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OSeMOSYS Modeling Primer in GurobiPy

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Abstract

This paper presents an optimization model that utilizes the OSeMOSYS framework to identify the optimal combination of renewable energy sources to minimize costs and CO2 emissions. The model is designed to incorporate various types of renewable energy sources such as solar, wind, hydro, and biomass, and to allocate them in an optimal manner to meet the demand. We demonstrate the effectiveness of the proposed approach by applying it to a case study of a regional energy system. The results show that the optimized use of renewable energy sources can significantly reduce both costs and emissions compared to a business-as-usual scenario. Our findings can inform policymakers and energy planners in making informed decisions to transition towards a more sustainable and cost-effective energy system.

Keywords: *Optimization, emission, decisions, sustainable, renewable energy.*

1. Introduction

Energy-related carbon dioxide (CO2) emissions are a significant source of greenhouse gas emissions and climate change on a worldwide scale. Finding sustainable and renewable energy sources that can lower CO2 emissions are becoming more and more important as energy demand rises. The production of solar energy is one such source.

Solar power generation is a clean, sustainable energy source that emits no greenhouse gasses. It operates by catching solar energy and transforming it into electricity by the use of solar panels; which are composed of photovoltaic cells that convert sunlight energy into direct current (DC) power.

Many techniques may be done to reduce CO2 emissions from solar energy generation. First, the installation of solar power systems in homes and businesses can lower the demand for electricity from traditional fossil fuel-based power plants. This can be accomplished by government incentives or tax cuts that stimulate the use of solar electricity. Second, large-scale solar power facilities may be built to power entire cities or regions. This may be accomplished through the deployment of solar farms, which are vast arrays of solar panels that provide utility-scale power. These solar farms may be incorporated into the current

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power system and offer users with clean energy. Finally, the utilization of energy storage solutions such as batteries can assist in increasing the efficiency of solar power generation. Batteries may supply electricity to homes and businesses during periods of low sunshine or at night by storing extra energy produced during the day, decreasing the demand for energy from traditional power plants.

2. Background

The global energy system is undergoing a transformation towards sustainability, driven by the urgent need to reduce greenhouse gas emissions and mitigate the impact of climate change. Renewable energy technologies, such as solar power, wind power, and hydropower, are increasingly being adopted as alternatives to fossil fuel-based energy sources. Energy system modeling plays a crucial role in understanding the potential of these technologies in reducing CO2 emissions and achieving a sustainable energy future.

Renewable Energy and CO2 Emissions: New Evidence with the Panel Threshold Model1 examines the relationship between renewable energy and CO2 emissions using a panel threshold model. The authors find evidence of a threshold effect which indicates that renewable energy can only reduce CO2 emissions up to a certain point, beyond which the impact diminishes. The paper highlights the need for a balanced approach to renewable energy deployment, taking into account the technological and economic constraints.

Solar Power for CO2 Mitigation2 discusses the potential of solar power as a means of mitigating CO2 emissions. The authors argue that solar power has the potential to significantly reduce global CO2 emissions and can be a cost-effective alternative to fossil fuel-based power generation. The paper highlights the need for policy support to accelerate the deployment of solar power, particularly in developing countries.

A Qualitative Evaluation Approach for Energy System Modelling Frameworks3 proposes a framework for evaluating energy modeling tools based on various criteria including flexibility, transparency, and scalability. The authors emphasize the importance of a transparent and collaborative approach to energy modeling, allowing for wider participation and stakeholder engagement. The paper provides a useful framework for evaluating energy modeling tools and can guide decision-making in selecting appropriate modeling tools for specific applications.

OSeMOSYS: The Open Source Energy Modeling System - An Introduction to Its Ethos, Structure and Development4 introduces the OSeMOSYS software tool for creating transparent and collaborative energy system models. The paper also provides a detailed description of the development and evolution of OSeMOSYS, from its early stages to its current version. The authors discuss the challenges faced during the development process, as well as the opportunities and benefits of open-source development. The paper highlights several key advantages of OSeMOSYS, one of which is its transparency that allows policymakers and stakeholders to understand the underlying assumptions and data inputs used in energy system modeling. This transparency can help to build trust and increase the effectiveness of energy policy analysis. Another advantage is the flexibility of the framework, which enables users to modify and adapt it to suit their specific needs and requirements. The paper also discusses the potential applications of OSeMOSYS in a range of energy policy contexts, including electricity system planning, renewable energy integration, and climate change mitigation.

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3. Methodology

Linear programming is a mathematical optimization approach for determining the best mix of energy sources and the distribution of energy to various loads. A linear programming technique may be used to maximize the usage of grid and solar energy while minimizing energy costs and CO2 emissions. The goal function seeks to reduce the cost of energy and CO2 emissions, while the constraints represent the system's physical and operational restrictions. The program may solve the optimization problem and offer optimal operating points that reduce costs and CO2 emissions while keeping the energy system within restrictions. This method may be used to solve a wide range of energy management issues in residential, commercial, and industrial settings.

Abstract modeling is the process of representing a complex real-world system or problem in a simplified form using mathematical or computational models. These models typically involve equations, rules, or algorithms that capture the essential characteristics of the system being modeled. The advantages of abstract modeling include its ability to make complex systems more manageable, identify patterns and dependencies, and test hypotheses or strategies without having to implement them in the real world. Abstract modeling is used in fields such as physics, engineering, economics, and biology, and includes techniques such as mathematical models, computer simulations, and econometric models.

The objective function represents the goal that the model is trying to achieve, such as minimizing the cost of energy production. The objective function is typically formulated as an algebraic expression that combines various inputs and outputs of the model.

Figure - 1: *The Algebraic Formula of Operating Costs*

COSTS

TOTAL DISCOUNTED COSTS

$\forall_{y,t,r}$ TotalDiscountedCost$_{y,t,r}$	=	DiscountedOperatingCost$_{y,t,r}$+DiscountedCapitalInvestment$_{y,t,r}$ + DiscountedTechnologyEmissionsPenalty$_{y,t,r}$- DiscountedSalvageValue$_{y,t,r}$	(TDC1)

OPERATING COSTS

$\forall_{y,l,t,r}$ VariableOperatingCost$_{y,l,t,r}$	=	$\sum_m$ RateOfActivity$_{y,l,t,m,r}$***VariableCost**$_{y,t,m,r}$	(OC1)
$\forall_{y,t,r}$ AnnualVariableOperatingCost$_{y,t,r}$	=	$\sum_l$ VariableOperatingCost$_{y,l,t,r}$	(OC2)
$\forall_{y,t,r}$ AnnualFixedOperatingCost$_{y,t,r}$	=	TotalCapacityAnnual$_{y,t,r}$***FixedCost**$_{y,t,r}$	(OC3)
$\forall_{y,t,r}$ OperatingCost$_{y,t,r}$	=	AnnualFixedOperatingCost$_{y,t,r}$ + AnnualVariableOperatingCost$_{y,t,r}$	(OC4)
$\forall_{y,t,r}$ DiscountedOperatingCost$_{y,t,r}$	=	OperatingCost$_{y,t,r}$/((1+**DiscountRate**$_{t,r}$)^(y-**StartYear**+0.5))	(OC5)

The operating cost function in OSeMOSYS typically includes several cost components, such as capital costs, fixed costs, variable costs, and maintenance costs. These costs are combined in an algebraic equation that represents the total operating cost for each component of the energy system.

The capital cost function in OSeMOSYStypically includes several cost components, such as equipment costs, installation costs, and financing costs. These costs are combined in an algebraic equation that represents the total capital cost for each component of the energy system.

Figure - 2: *The Algebraic Formulation of Capital Costs*

CAPITAL COSTS

$\forall_{y,t,r}$ CapitalInvestment$_{y,t,r}$	=	**CapitalCost**$_{y,t,r}$ * NewCapacity$_{y,t,r}$	(CC1)
$\forall_{y,t,r}$ DiscountedCapitalInvestment$_{y,t,r}$	=	CapitalInvestment$_{y,t,r}$/((1+**DiscountRate**$_{t,r}$)^(y-**StartYear**))	(CC2)

In OSeMOSYS, energy balance constraints ensure that the total energy produced by the system is equal to the total energy consumed, plus any changes in the energy stored within the system. This is expressed as a set of linear equations that track the flow of energy through different components of the energy system.

Figure - 3: *The Algebraic Formulation of Energy Balance*

ENERGY BALANCE

ENERGY BALANCE "A"

$\forall_{y,l,f,t,m,r}$ RateOfActivity$_{y,l,t,m,r}$***OutputActivityRatio**$_{y,f,t,m,r}$	= RateOfProductionByTechnologyByMode$_{y,l,t,m,f,r}$
$\forall_{y,l,f,t,r}$ RateOfProductionByTechnology$_{y,l,t,f,r}$	= $\sum_m$ RateOfProductionByTechnologyByMode$_{y,l,t,m,f,r}$
$\forall_{y,l,f,r}$ RateOfProduction[y,l,f,r]	= $\sum_t$ RateOfProductionByTechnology$_{y,l,t,f,r}$
$\forall_{y,l,f,t,m,r}$ RateOfUseByTechnologyByMode$_{y,l,t,m,f,r}$	= RateOfActivity$_{y,l,t,m,r}$***InputActivityRatio**$_{y,f,t,m,r}$
$\forall_{y,l,f,t,r}$ RateOfUseByTechnology$_{y,l,t,f,r}$	= $\sum_m$ RateOfUseByTechnologyByMode$_{y,l,t,m,f,r}$
$\forall_{y,l,f,r}$ RateOfUse$_{y,l,f,r}$	= $\sum_t$ RateOfUseByTechnology$_{y,l,t,f,r}$
$\forall_{y,l,f,r}$ Production$_{y,l,f,r}$	= RateOfProduction$_{y,l,f,r}$***YearSplit**$_{y,l}$
$\forall_{y,l,f,r}$ Use$_{y,l,f,r}$	= RateOfUse$_{y,l,f,r}$***YearSplit**$_{y,l}$
$\forall_{y,l,f,r}$ Demand$_{y,l,f,r}$	= RateOfDemand$_{y,l,f,r}$***YearSplit**$_{y,l}$
$\forall_{y,l,f,r}$ Production$_{y,l,f,r}$	≥ Demand$_{y,l,f,r}$ + Use$_{y,l,f,r}$

In OSeMOSYS, emission accounting constraints ensure that the model considers

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the environmental impacts of the energy system, specifically the emissions of greenhouse gasses and other pollutants. These constraints set limits on the amount of emissions that can be produced by different sectors and technologies within the energy system, in order to meet environmental targets such as emissions reduction goals.

Figure - 4: *The Algebraic Formulation of Emission Accounting*


EMISSIONS ACCOUNTING

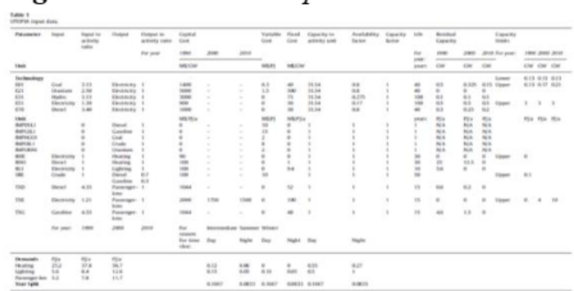
∀ AnnualTechnologyEmissionByMode	= ∑ **EmissionActivityRatio** * AverageAnnualTechnologyActivityByMode	(E1)
∀ AnnualTechnologyEmission	= ∑ AnnualTechnologyEmissionByMode	(E2)
∀ AnnualTechnologyEmissionPenaltyByEmission	= AnnualTechnologyEmission * **EmissionsPenalty**	(E3)
∀ AnnualTechnologyEmissionsPenalty	= ∑ AnnualTechnologyEmissionPenaltyByEmission	(E4)
∀ AnnualEmissions	= ∑ AnnualTechnologyEmission + **AnnualExogenousEmission**	(E5)
∀ ModelPeriodEmissions	= ∑ AnnualEmissions + **ModelPeriodExogenousEmission**	(E6)
∀ AnnualEmissions	≤ **AnnualEmissionLimit**	(E7)
∀ ModelPeriodEmissions	≤ **ModelPeriodEmissionLimit**	(E8)

We utilize our approach to optimize the allocation of these renewable energy sources to meet the growing demand while minimizing costs and emissions. We make necessary changes and additions to the code to enable running the model in Jupyter Lab or Colab and print the results. The results show that our approach is effective in identifying the optimal combination of renewable energy sources, resulting in a reduction in both costs and emissions compared to a business-as-usual scenario.

Our findings suggest that our approach can be applied to other regions and countries to identify the optimal combination of renewable energy sources to meet their energy demands. The proposed approach can help policymakers and energy planners make informed decisions towards a more sustainable and cost-effective energy system.

In the UTOPIA application, a single region is represented as having three demands: lighting, heating, and transport. The lighting and heating demand fluctuate: more lighting is required at night and more heating is required in winter. Lighting is met by the stock of light bulbs (RL1); heating by either electrical (RHE) or oil heaters (RHO); and transport by three different types of vehicles: electric (TXE), diesel (TXD) or gasoline (TXG). To generate electricity, five different power stations are available: coal (E01), nuclear (E21), hydro (E31), pumped storage (E51) and diesel (E70). Diesel and gasoline are imported (IMPDSL1 and IMP SL1, respectively) and/or produced by a refinery (SRE) that converts imported crude oil (IMPOIL1). Used only for electricity generation, uranium and coal are also imported (via technologies IMPURN1 and IMPHCO1, respectively).

Figure - 5: *UTOPIA Input Data*



4. Implementation

The OSeMOSYS model is implemented using the PYOMO library, which is an open-source Python package for modeling optimization problems. PYOMO provides a high-level, object-oriented interface for formulating mathematical optimization problems, including linear programming problems, and it supports a wide range of solvers for solving these problems.

One of the solvers that can be used with PYOMO to solve the OSeMOSYS model is Gurobi, which is a commercial optimization solver that is widely used in industry and academia. Gurobi is known for its speed and performance in solving linear programming problems and other types of optimization problems. To solve the OSeMOSYS model using PYOMO and Gurobi, the user would need to write a Python script that formulates the optimization problem using the PYOMO interface and specifies the input data and optimization constraints. The script would then call the Gurobi solver to

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solve the problem and generate the optimal solution.

The use of PYOMO and Gurobi provides a flexible and powerful platform for implementing and solving the OSeMOSYS model, allowing for customization and optimization of the model to fit specific contexts and requirements.

Figure - 6: *Corresponding solution values for UTOPIA*

Year	Rate of Production	Annual Technology Emission	Rate of Demand	Annual Tech emission CO2	Annual vari OC
1990	31.13036437	5.2	41.33465	1.249639616	28.08178913
1991	32.68688259	5.46	43.40139	1.30383309	29.29962
1992	34.24340081	5.72	45.46812	1.38170809	31.04962
1993	35.79991903	5.98	47.53485	1.435901525	32.26745
1994	37.35643724	6.24	49.60158	1.513776525	34.01745
1995	38.91295546	6.5	51.66832	1.591651525	35.76745
1996	40.46947368	6.76	53.73505	1.64584496	36.98528
1997	42.0259919	7.02	55.80178	1.72371996	38.73528
1998	43.58251012	7.28	57.86851	1.80159496	40.48528
1999	45.13902834	7.54	59.93525	1.87946996	42.23528
2000	41.88592989	7.8	62.00198	2.635942789	59.23466941
2001	38.07671048	8.189	65.10208	3.578684371	80.41987351
2002	34.12463396	8.578	68.20218	4.613330024	103.6703376
2003	30.31541455	8.967	71.30228	5.627116302	126.4520517
2004	26.36333803	9.356	74.40238	6.661761955	149.7025158
2005	22.55411862	9.745	77.50248	7.675548233	172.48423
2006	18.6020421	10.134	80.60257	8.710193886	195.7346941
2007	14.79282269	10.523	83.70267	9.723980163	218.5164082
2008	10.912	10.912	86.80277	10.75409761	241.6651149
2009	11.301	11.301	89.90287	11.56351075	259.8541743
2010	11.69	11.69	93.00297	12.36314858	277.8235637

Figure - 7: *Annual Technology Emissions by mode vs Annual Variable Operating cost*

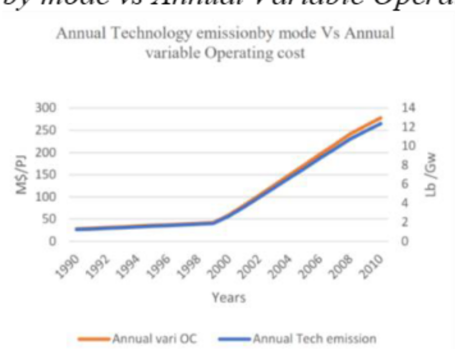
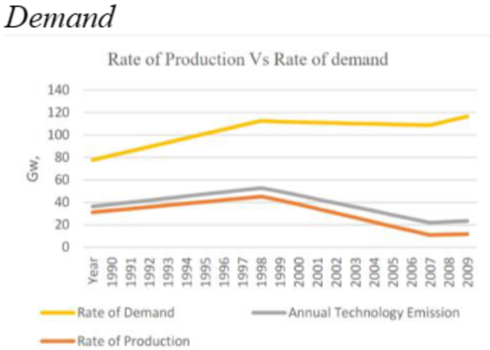


Figure - 8: *Rate of Production vs Rate of Demand*



5. Energy Demand Prediction

Energy demand prediction is an essential tool for energy companies, policymakers, and consumers. It helps in planning and decision-making processes related to the energy sector, such as investment in infrastructure, energy pricing, and development of new energy sources. Predicting energy demand is a challenging task, as it is influenced by various factors, such as economic growth, population, weather conditions, and technological advancements.

Energy demand prediction can help energy companies to ensure a reliable supply of energy to their customers and avoid overproduction or underproduction of energy, which can lead to increased costs. It also helps policymakers in developing energy policies and regulations that promote sustainable and affordable energy production and consumption.

Consumers can benefit from energy demand prediction as it can help them in making informed decisions regarding energy usage, such as reducing energy consumption during peak hours or using energy-efficient appliances. Moreover, energy demand prediction can help in promoting energy conservation and reducing carbon emissions.

Monte Carlo simulation and Markov chain can be used to predict energy demand by generating multiple possible outcomes based on statistical models and probabilistic analysis. Monte Carlo simulation involves creating a large number of simulated scenarios, each with its own set of possible outcomes. In the case of energy demand prediction, Monte Carlo simulation can be used to create simulations of possible future energy consumption rates based on historical data, estimated growth rates, and other factors that can affect energy demand. By generating a large number of simulations, it is possible to obtain a range

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of possible outcomes and to estimate the likelihood of each scenario.

Markov chains, on the other hand, are mathematical models that can be used to predict the probability of a certain event occurring, based on the probability of the previous event. In the case of energy demand prediction, Markov chains can be used to model the probability of future energy consumption rates based on past trends and other factors. By using Markov chains, it is possible to estimate the likelihood of certain future energy demand scenarios and to make informed decisions based on these estimates.

Overall, Monte Carlo simulation and Markov chain can be powerful tools for predicting energy demand by providing estimates of likely future outcomes based on statistical models and probabilistic analysis.

Once the predicted energy consumption is calculated, the code saves the output to an Excel file with the years, primary energy consumption in TWh, and growth rate shown as a percentage. It also plots the predicted energy consumption over time, with years on the x-axis, primary energy consumption on the y-axis, and the growth rate shown as a secondary y-axis.

6. Results

Figure - 9: *Energy prediction for 15 years*

	Year	Primary energy consumption (TWh)	Growth Rate
0	1965	14439.701000	NaN
1	1966	15247.363000	5.593343
2	1967	15778.539000	3.483724
3	1968	16719.385000	5.962821
4	1969	17583.424000	5.167887
...	...	...	...
67	2032	28956.416140	1.042764
68	2033	29250.948354	1.093013
69	2034	29569.939785	1.075875
70	2035	29866.691054	1.107043
71	2036	30176.558932	1.098975

72 rows × 3 columns

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