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ORIGINAL PAPER

Multiobjective evolutionary algorithm for long-term planning of the national energy and transportation systems

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Abstract The transportation and electric sectors are by far the largest producers of greenhouse emissions in the United States while they consume a significant amount of the national energy. The ever rising demand for these systems, the growing public concern on issues like global warming or national security, along with emerging technologies that promise great synergies between both (plug-in hybrid vehicles or electrified rail), creates the necessity for a new framework for long-term planning. This paper presents a comprehensive methodology to investigate long-term investment portfolios of these two infrastructures and their interdependencies. Its multiobjective nature, based on the NSGA-II evolutionary algorithm, assures the discovery of the Pareto front of solutions in terms of cost, sustainability and resiliency. The optimization is driven by a cost-minimization network flow program which is modified in order to explore the solution space. The modular design enables the use of metrics to evaluate sustainability and resiliency and better characterize the objectives that the systems must meet. An index is presented to robustly meet long-term emission reduction goals. An example of a high level representation of the continental United States through 2050 is presented and analyzed using the present methodology.

Keywords Energy · Transportation · Long-term investment · Multiobjective optimization · Evolutionary programming

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1 Introduction

Most US energy usage is for electricity production and vehicle transportation, two interdependent infrastructures. The strength and number of the interdependencies will increase rapidly as hybrid electric transportation systems, including plug-in hybrid electric vehicles and hybrid electric trains, become more prominent. There are several new energy supply technologies reaching maturity, accelerated by public concern over global warming. The US Energy Information Administration [27] suggests that national expenditures on electric energy and transportation fuels over the next 20 years will exceed $14 trillion, four times the 2010 federal budget [30]. Additionally in 2008, electricity generation and transportation accounted for almost 60% of US greenhouse emissions [29]. Intentional and strategic energy system design at the national level will have very large economic and environmental impact.

The proposed work is motivated by a recognition that tools, knowledge, and perspective are lacking to design a national system integrating energy and transportation infrastructures while accounting for interdependencies between them, new energy supply technologies, sustainability, and resiliency. This vision is captured in Fig. 1, where the two systems are represented, along with their interactions.

This research is part of an ongoing project known as *The 21st Century National Energy and Transportation Infrastructures Balancing Sustainability, Costs, and Resiliency* or *NETSCORE-21*, funded by the US National Science Foundation. Our objective is to identify optimal infrastructure designs in terms of future power gen-

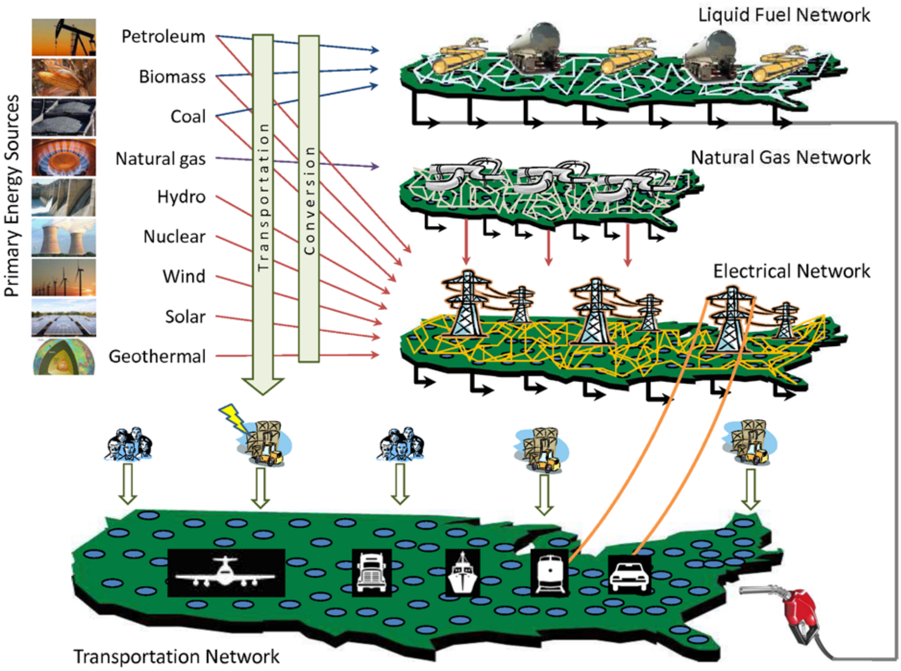


Fig. 1 Conceptual representation of the energy and transportation systems

eration technologies, energy transport and storage, and hybrid-electric transportation systems, with balance in sustainability, costs, and resiliency. Special attention is given to characterizing interdependencies between energy resource portfolio and energy/vehicular transportation systems at the national level.

2 Modeling approach

The energy system is comprised of (but not limited to) electricity, natural gas, liquid fuels, nuclear, biomass, hydroelectric, wind, solar, and geothermal resources. Modeling of national freight and passenger transportation focuses on state-to-state travel; we consider both infrastructures (rail, highways, locks/dams, roads, ports, airports) and fleets (trains, barges, trucks, personal vehicles, airplanes, etc.), and there may be different kinds of fleets for each mode (e.g., diesel trains and electric trains or conventional and plug-in hybrid electric).

Figure 2 captures the scope of the modeling effort. The transportation and energy systems interact mainly at two different stages: operation and investment. At the operational level each system needs to satisfy its demand with the existing capacity. However, operation of the two systems, and ultimately investment, are interdependent; while the transportation sector demands energy in the form of fuel, the energy sector requires the movement of raw bulk energy sources (e.g. coal or natural gas for thermal power plants). At the same time, the cost of meeting those reciprocal demands has an impact on final prices for energy and transportation. The ever-growing public need for energy and transportation creates the necessity to invest in new capacity. Given the potential for increased coupling between energy and transportation, it is apparent that better designs of both can be achieved if these designs are performed together.

Our modeling approach consists of two levels. The lower level performs a cost minimization on a 40 year infrastructure investment plan, constrained by lower and upper limits on technology investments, and evaluates resiliency and sustainability metrics. The higher level uses an evolutionary program to perform a multiobjective

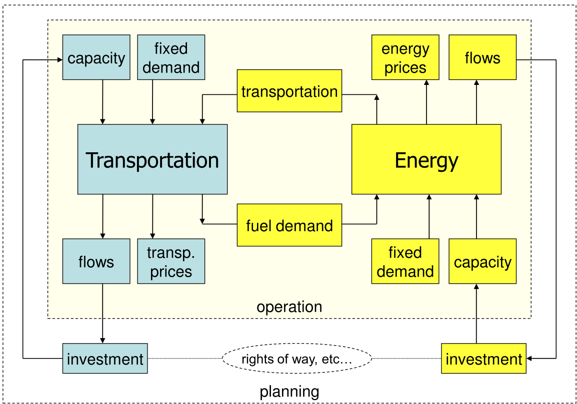


Fig. 2 Proposed model that integrates the energy and transportation systems at two levels: operation and planning

search for the Pareto optimal front [5, 6] in the space of cost, resiliency, and sustainability metrics, by manipulating the technology investment lower and upper limits. The remainder of this section, together with Sect. 3, is devoted to describing the lower level. The higher level is described in Sect. 5.

2.1 Energy systems modeling

A generalized network flow transportation model [11, 16, 17] is used to model energy systems, where commodity flow is energy, and transportation paths are AC and DC electric transmission, gas pipelines (for natural gas and/or hydrogen), and liquid fuel pipelines (for petroleum-based fuels, biofuels such as ethanol or biodiesel, and anhydrous ammonia). Energy transport by rail, barge, and truck is included in the freight transport model.

Each source node, specified with location, is connected to a fictitious source node that supplies all energy. Arcs emanating from each source are characterized by maximum extraction rate and extraction cost. Petroleum, coal, natural gas, and uranium have finite capacities, while renewables have infinite capacities. All sources have finite maximum extraction rates. Conversion and transportation are endowed with: capacity, efficiency, operational cost, investment cost, lifetime, component sustainability metrics (e.g., CO_2), and component resiliency (e.g., reliability).

2.2 Transportation systems modeling

The freight transport system is modeled as a multicommodity flow network where the flows are in the units of tons of each major commodity. A commodity is major if its transportation requirements comprise at least 2% of the nation's total freight ton-miles. Data available to make this determination [22] indicates this criterion includes 23 commodities that comprise 90% of total ton-miles (e.g., the top eight, comprising 55%, are in descending order: coal, cereal grains, foodstuffs, gasoline and aviation fuel, chemicals, gravel, wood products, and base metals).

There are two fundamental differences between this formulation and that of the energy formulation. Whereas the energy formulation must restrict energy flows of specific forms to particular networks (for example, natural gas or hydrogen cannot move through electric lines or liquid fuel lines), commodities may be transported over any of the transport modes (rail, barge, truck). Also whereas energy movement requires only infrastructure (electric lines, liquid fuel pipelines, gas pipelines), commodity movement requires infrastructure (rail, locks/dams, roads, ports) and fleet (trains, barges, trucks), and there may be different kinds of fleets for each mode (e.g., diesel trains or electric trains).

To accommodate these differences, the transportation formulation is comprised of two multicommodity flows [2], one embedded inside the other. Commodities flow through the network formed by the different types of fleet available. At the same time, the units in those fleets travel along the network formed by the different infrastructures. An easy way to visualize this is captured in Fig. 3, where the flow from node A to node B is divided according to the types of infrastructures first and then into the different types of available fleets.

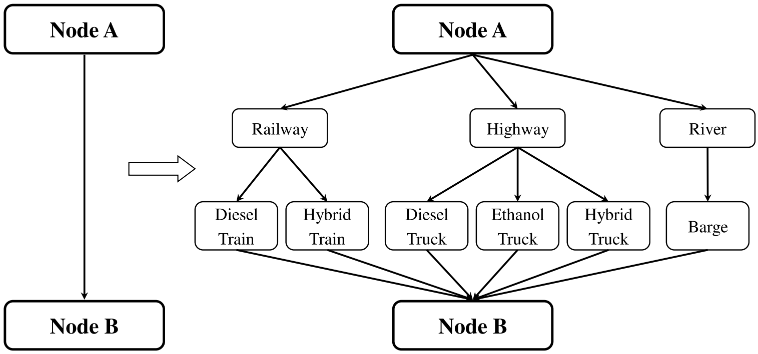


Fig. 3 Decomposition of transportation arc in two steps: infrastructure and fleet

2.3 Review of other planning tools

There is a wide range of modeling tools that are used to study the energy and transportation systems, both together and independently. An extensive description of the issues related to modeling and more information on methodology classification can be found in [3] and [14].

There are only a few planning tools that expand beyond one sector and are most closely related to the scope of this work. The most prominent cases are the National Energy Modeling System (NEMS) [25] and the MARKAL/TIMES suite [8]. NEMS is an equilibrium model (it only evaluates proposed portfolios) which represents the petroleum, natural gas, coal, and electric supply and transport/transmission sectors together with energy/economy macroeconomic interactions and international energy activity. MARKAL/TIMES, an optimization model, represents resources associated with the petroleum, natural gas, coal, and electric sectors but not the transport/transmission associated with these sectors. In addition, whereas NEMS iterates to equilibrium through sequential solutions of each sector, MARKAL/TIMES minimizes total cost in a single optimization and allows the usage of stochastic programming to address uncertainty.

There are two interesting tools developed by National Renewable Energy Laboratory, the Regional Energy Deployment System (ReEDS) [21] and the Stochastic Energy Deployment System (SEDS) [20]. ReEDS is a multiregional, multiperiod linear programming model of capacity expansion in the electric sector of the United States. The model performs capacity expansion but with detailed treatment of the full potential of conventional and renewable electricity generating technologies as well as electricity storage. The principal issues addressed include access to and cost of transmission, access to and quality of renewable resources, the variability of wind and solar power, and the influence of variability on the reliability of the grid. On the other hand, SEDS focuses on a more global approach, similar to that in NEMS, considering multiple energy sectors and the inclusion of light and heavy duty vehicles. REDS is designed to be more flexible and easier to use than NEMS and, like it name suggests, is also able to represent risk and uncertainty through stochastic programming.

3 General cost minimization formulation

The optimization problem associated with this model can be conceptually described by (1),

$$\begin{aligned}
&\mathbf{min}\ \mathit{CostOp} + \mathit{CostInv}\\
&\mathbf{subject\ to:}\\
&\text{Meet energy demand,}\\
&\text{Meet transportation demand,}\\
&\text{Capacity constraints,}\\
&\text{Power flow constraints on electric transmission.}
\end{aligned} \tag{1}$$

The objective is to minimize the combined energy and a transportation cost with constraints of meeting demands on energy, and freight transport while following the capacity constraints. The operational characteristics of the model provide additional constraints on the system, such as the inclusion of power flow relations for electric transmission lines (we used the so-called "DC" power flow approximation for this purpose).

This section contains a rigorous description of the formulation needed to achieve the characteristics described above. The explanation of the formulation is preceded by an introduction to the nomenclature used.

3.1 Nomenclature

3.1.1 Decision variables

$e_{(i,j)}(t)$: Operational flow of energy arc from node i to node, j, for time step t (MWh)
$eInv_{(i,j)}(t)$: Capacity investment on energy arc from node i to node j, for time step t (MW)
$f_{(i,j,k,m)}(t)$: Operational flow of transportation arc from node i to node j for commodity k using transportation mode m during time step t (ton)
$fleetInv_{(i,j,m)}(t)$: Fleet m capacity investment for transportation arc from node i to node j during time step t (ton/hour)
$infInv_{(i,j,l)}(t)$: Infrastructure l capacity investment for transportation arc from node i to node j for time step t (ton/hour)
$\theta_i(t)$: Phase angle at node i, used to model DC power flow (radians).

3.1.2 Sets and networks

$\mathcal{N}^E$: Set of energy nodes
$\mathcal{A}^E$: Set of energy arcs

$\mathcal{A}^E_{DC} \subset \mathcal{A}^E$: Set of AC electric transmission arcs, which satisfy DC power flow equations
$\mathcal{N}^T$: Set of transportation nodes
$\mathcal{A}^T$: Set of transportation arcs
$\mathcal{A}^T_j \subset \mathcal{A}^T$: Subset of transportation arcs that create an energy demand at energy node j
$\mathcal{K}$: Set of commodities
$\mathcal{K}_c \subset \mathcal{K}$: Subset of commodities used by the energy system, e.g. coal
$\mathcal{M}$: Set of fleet or transportation modes
$\mathcal{M}_l \subset \mathcal{M}$: Subset of fleet that can use transportation infrastructure l
$\mathcal{M}_j \subset \mathcal{M}$: Subset of fleet that require energy from energy node j
$n^E_{(i,k)} \in \mathcal{N}^E$: Energy node that corresponds to the geographic location i and commodity k in the transportation system.

3.1.3 Energy parameters

$\eta_{(i,j)}(t)$: Efficiency of arc (i, j) during time t (unitless)
$lbe_{(i,j)}(t)$: Lower bound for flow in arc (i, j) for time t (MWh)
$ube_{(i,j)}(t)$: Upper bound for flow in arc (i, j) during time t due to the initial existing infrastructure (MW)
$lbeInv_{(i,j)}(t)$: Minimum allowed capacity increase in arc (i, j) at time t (MW)
$ubeInv_{(i,j)}(t)$: Maximum allowed capacity increase in arc arc (i, j) at time t (MW)
$costOp_{(i,j)}(t)$: Operational cost for flow in arc (i, j) during time t (\$/MWh)
$costInv_{(i,j)}(t)$: Investment cost for capacity increase in arc (i, j) in network l, at time t (\$/MW)
$heatContent_k(t)$: Heat content of commodity k, at time t (MWh/ton)
$d^E_j(t)$: Fixed energy demand at node j during time t (MWh)
$b_{(i,j)}$: Susceptance of transmission line between nodes i and j (Ω^{-1}).

3.1.4 Transportation parameters

$ubFleet_{(i,j,m)}(t)$: Upper bound for total transportation flow for fleet m in arc (i, j) during time t due to the initial existing fleet (ton/h)
$lbFleetInv_{(i,j,m)}(t)$: Minimum allowed capacity increase in arc (i, j) for fleet m at time t (ton/h)
$ubFleetInv_{(i,j,m)}(t)$: Maximum allowed capacity increase in arc arc (i, j) for fleet m at time t (ton/h)
$ubInf_{(i,j,l)}(t)$: Upper bound for total transportation flow across infrastructure l in arc (i, j) during time t due to the initial existing infrastructure (ton)
$lbInfInv_{(i,j,l)}(t)$: Minimum allowed capacity increase in arc (i, j) for transportation infrastructure l at time t (ton/h)
$ubInfInv_{(i,j,l)}(t)$: Maximum allowed capacity increase in arc arc (i, j) for transportation infrastructure l at time t (ton/h)
$costOp_{(i,j,k,m)}(t)$: Operational cost for transportation flow in arc (i, j) in fleet m, commodity k and time t (\$/ton)

$costFleetInv_{(i,j,m)}(t)$: Investment cost for capacity increase in fleet m for arc (i, j) and time t (\$ h/ton)
$costInfInv_{(i,j,l)}(t)$: Investment cost for capacity increase in transportation infrastructure l for arc (i, j) and time t (\$ h/ton)
$fuelCons_{(i,j,m)}(t)$: Fuel consumption for transportation mode m for transportation arc (i, j) during time step t (MWh/ton)
$d^T_{(i,j,k)}(t)$: Fixed transportation demand of commodity k for arc (i, j) during time t (ton).

3.1.5 Auxiliary parameters

These parameters are calculated as a combination of decision variables and predetermined parameters.

$costOp^E$: Operational cost from the energy system (\$)
$costInv^E$: Cost due to the investment upgrades on the energy system (\$)
$costOp^T$: Operational cost for transportation system (\$)
$costFleetInv^T$: Investment cost on transportation fleet (\$)
$costInfInv^T$: Cost on transportation infrastructure (\$)
$d^{ET}_j(t)$: Energy demand at node j during time t due to the transportation of commodities (MWh).

3.1.6 Other parameters

r: Discount rate
Δt: Length of time step t (h).

3.2 General formulation

The following formulation (2) incorporates the modeling capabilities that have been previously described in this paper.

$$\mathbf{min}\ \{costOp^E + costInv^E + costOp^T + costFleetInv^T + costInfInv^T\} \tag{2a}$$

subject to:

Meet energy demand at every node

$$\sum_k \eta_{(j,k)}(t)e_{(j,k)}(t) - \sum_i e_{(i,j)}(t) = d^E_j(t) + d^{ET}_j(t) \tag{2b}$$

Energy flow lower and upper bounds

$$lbe_{(i,j)}(t) \leq e_{(i,j)}(t) \leq ube_{(i,j)}(t)\,\Delta t + \sum_{z=0}^{t} eInv_{(i,j)}(z)\,\Delta z \tag{2c}$$

DC power flow equations

$$e_{(i,j)}(t) = b_{(i,j)}\Big(\theta_i(t) - \theta_j(t)\Big), \quad \forall (i,j) \in \mathcal{A}^E_{DC} \tag{2d}$$

Transportation demand for non-energy commodities

$$\sum_m f_{(i,j,k,m)}(t) = d^T_{(i,j,k)}(t), \quad k \in \mathcal{K} \backslash \mathcal{K}_c \tag{2e}$$

Transportation demand for energy commodities

$$\sum_m f_{(i,j,k,m)}(t) = heatContent_k^{-1}(t)\, e_{(n^E_{(i,k)}, n^E_{(j,k)})}(t), \quad k \in \mathcal{K}_c \tag{2f}$$

Fleet upper bound for transportation flows

$$\sum_k f_{(i,j,k,m)}(t) \leq ubFleet_{(i,j,m)}(t)\, \Delta t + \sum_{z=0}^{t} fleetInv_{(i,j,m)}(z)\, \Delta z \tag{2g}$$

Infrastructure upper bound for transporatation flows

$$\sum_k \sum_{m \in \mathcal{M}_l} f_{(i,j,k,m)}(t) \leq ubInf_{(i,j,l)}(t) + \sum_{z=0}^{t} infInv_{(i,j,l)}(z)\, \Delta z \tag{2h}$$

where:

$$costOp^E = \sum_t \sum_{(i,j)} (1+r)^{-t} costOp^E_{(i,j)}(t)\, e_{(i,j)}(t) \tag{2i}$$

$$costInv^E = \sum_t \sum_{(i,j)} (1+r)^{-t} costInv^E_{(i,j)}(t)\, eInv_{(i,j)}(t) \tag{2j}$$

$$costOp^T = \sum_t \sum_{(i,j,k,m)} (1+r)^{-t} costOp^T_{(i,j,k,m)}(t)\, f_{(i,j,k,m)}(t) \tag{2k}$$

$$costFleetInv^T = \sum_t \sum_{(i,j,m)} (1+r)^{-t} costFleetInv_{(i,j,m)}(t) fleetInv_{(i,j,m)}(t) \tag{2l}$$

$$costInfInv^T = \sum_t \sum_{(i,j,l)} (1+r)^{-t} costInfInv_{(i,j,l)}(t)\, infInv_{(i,j,l)}(t) \tag{2m}$$

Energy demand from the transportation system

$$d^{ET}_j(t) = \sum_{(a,b) \in \mathcal{A}^T_j} \sum_{m \in \mathcal{M}_j} fuelCons_{(a,b,m)}(t) \sum_k f_{(a,b,k,m)}(t) \tag{2n}$$

Decision variables:

Energy flows: $\quad e_{(i,j)}(t) \geq 0$ (2o)

Energy capacity inv.: $\quad lbeInv_{(i,j)}(t) \leq eInv_{(i,j)}(t) \leq ubeInv_{(i,j)}(t)$ (2p)

$$\text{Transportation flows:} \quad f_{(i,j,k,m)} \geq 0 \tag{2q}$$

$$\text{Fleet inv.:} \quad \mathit{lbFleetInv}_{(i,j,m)}(t) \leq \mathit{fleetInv}_{(i,j,m)}(t) \leq \mathit{ubFleetInv}_{(i,j,m)}(t) \tag{2r}$$

$$\text{Infrastucture inv.:} \quad \mathit{lbInfInv}_{(i,j,l)}(t) \leq \mathit{infInv}_{(i,j,l)}(t) \leq \mathit{ubInfInv}_{(i,j,l)}(t) \tag{2s}$$

$$\text{Phase angles:} \quad -\pi \leq \theta_i(t) \leq \pi. \tag{2t}$$

The energy sector is represented by a set of nodes $\mathcal{N}^E$ and arcs $\mathcal{A}^E$. Each node represents an energy subnetwork in a geographic location. For example, for a particular location, there might be three energy nodes; one for electricity, one for gas, and one for petroleum. Energy arcs link these various nodes, both within same subnetwork (representing transmission lines, natural gas pipelines, or petroleum pipelines) or different, where conversion takes place (e.g., power plants).

The flow across these arcs, $e_{(i,j)}$, are part of the decision variables of the problem. These flows must be such that they satisfy the demand for energy (2b), part of which is due to the energy required to perform the movement of commodities in the transportation system (2n). Energy flows are also required to meet lower and upper bound constraints (2c). The upper bound is determined by the capacity of the existing energy infrastructure and is a combination of the initial capacity, $\mathit{ube}_{(i,j)}(t)$, and investment on upgrades, $\mathit{eInv}_{(i,j)}(t)$. The first is a parameter while the second is another decision variable, with its corresponding lower and upper bound (2p). Energy flow must also satisfy other constraints, such as DC power flow equations for electric transmission (2d).

The transportation system is also formed by a set of nodes $\mathcal{N}^T$ and a set of arcs $\mathcal{A}^T$, although the nomenclature is slightly different. Here, each node represents a unique geographic location, while the transportation flows are referred to as $f_{(i,j,k,m)}$, where (i, j) represent the origin and destination nodes, k the commodity that is being transported and m the mode of transportation used.

These flows must satisfy the transportation demand, which is predetermined (2e) for all commodities except for those that are energy related (e.g., coal, uranium). In that case, the transportation demand depends on the use of that commodity in the energy system (2f). Transportation flows are limited by the capacity of the available fleet (2g) and transportation infrastructure(2h). Both can be increased by the their respective investments, $\mathit{fleetInv}_{(i,j,m)}(t)$ and $\mathit{infInv}_{(i,j,m)}(t)$, which have upper and lower bound constraints (2r, 2s).

3.3 Compact notation

A more compact version of (2) can be produced using vectorial and matrix notation. First of all, the vector **capInv** includes all capacity investment variables, while the operational variables are grouped in vectors called $\mathbf{flows}_t$. The subscript t in this section represents the operational year to which a variable belongs. When using this notation we can reduce the model to the expressions (3).

$$\textbf{min}\ \left[\mathbf{CostInv}^{\top}\ \mathbf{CostOp}_1^{\top}\ \mathbf{CostOp}_2^{\top}\ \ldots\right]\begin{bmatrix}\mathbf{capInv}\\ \mathbf{flows}_1\\ \mathbf{flows}_2\\ \vdots\end{bmatrix}$$

$$\textbf{subject to:}$$

$$\begin{bmatrix}-\mathbf{I} & \mathbf{0} & \mathbf{0} & \ldots\\ \mathbf{I} & \mathbf{0} & \mathbf{0} & \ldots\\ \mathbf{0} & \mathbf{A}_1 & \mathbf{0} & \ldots\\ \mathbf{0} & -\mathbf{I} & \mathbf{0} & \ldots\\ \mathbf{L}_1 & \mathbf{I} & \mathbf{0} & \ldots\\ \mathbf{0} & \mathbf{0} & \mathbf{A}_2 & \ldots\\ \mathbf{0} & \mathbf{0} & -\mathbf{I} & \ldots\\ \mathbf{L}_2 & \mathbf{0} & \mathbf{I} & \ldots\\ \vdots & \vdots & \vdots & \ddots\end{bmatrix}\begin{bmatrix}\mathbf{capInv}\\ \mathbf{flows}_1\\ \mathbf{flows}_2\\ \vdots\end{bmatrix}\leq\begin{bmatrix}-\mathbf{lbInv}\\ \mathbf{ubInv}\\ \mathbf{d}_1\\ -\mathbf{lb}_1\\ \mathbf{ub}_1\\ \mathbf{d}_2\\ -\mathbf{lb}_2\\ \mathbf{ub}_2\\ \vdots\end{bmatrix} \tag{3}$$

The objective value is (2a), which is developed in expressions (2i–2m). The first two rows in the constraints are directly related to the minimum and maximum investment allowed (2p, 2r, 2s).

Following that there are three rows that are repeated for each year. The first two correspond to operational constraints, such as demand balances (2b, 2e, 2f) or DC power flow constraints (2d). Such expressions are summarized in the matrix $\mathbf{A}_t$ and the vector $\mathbf{d}_t$. The next two lines correspond to the minimum and maximum operational flows from (2c, 2g, 2h). The matrix $\mathbf{L}_t$ accounts for the fact that only investments done prior to the operational year can account for available capacity.

Inspection of (3) reveals an underlying structure (4) that would allow the use of Benders decomposition methods [10]. This approach is not new to the field and it has been implemented, for instance, in EGEAS [4], a very extended investment software used in the electric industry. This special structure could be used to reduce the complexity of the linear problem [15] and to increase solution speeds, an issue we are currently studying.

$$\textbf{min}\ \left[\mathbf{CostInv}^{\top}\ \mathbf{CostOp}_1^{\top}\ \mathbf{CostOp}_2^{\top}\ \ldots\right]\begin{bmatrix}\mathbf{capInv}\\ \mathbf{flows}_1\\ \mathbf{flows}_2\\ \vdots\end{bmatrix}$$

$$\textbf{subject to:} \tag{4}$$

$$\begin{bmatrix}\mathbf{C}_0 & \mathbf{0} & \mathbf{0} & \ldots\\ \mathbf{C}_1 & \mathbf{D}_1 & \mathbf{0} & \ldots\\ \mathbf{C}_2 & \mathbf{0} & \mathbf{D}_2 & \ldots\\ \vdots & \vdots & \vdots & \ddots\end{bmatrix}\begin{bmatrix}\mathbf{capInv}\\ \mathbf{flows}_1\\ \mathbf{flows}_2\\ \vdots\end{bmatrix}\leq\begin{bmatrix}\mathbf{b}_0\\ \mathbf{b}_1\\ \mathbf{b}_2\\ \vdots\end{bmatrix}$$

4 Emission index for greenhouse emissions

The previous sections, a modular methodology to optimize future investment portfolios in terms of cost, resiliency and sustainability is presented. We can use this multiobjective approach to find solutions which minimize both costs and greenhouse gas emissions, while maximizing resiliency. Other studies [9, 13, 19] rely on the evaluation of social costs associated with these emissions as well as trying to capture the time value of carbon.

We have developed an index that compares solutions to projected trends. Let us define a pessimistic scenario in which nothing is done to palliate greenhouse gas emissions and an optimistic case in which an aggressive reduction is accomplished. Other emission forecasts can be compared to those references with the following metric (5).

$$I_{GHG} = \frac{1}{n-k} \sum_{t=k}^{n} \frac{ActualEm(t) - LowEm(t)}{HighEm(t) - LowEm(t)} \tag{5}$$

where k and n are the first and last year considered for the index, *ActualEm* is the emission forecast, and *HighEm* and *LowEm* are the yearly emissions for the pessimistic and optimistic cases, respectively. Because of lead times for new infrastructures, the first k years are not considered in the calculation of the index.

In Fig. 4 we can see a representation of this approach. The top continuous line represents the pessimistic scenario, with emissions increasing at the same rate as electric demand. The bottom line represents the optimistic case, with reductions in greenhouse emissions every year comparable to proposed bills in the US House and Senate [18]. In between those lines we can see how the index takes different fractional values. The index is not limited to values between 0 and 1 because emissions could go beyond the reference cases.

5 Multiobjective optimizer

NETPLAN, an energy and transportation investment multiobjective evolutionary algorithm is proposed as an approach to efficiently solve the problem described above and produce an approximation to the Pareto front. It has been conceived in a modular fashion, to allow the independent development of each one of its components. Figure 5 introduces the block diagram behind the organization of the different parts that form the multiobjective optimization.

The popular NSGA-II algorithm [7] is used in the search and selection stage, while the evaluation of the different candidates is based on the minimum cost formulation described in Sect. 3 and resiliency and sustainability metrics, such as the one in Sect. 4.

The process is carried out through the following steps:

1. The NSGA-II algorithm proposes a number of candidates to the multiobjective optimization problem. Each one of these candidates is characterized by a vector

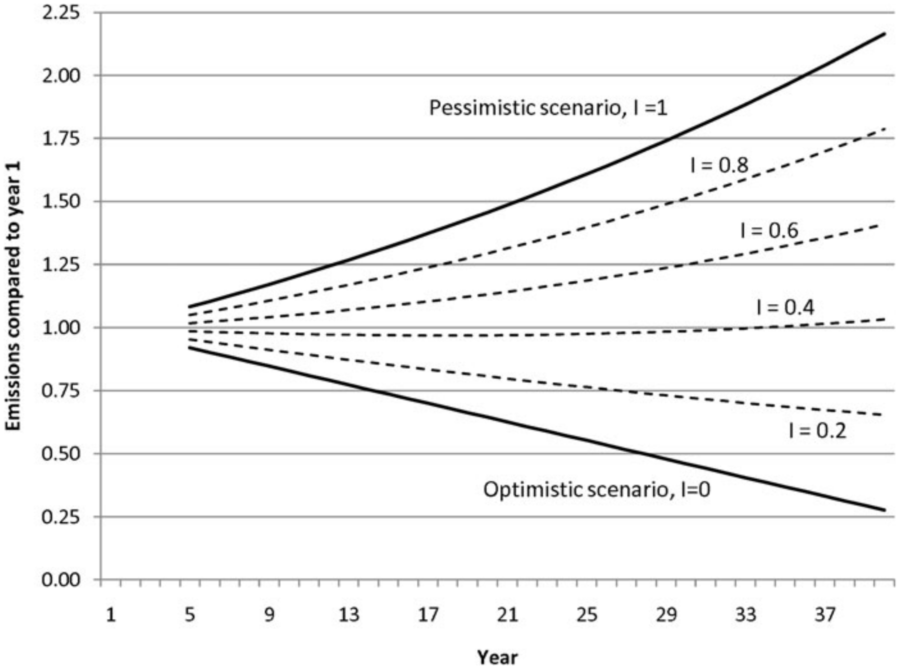
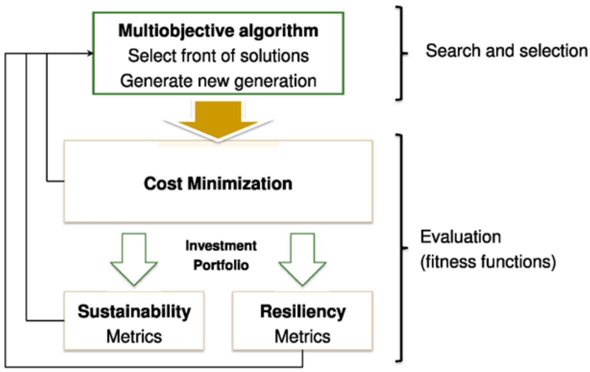


Fig. 4 Greenhouse emission index for best, worst scenarios and fractions in between

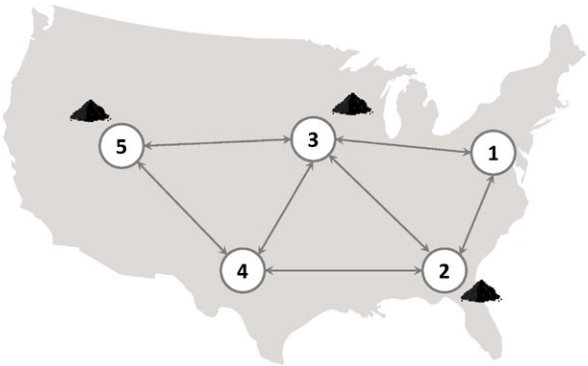
Fig. 5 NETPLAN multiobjective approach



of minimum investments. So, for instance, we could have a vector with high investments in wind energy and low investments on pulverized coal plants.

2. For each of the candidate, the minimum investments are coded into constraints and they become the lower bound for **capInv** in (4).
3. The minimum cost optimization (with the minimum investments enforced) is performed. As a result, the investment portfolio and operational flows for the candidate solution are found, as well as the operational and investment costs.
4. Metrics for sustainability are calculated, based on the minimum cost solution. In this paper, the emission index in Sect. 4 is used.

Fig. 6 Nodal representation of the Continental United States



5. Resiliency calculations are performed. In this case, the average reserve margin for each electrical region is considered as a measure of the strength of the system.
6. For each candidate solution the objective values for cost, sustainability and resiliency have been found. These values are returned to the NSGA-II algorithm, which will take them into account in the creation of subsequent generations. The algorithm is returned until the maximum number of iterations is reached.

In the current implementation, the use of minimum investment vectors facilitates shifting from the minimum cost solutions to others with better performance in terms of sustainability or resiliency. This approach is very simple to implement but, if needed, could be complemented with other methods such as subsidies for clean alternatives, taxes for polluting technologies (e.g., carbon tax) or preventing certain technologies to be used in favor of others. Similarly, the metrics for sustainability and resiliency metrics are linear combinations of the arc flows and investments. More computationally demanding metrics could include, for example, the simulation of large-scale failures in the energy and transportation systems [12].

6 Numerical example

6.1 Example description

A small numerical example is presented in this section and uses the methodologies presented in this paper. The continental US is divided into 5 regions as shown in Fig. 6. Data for this example was obtained from [1, 23, 24, 26, 28].

We assume that the electricity demand for each region is known with an annual growth forecast of 2%. Initially, the demand is satisfied by the existing pulverized coal (PC) installed capacity. Data can be found in Table 1.

The increasing demand and the continuous retirement of PC plants along the 40 years of the simulation creates the need to invest in new generation. Four technologies are considered: pulverized coal, integrated gasification combined cycle (IGCC), wind and solar. Table 2 summarizes the characteristics of these technologies. The efficiency of wind and solar generation is considered to vary geographically as shown in Table 3. Each year, up to 4 GW of each technology is allowed to be invested in each region.

Table 1 Electricity demand by region

Region	Avg. demand (GW)	Peak demand (GW)	Initial PC capacity (GW)
1	148	230.9	318.8
2	159	248.0	342.5
3	25.8	40.23	55.6
4	68.7	107.1	147.9
5	87.6	136.7	188.8

Table 2 Generation technology data

Technology	PC	IGCC	Wind	Solar
Life span (years)	40	30	20	25
Operational cost ($/MWh)	2.95	2.84	0	0
Investment cost (million $/GW)	4262.2	3725.9	2176.2	7603.7
Operation CO_2 (lb CO_2e/MMBtu)	206	206	0	0
Investment CO_2 (lb CO_2e/MMBtu)	2.33	0.79	14.9	32.1
Heat rate (MMBtu/MWh)	9.2	8.8	–	–
Capacity factor	1	1	0.2	0.15

Table 3 Wind and solar efficiency by region

Region	1	2	3	4	5
Wind	0.3	0.3	0.35	0.35	0.31
Solar	0.11	0.18	0.12	0.17	0.2

The arcs shown in Fig. 6 represent electrical transmission lines between the different regions. Each arc has a maximum capacity of 15 GW, which remains constant throughout the simulation. Regions are also interconnected by rail, which allows coal to be transported. Transportation is not constrained in this example, but we account for energy consumption (341 Btu/ton mile), diesel cost (20.6 $/Btu) and CO_2 emissions (0.2 lb CO_2e/ton-mile).

Coal is produced is regions 2, 3, and 5 (Appalachia, Illinois basin, and Western regions, respectively). The coal from each region is treated as a separate commodity and their characteristics are summarized in Table 4.

All costs are subject to a 2% annual inflation rate and a 7% discount rate. Salvage values are assigned for the investments close to the end of the simulation period. The objective functions used are operational and investment cost, the greenhouse emission index presented before and the average reserve margin at electrical nodes. This

Table 4 Coal production parameters

Region	2	3	5
Annual Capacity (million short tons)	534	125	651
Avg. price ($/short ton)	30.2	22.7	10
Avg. heat value (MMBtu/ton)	25.03	22.73	17.45

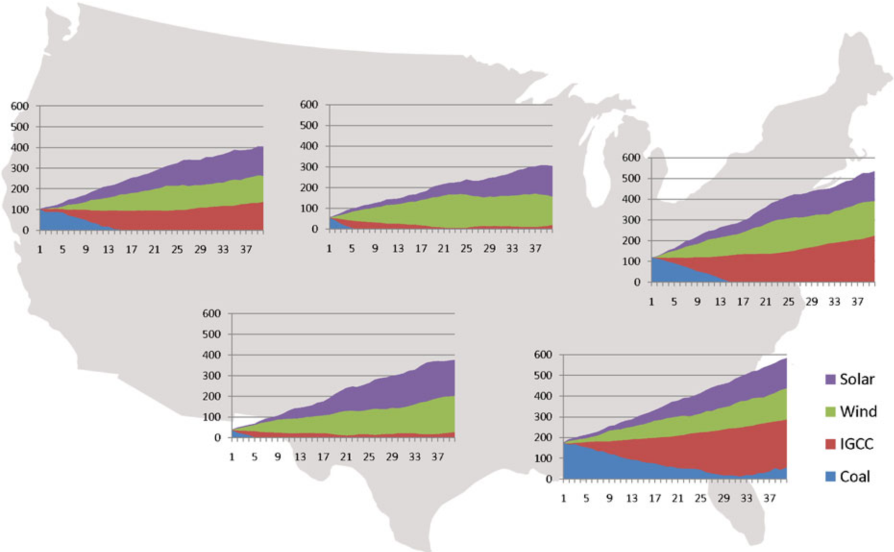


Fig. 7 Average electricity generation for least cost solution by type and region over simulation time

margin is defined as the difference between the available generation capacity at an electrical node (weighted by the capacity factor) minus the peak demand, divided by the peak demand. For the greenhouse gas index the pessimistic scenario is defined as a geometrical 2% annual growth (equal to the demand growth) and the best scenario as a constant 3% annual reduction.

6.2 Results

The multiobjective algorithm is executed for 200 generation with 20 individuals each. Each cost minimization program has 9020 variables and 6360 constraints and its solved in 0.12 seconds using version 10 of CPLEX, running on 3.6 GHz Pentium 4 processor with 2 GB of RAM.

Cost estimates for the Pareto front range from 4.9 to 6.2 trillion dollars, which is a low estimate compared to the 14 trillion dollars over 20 years projected by DOE-EIA [27]. This difference is mainly due to the simplicity of the example in terms of granularity as well as the lack of more expensive generation technologies such as gas turbines.

Figure 7 represents the average electricity generation by source for the best case scenario. We notice that even in this case renewables take an important role, espe-

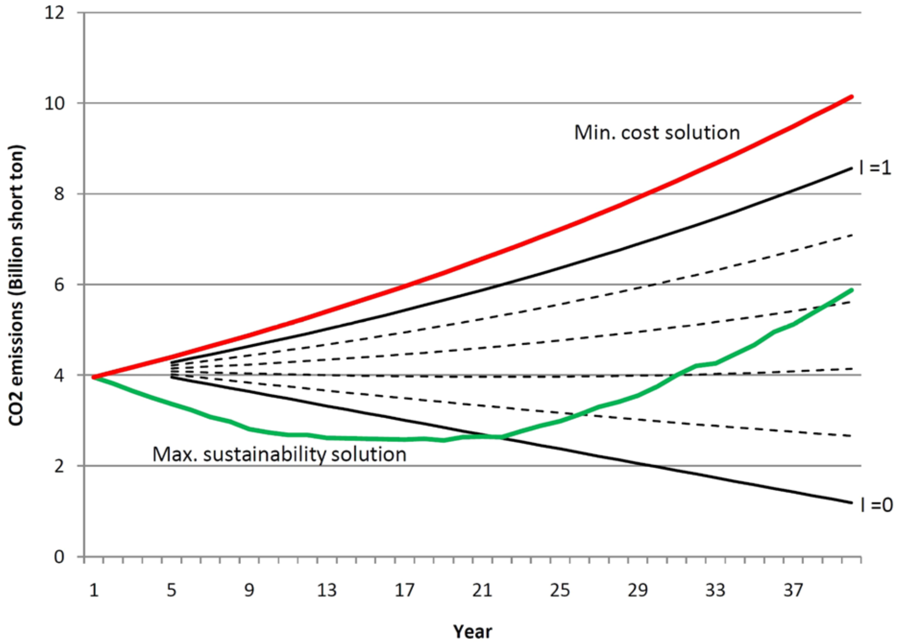


Fig. 8 (Color online) Comparison of actual best (*low*, *green*) and worst (*top*, *red*) emission index to reference

cially in areas where their efficiency is best. Also, it is not surprising to find that IGCC becomes almost the only coal-fired generation, since its higher efficiency than pulverized coal reduces its overall cost and emissions.

In Fig. 8 the most sustainable solution is compared to the absolute best cost solution in terms of annual greenhouse emissions. The most sustainable solution returns an average index of 0.15, due mostly to a very aggressive reduction of emissions in the first half of the simulation, well below the reference low case. This trend is not continued in the second half of the simulation due to the fact that renewables have a shorter life time (20 and 25 years) and coal based generation comes into play in the final stages. The lowest cost solution relies heavily on carbon-based generation and presents an emission index of 1.23, which is above the pessimistic reference case. This is due to the fact that apart from the operational emissions that grow proportional to the load, we are also considering the emissions associated with the construction of new infrastructure.

Finally, all the candidate solutions tested by the multiobjective optimizer are plotted in Fig. 9. The final Pareto Front of solutions identified by the NSGA-II algorithm are represented with red stars.

7 Conclusions

A new multiobjective approach to analyze long-term investment portfolios for the national energy and transportation systems has been presented. It features a modular

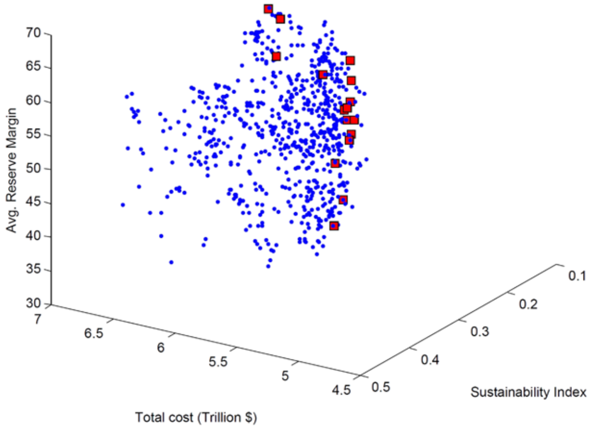


Fig. 9 (Color online) 3D representation of candidate solutions (*blue dots*) and Pareto front solutions (*red squares*)

design with a fast linear program model for cost minimization and sustainability and resiliency metrics. We have also presented a new metric that accounts for time value of green-house emissions and compares trends over time.

Finally, a small numerical example has been developed and tested using the approach presented in this paper. Although this example utilizes a highly aggregated model of the United States, the approach may be applied using significantly more granular models by increasing the number of regions, energy networks, means of transportation and time steps used.

The NETPLAN tool performs long-term, multi-sector, multiobjective investment planning at the national level. This tool uniquely addresses a serious need today in that it provides a basis for setting long-term policy associated with supplying economic energy and transportation services while reducing greenhouse gas emissions and maintaining a resilient system.

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