost advantage, added to the lack of fuel usage, thus has the larger share without any incentive and subsidies. PV accounts for the larger part of the increase in renewable shares with higher incentives, but only with visible increases in program expense. With around 50 billion £ in expenditures, the share of renewables reaches 100% even at night (for the overall advanced scenario), but during peak demand, it remains around 50%, despite increased spending. During this interval of high demand, generation from natural gas compensates when wind installations are not enough and PV cannot contribute.

The accounting scheme, reflecting the investor attitude on patience for returns, is highly influential. This is clearly indicated by the SYD_{10} setting in Scenario 1, as installed capacity reaches 65% with more than 40 billion £ program expenses, while the moderate Scenario 3 with the only difference of milder SYD_{20} accounting achieves 75% with less expense (Fig. 6, left). Yet, a rather extravagant program costing above 40 billion £ promises 82% renewable share in generation

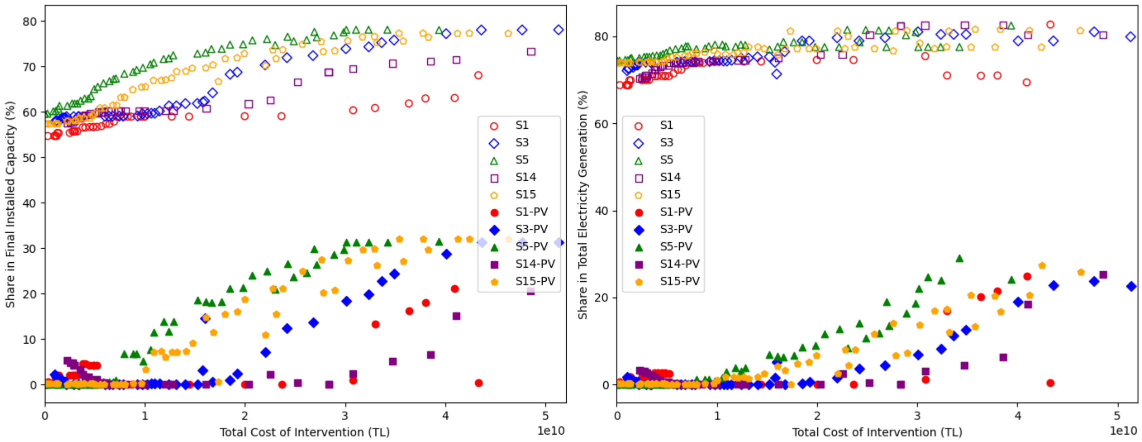

FIGURE 6. **The share of renewables (wind+PV) and PV in the end-of-horizon installed generation capacity against the total intervention program expense for generation incentives and investment subsidies is compared for the Pareto optimal solutions of scenarios 1, 3, 5, 14, and 15 (left). Scenario 1 (S1) differs from the overall moderate Scenario 3 (S3) by the risk averse depreciation scheme SYD10, and Scenario 5 (S5) considers the milder SYD30 depreciation schedule. Scenario 14 (S14) differs from S3 by assuming conservative renewable capacity factor and cost processes, while Scenario 15 (S15) assumes advanced scenarios in renewables. The corresponding share of renewables and PV only in total energy generation throughout the planning horizon (right).**

despite the strict SYD_{10} accounting under Scenario 1 (Fig. 6, right). In this case, generation incentives and wind modality are prioritized. Scenario 5, with a tolerant SYD_{30} depreciation scheme once again indicates the strong effect, as it entails large renewable capacity installations in response to modest incentives. In this case, generation incentive and investment subsidy expenses are allocated more evenly, and PV investments support wind installations under smaller program budgets. With a budget of 27 billion £, 75% renewable shares in installation are achieved in Scenario 5 (Fig. 6), thus depreciation scheme accounts for most of the variability in the overall optimistic scenario – moderate scenario difference (75 vs 72%). In Scenario 15, renewable cost and technology have an advanced flow, yet compared to Scenario 5, the reduction on installations due to the SYD_{20} depreciation scheme can be compensated only at high incentive expenditures. Scenarios 1, 3 and 5 presenting the depreciation scheme differences also demonstrate the major portion of the variability in the range of overall pessimistic-overall optimistic scenarios. The accounting scheme points out the importance of stimulating risk averse investors, and upon anticipating such attitude, the central planner can elicit higher renewable investments with a relatively higher program budget. Favorable wholesale prices are not persuasive by themselves, as Scenario 2, Scenario 3 and Scenario 4, have very similar outcomes, despite conservative, moderate and advanced wholesale price scenarios, respectively (no visible difference from Scenario 3, Fig. 4). Scenario 14 achieves higher renewable installations than Scenario 1, thus conservative technology and cost scenarios in renewables are not as tolling as the accounting scheme (Fig. 6). The difference in renewable shares in final installed capacity do not directly reflect on shares in generation, since the day mode is fully covered by renewables even in low incentive programs, night mode is also mostly covered by renewables with moderate program scales, and thus the effect

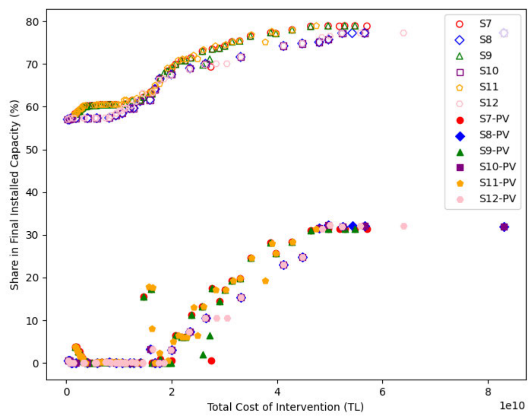

FIGURE 7. **The share of renewables (wind+PV) and PV in the end-of-horizon installed generation capacity against the total intervention program expense for generation incentives and investment subsidies is compared for the Pareto optimal solutions of scenarios 7-12. In Scenarios 7, 9, 11 (S7, S9, S11), renewable energy capacity factors evolve according to their conservative settings, while investment costs are on the advanced side. In Scenarios 8, 10, 12 (S8, S10, S12) the case is the other way round. S9 and S10 explore effects of high demand in comparison to moderate demand, and S11 and S12 explore effects of conservative natural gas capacity factor and investment costs -both of which are negligible. As factors differentiating S7, S9 and S11 (similar for S8, S10, S12) have negligible effect, plots follow similar curves, thus the figure effectively displays two curves differentiated by investor response to investment cost and CF scenarios.**

of increasing installed capacity is mostly restricted to the peak mode.

Scenarios 7, 9, 11 achieve higher installed renewable capacities under similar program expenses along the major portion of the program expense spectrum, compared to 8, 10, 12, clearly due to more advantageous investment and O&M costs (Fig. 7). However, the latter group has the advantage in CFs, thus achieves slightly higher renewable shares in total generation. There are no visible differences within the two groups, thus neither NG cost scenarios nor demand level scenarios are critical in program outcomes.

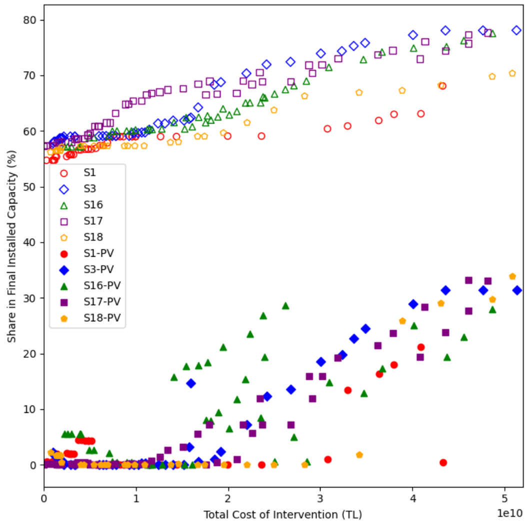

FIGURE 8. The share of renewables (wind+PV) and PV in the end-of-horizon installed generation capacity against the total intervention program expense for generation incentives and investment subsidies is compared for the Pareto optimal solutions of scenarios 1, 3, 16, 17, and 18 (left). Scenario 18 (S18) differs from Scenario 1 (S1) by advanced scenarios for PV capacity factors, investment costs and conservative scenarios for wind capacity factors, investment costs; while S1 assumes moderate scenarios in both modalities. Scenario 16 (S16) shares the same settings with the overall moderate Scenario 3 (S3), except advanced PV and conservative wind scenarios like S18. In Scenario 17 (S17), roles in S16 change sides, with advanced wind and conservative PV scenarios. The corresponding share of renewables and PV only in total energy generation throughout the planning horizon (right).

Scenarios 3, 14, and 15 compare combined effect of CF, O&M costs and investment costs in both PV and wind, Scenario 14 having conservative, Scenario 3 moderate and Scenario 15 advanced positions on all. The difference between these scenarios is where PV becomes commercially viable for investors. Once investment subsidies and generation incentives render PV investments more profitable, day time generation from PV augments wind installations and shares of renewable exceed 75% for Scenario 3, reaching levels similar to Scenario 15 (Fig. 6, left). When PV and wind parameters drift to two different sides, shares in installed capacity at similar expenses can turn slightly lower, but the advantageous modality pays off in terms of the renewable shares in generation. When PV is in the advantageous side, as in Scenario 18, at moderate incentive program expense levels, PV installations and shares in generation increase, surpassing the balanced setting in Scenario 1 (Fig. 8). However, with a milder depreciation scheme, Scenario 3 dominates Scenario 16 in low and moderate budget programs, as a moderate scenario setting in wind combined with less strict accounting encourages investment into wind plants under low incentives. When the wind modality is more advantageous, comparing Scenario 17 with Scenario 3, for instance, low budget programs achieve higher renewable installation shares by wind investments.

With restricted investment program budgets, the strategy is to keep weight on wind, since it assures more capacity installation per unit cost, and renewable shares in outputs during all modes of the day. However, higher targets and completely renewable day time generation can be achieved only by resorting into additional capacity from PV. Scenario 16 where PV CF and costs evolve according to their advanced scenarios whereas wind evolves conservative compares in this respect to Scenario 17, where wind is advanced and PV is conservative. With moderate program expenses of 20 billion ₤, 70% in renewable installations are achieved, while 65% is not achieved in Scenario 16. However, the PV advantage pays off in Scenario 16 with moderate program expenses, and at 40 billion ₤, shares approach 75% in both scenarios, Scenario 16 taking the lead.

Scenarios 7 and 8 (Fig. 7) compare how circumstances in technology evolution and investment costs trade off. In scenario 7, higher renewable installations are achieved at similar program costs by the higher pace of reduction in renewable investment costs, again, these do not translate into renewable shares in output as high as in Scenario 8, due to the faster technological advancement and higher CFs in Scenario 8.

V. CONCLUSION

The presented mixed-integer programming model addresses the crucial challenge of incentivizing renewable energy production while meeting the growing energy demand. Acting as a central planner, the government efficiently identifies suitable energy project sites and sets annual capacity installation limits for each location. Investors, acting as profit-maximizing agents, strategically analyze cost components and revenue potentials to plan capacity installations for various energy modalities across different locations. Considering the energy retail price, an essential factor in the profit model, the model devised in this study focuses on purchase price incentives, which differ in their impact on motivating investments compared to quantity-based subsidy models found in existing literature.

Computational results demonstrate that significant renewable shares can be achieved, covering a major part of the achievement at a fraction of the cost required for ambitious policies with costly wind and PV incentives. Under a moderate scenario, final installed capacity share of renewables below 60% is boosted to 72%, and share in overall electricity generation reaches 80%, allocating a fractional 27 billion ₤ intervention budget. While an overall optimistic scenario achieves 75% renewables in installations with this level of intervention expense, an overall pessimistic scenario attains 60%, although this also corresponds to a visible stimulation in investment. The variability observed is mainly attributable to the choice of the depreciation scheme. For instance, using a milder depreciation scheme in an otherwise moderate scenario achieves a 75% installation rate, emphasizing the importance of how the investor accounts for costs, and the attitude towards risk.

Wind plants, with their cost advantage, emerge as the course of action with smaller incentives. However, if technology evolves favorably for photovoltaics, the combined effect of increasing capacity factors and reducing investment costs provides opportunities for attaining above 75% renewable installation shares with policies requiring restricted budgets, similar to an overall optimistic scenario. This is crucial for renewable transformation, especially in regions abundant with locations featuring moderate to high irradiation but a limited wind speed range for efficient generation. Exploring cases by scenarios covering differences in parameters, including electricity demand, wholesale prices, technology, and the cost of the natural gas alternative, uncertainties in these parameters are shown to have negligible impact on the outcomes of the incentive policy choice.

Limitations of this study suggest a prospective research direction. With a case involving relevant data, and incorporating equipment degradation, transmission network, local demand and local electricity pricing models; period and location-specific incentive rates under a scenario-based or possibly stochastic dynamic setting should be considered in a follow-up study. Additionally, expanding the research to include a larger number of plant location alternatives and higher demand coverage would necessitate more efficient approaches for successfully handling such complex scenarios in the mathematical programming model solution.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work the authors used Elicit (Elicit.org) and Paper Digest (Paperdigest.org) along with scientific article search databases to search related articles during the literature review. ChatGPT has been used to revise the language and presentation of the content. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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