Resilience and robustness in long-term planning of the national energy and transportation system

Eduardo Ibanez

National Renewable Energy Laboratory
16253 Denver West Pkwy., Golden, CO, 80401-3305, USA
E-mail: eduardo.ibanez@nrel.gov

Steven Lavrenz, Konstantina Gkritza

School of Civil Engineering
Purdue University, West Lafayette, IN 47907
E-mail: slavrenz@purdue.edu
E-mail: nadia@purdue.edu

Diego Mejía

Department of Electrical Engineering
Universidad de Antioquia, Medellín, Colombia
E-mail: diegomej@udea.edu.co

Diego Mejía, Venkat Krishnan, James McCalley, Arun K. Somani

Department of Electrical and Computer Engineering
Iowa State University, Ames, IA 50011, USA
E-mail: vkrish@iastate.edu
E-mail: jdm@iastate.edu
E-mail: arun@iastate.edu

Abstract: The most significant energy consuming infrastructures and the greatest contributors to greenhouse gases for any developed nation today are electric and freight/passenger transportation systems. Technological alternatives for producing, transporting, and converting energy for electric and transportation systems are numerous. Addressing costs, sustainability, and resilience of electric and transportation needs requires long-term assessment since these capital-intensive infrastructures take years to build with lifetimes approaching a century. Yet, the advent of electrically driven transportation, including cars, trucks, and trains, creates potential interdependencies between the two infrastructures that may be both problematic and beneficial. We are developing modeling capability to perform long-term electric and transportation infrastructure design at a national level, accounting for their interdependencies. The approach combines network flow modeling with a multiobjective solution method. We describe and compare it to the state of the art in energy planning models. An example is presented to illustrate important features of this new approach.

Keywords: Energy; infrastructure; investment planning; optimization; resilience; transportation.

Bibliographical notes:

Eduardo Ibanez received the Diploma in Industrial Engineering from Universidad Pública de Navarra, Pamplona, Spain in 2007. In 2011 he received the Ph.D. degree in Electrical Engineering and M.S. degree in Statistics from Iowa State University, Ames, Iowa. He is currently employed as an engineer in the Transmission and Grid Integration Group at the National Renewable Energy Laboratory (NREL). His research interests include power systems and transmission planning, high-level penetrations of renewables, and integration of energy and transportation systems.

Steven Lavrenz received a Bachelor of Science degree and a Master of Science degree in Civil Engineering from Iowa State University in 2010 and 2011, respectively. Currently he is a PhD student in the School of Civil Engineering at Purdue University. His research interests are transportation operations, infrastructure management, and econometric modelling of transportation data.

Konstantina Gkritza received the Diploma in Civil Engineering from the National Technical University of Athens, Athens, Greece, in 2001; the M.S. degree in Civil Engineering from the Virginia Polytechnic Institute and State University, Falls Church, in 2003; and the Ph.D. degree from Purdue University, West Lafayette, IN, in 2006. She is currently an Associate Professor of Civil Engineering at Purdue University, West Lafayette. Her research interests lie in the application of economic concepts and statistical methods to problems and decisions in the transportation field.

Diego A. Mejia-Giraldo received an Electrical Engineering degree and a Master of Science from Universidad Tecnológica de Pereira, Pereira, Colombia in 2004 and 2005 respectively; and the PhD degree in Electrical Engineering at Iowa State University. Currently, he is an auxiliary Professor of Electrical Engineering at Universidad de Antioquia, Medellin, Colombia. His research interests are power system planning as well as decision-making models under uncertainty.

Venkat Krishnan received the B.E. degree from the College of Engineering Guindy, Anna University, Chennai, India, in 2005 and the M.S. and Ph.D. degrees from Iowa State University, Ames, in 2007 and 2010, respectively. He is currently a post-doctoral research associate in the Department of Electrical and Computer Engineering at Iowa State University.

James D. McCalley received the B.S., M.S., and Ph.D. degrees in electrical engineering from Georgia Institute of Technology, Atlanta, in 1982, 1986, and 1992, respectively. He was employed with Pacific Gas & Electric Company, San Francisco, CA, from 1985 to 1990 as a Transmission Planning Engineer. He is Harpole Professor of Electrical and Computer Engineering at Iowa State University, Ames, where he has been employed since 1992. He is a registered professional engineer in California and an IEEE Fellow.

Arun Somani is serving as Anson Marston Distinguished Professor of Electrical and Computer Engineering at Iowa State University. His research interests are in the areas of design and implementation of dependable and high-performance computing and networking systems, critical infrastructure protection, and system performance analysis. He is a Fellow of IEEE, a Fellow of AAAS, and Distinguished Engineer Member of ACM.

1 Introduction

MOST United States (U.S.) energy usage is for electricity production and vehicle transportation, two interdependent infrastructures. The strength and number of these 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 U.S. Departments of Energy's Energy Information Agency (EIA, 2008) suggests that national expenditures on electric energy and transportation fuels over the next 20 years will exceed $14 trillion, six times the 2008 federal budget (USG, 2009). Intentional and strategic energy system design at the national level will have very large economic 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 resilience. Our goal is to identify optimal infrastructure designs in terms of future power generation technologies, energy transport and storage, and hybrid-electric transportation systems, with balance in sustainability, costs, and resilience. In recent years, many decisions in the transportation and energy systems have been mainly driven by other factors, other than resilience, such as short term economics, or political positions. Traditionally, before the deregulation of these sectors, individual players would strongly consider resilience and robustness within their portfolios. For instance, electrical utilities would diversify their assets by considering a mix of power generation fuels or different manufactures of equipment.

Our electric systems today depend heavily on rail transportation to move coal to power plants. With this exception, assuming petroleum production, refining, and transportation to be a part of the transportation infrastructure, then energy systems and transportation systems can rightly be considered as independent systems today, and this feature is unlikely to significantly change in the near term. However, consideration of long-term (40 years or more) infrastructure needs that achieve aggressive reduction in anthropogenic CO_2 emissions must consider increased dependence between these two systems, because electrification of passenger travel via plug-in light-duty vehicles and via high-speed rail, coupled with increased presence of non-CO_2 emitting electric resources, represents an attractive development plan.

The notion of resilience is present in many disciplines, but there is no universal consensus on its exact definition. In this paper, we provide the groundwork to formally define and analyze resilience in long-term energy and transportation planning. The remainder of the paper is organized as follows: Section 2 provides a survey of resilience and similar concepts across several disciplines; Section 3 presents the basis for our definition of resilience; Section 4 introduces NETPLAN, a new tool that implements the concepts described in this paper, and a description of the operation and investment of the energy and transportation systems, respectively; Section 5 presents a numerical example; Section 6 provides some additional discussion of events to be considered in the United States; and, finally, Section 7 concludes.

2 Common Resilience Definitions

The concept of resilience is ubiquitous and can be found in the literature of many technical and non-technical fields. However, there is no consensus on its definition. In this section, we present definitions used within various disciplines.

In computer network systems, resilience is defined as “the ability to provide and maintain an acceptable level of service in the face of faults and challenges to normal operation.” Common elements of resilience include the support of distributed processing and networked storage, as well as the ability to maintain service of communication technologies such as video conferencing, instant messaging, and other online collaboration. In a more general sense, resilience in computer systems can be thought of as the ability to access applications and data as needed (Sterbenz, 2006).

In the communications industry, resilience is defined as the assurance that “the interoperability of communications systems is not affected by known or unknown circumstances of change.” It is further defined as the ability to evolve and advance as new technologies and capabilities are developed. Alternatively, resilience can be considered “a reflection of the flexibility of the system to respond to changes in operational requirement, or implementation strategies and technologies” (FCC, 2010).

Within the nuclear power industry, resilience is defined as “the ability of an organization (system) to maintain, or recover quickly to, a stable state, allowing it to continue operations during and after a major mishap or in the presence of continuous stress.” Common elements of a resilient nuclear power system include continuous feedback and monitoring of critical systems, as well as a consistent plan of communications and syntax to minimize human error (de Carvalho, 2006).

One definition of resilience frequently used in the process control industry is the ability of a system to return to its original (or desired) state after being disturbed. In this conceptualization, risk management is viewed as a central component to resilience. Ultimately, the goal of a resilient system in process control is to minimize output variability across all possible scenarios (Christopher, 2004).

Within the aerospace industry, the general definition of resilience is very similar to that used in other areas of engineering – resilience is the ability to change when a force is enacted, as well as the ability to perform adequately or optimally while the force is in effect. Resilience is also characterized by the return to a predefined normal state when the force relents or is rendered ineffective (Castet, 2008).

There are fields beyond engineering that make extensive use of resilience metrics and definitions within the scope of their societal roles. One such field is health care. Resilience-related terminology includes buffer capacity, flexibility vs. stiffness, margin, tolerance, and cross-scale interactions. Buffer capacity is the size or kinds of disruptions the system can absorb or adapt to without a fundamental breakdown in performance or in the system’s structure. Flexibility vs. stiffness is the system’s ability to restructure itself in response to external changes or pressures. Margin is the system’s proximity, in terms of operating conditions, to a performance boundary. Tolerance is how a system behaves near a boundary – that is, whether the system gracefully degrades as stress increases or collapses quickly when stress exceeds adaptive capacity. Cross-scale interactions are system interactions and effects that occur when changes are made on a microscopic or macroscopic level within the system (Anders, 2006).

3 Resilience for Long-term planning

In this section we provide a definition of resilience appropriate for long-term investment planning. This definition depends on three terms: states, events, and consequences, which we describe first.

States

We consider the system *state*, loosely, as those attributes of a system that completely characterize it at a particular time kT ($k=1,2,\ldots$), where T is a duration of time for which the system is considered to be in a steady-state. Define *topology* as the physical infrastructure operable at that instant in time, including, for example, electric generators and circuits, natural gas wells and pipelines, railways and trains, and highways, trucks, and cars.

Further define *operating conditions* as the characterization of the way the physical infrastructure is used at that instant in time in terms of, for example, electric system loading and generation dispatch, natural gas supply and transport, and movement of commodities and passengers. Then we define *state* as a tuple consisting of specification of the topology and operating condition of the system.

Events

System resilience is assessed when one or more changes occur or are simulated in the system so that a response is observed. Thus, resilience is considered relative to a defined system change or set of changes. Such changes may occur to the topology, to the operating conditions, or to both. For purposes of modeling and simulation, we conceive of such changes in terms of a first cause or *source*, which is exogenous to our modeling framework, and an *impact*, which characterizes the effect that the source has on the model. We refer to the combination of a particular source and its impact as an *event*.

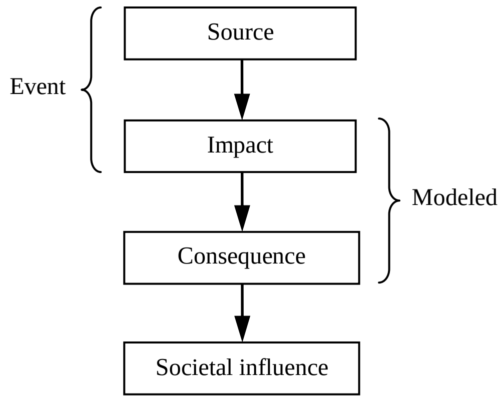
As an example, consider the effect of the 2005 Katrina/Rita hurricanes on the national energy system (Gil, 2011); the hurricanes are the source, and the loss of natural gas wells and pipelines together with loss of electric generation, transmission, and load in the gulf coast area comprise the impact.

Consequence and resilience

The kind of extreme events described above for which we believe to be appropriate for use in evaluating resilience cause observable performance deviation in our model; we call this performance deviation *consequence*.

Variation in consequence may in turn have observable influence on many other aspects of society, including prices of manufactured goods, job loss, and gross national product. We define these induced impacts, which we are not able to observe in our model, as *societal influences*. In Figure 1, we illustrate these definitions together with those associated with events. We are now in a position to define what we mean by resilience.

Figure 1 Relationship between events and consequences

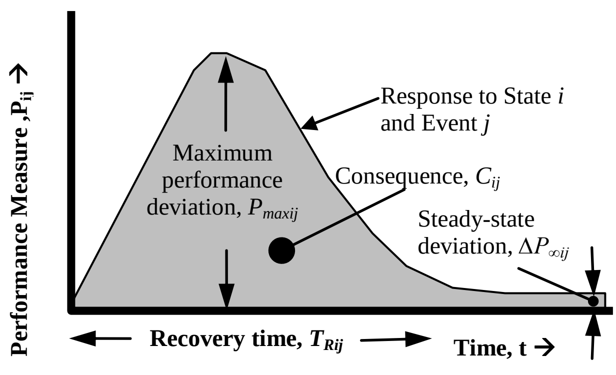


Resilience is the ability to minimize and recover from the *consequences* of an adverse *event*, whether natural or human-caused, for a given *state* of the system. Consequence is a measure of the system's resilience and the relationship between the two is inversely proportional. We assume that we can measure consequence in terms of system performance, as shown in Figure 2, where we observe that maximum performance deviation P_{maxij}, recovery time T_{Rij} (duration following event initiation for performance measure to reach a steady-state value), and steady-state deviation $\Delta P_{\infty ij}$ play important roles in the evaluation of consequence. Consider a set of events (E_1 ... E_I) and a set of states (S_1 ... S_J) that we deem relevant. Denote the performance measure as P and the consequence as C. Then, for event E_i occurring in state S_j, the consequence is given by (1) as illustrated in Figure 2.

$$C_{ij} = \int_0^\infty P_{ij}(t)\, dt \qquad (1)$$

A system becomes more resilient with respect to an event E_i occurring in state S_j as C_{ij} decreases.

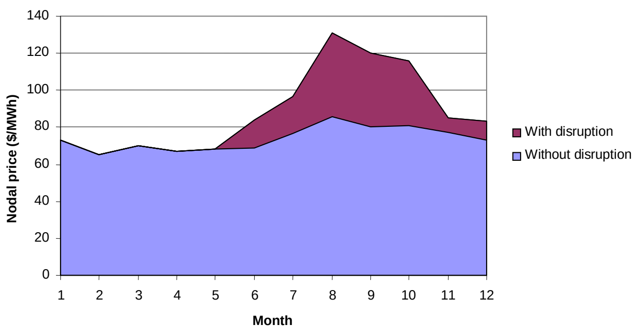
Figure 2 Resilience measure for an event and state



One quantitative performance measure for consequence in an energy system is expected unserved demand due to interruption. However, demand interruption is mainly a local and temporary phenomenon. We are interested in infrastructure design at the national level; failure at this level is rarely responsible for sustained demand interruption. Rather, this infrastructure supports production and transportation of bulk energy, on which the long-term stability of energy prices rely.

In Figure 3, we have illustrated by plotting the nodal price variation caused by a large-scale system disruption for a single node within the system. The resilience of this system corresponding to the location of the given node is characterized by the area between the nodal price variation with and without the disruption. The plot is from simulation which provides optimal operation of the energy (electric, natural gas, and coal) system. Therefore, the only effect influencing the nodal price is the system's ability to utilize its energy resources and corresponding infrastructure. Reference (Gil, 2011) uses this measure to assess resilience based on the effects of the 2005 Hurricanes Katrina and Rita.

Figure 3 Nodal price variation caused by a large-scale system disruption



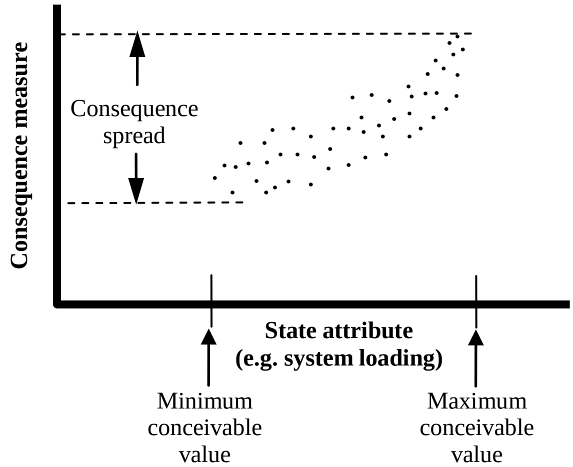
The next section introduces our modeling framework to analyze the long-term investment decisions for the energy and transportation systems. Said framework uses operational cost increase as a proxy of energy price increases in the systems. This increase will be used as a consequence measure to assess resilience in the remainder of the paper. Demand not served can also be incorporated in this framework by establishing a cost penalty for unit of demand curtailed. This cost becomes a cap for nodal prices under extreme conditions.

Robustness

A system is *robust* with respect to an event if it is resilient for that event under all defined states. The calculation of consequence under different states, as illustrated in Figure 4, yields a distribution from which one may extract an appropriate summary of the data (e.g. mean, median, spread, standard deviation). We interpret the consequence spread as a measure of robustness. We can extend this definition of robustness and consider it in terms of a measure characterizing performance variation of multiple events to one or more states.

One may feel it preferable to measure robustness with respect to a single threshold value of consequence beyond which we consider the performance unacceptable. However, we do not know what such a threshold value of consequence should be for the national energy/transportation system we are studying, as its robustness has not been assessed before. As we gain more experience in modeling and assessing this system, we will identify such acceptable performance levels. Until then, we view robustness as a reflection of the consequence spread, a measure that is meaningful in a relative sense, i.e., in terms of comparing one investment plan to another.

Figure 4 Resilience across states and measurement of consequence spread

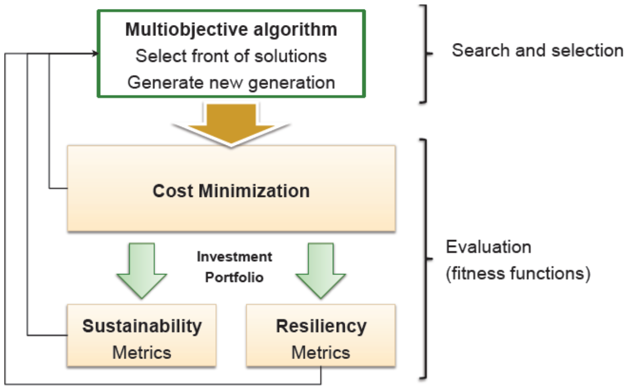


4 NETPLAN overview

NETPLAN is a new tool that we developed to optimize the planning of energy and transportation systems, including their investment and operation (Ibanez, 2011a). The optimization we propose is driven by multiple objectives, in order to identify a Pareto surface of optimal solutions. In multiobjective optimization, the Pareto surface is the collection of solutions that are nondominated. A solution is nondominated if there does not exist another solution whose objective values are better simultaneously. The study of that surface, the difference in suggested portfolios and the trade-offs that they generate are useful for policy design. The objectives are grouped in three distinctive categories: cost, sustainability and resilience.

Figure 5 contains the conceptual design of the multiobjective optimization solver, which is based on evolutionary techniques. The search and selection section consists of an implementation of the nondominated sorting genetic algorithm II (NSGA-II) (Deb, 2002). This algorithm was selected because its performance is well-understood, it is computationally efficient, and because it effectively preserves the breath of the solution space. Each individual of a generation is represented by a string of minimum investments to be made during the simulation span. That string is used to create lower bound constraints for the investment decision variables in the cost minimization engine (described in the next subsection). An investment portfolio is generated as an output, along with the cost and operational attributes of the system under normal conditions. These variables are fed into the sustainability and resilience evaluation blocks to compute the corresponding metrics. The process continues with the communication of the objective values to the search and selection algorithm in order to create the next generation of solutions.

Figure 5 NETPLAN multiobjective algorithm design



There are two components of the cost objective: operational and investment. The impact of the latter is often dominant given the amount of capital that it requires over a relative short period of time. However, given the long life of the facilities, the operational component has a large impact as well.

Sustainability is treated in terms of environmental impact and supply longevity. We capture four classes of environmental impacts related to energy and transportation systems: net emissions (NO_x, SO_x, CO_2, methane), nuclear waste, water consumption (thermal power plants, biofuel production), and resource displacement (e.g., land usage). We also characterize supply longevity for depletable resources: coal, natural gas, uranium.

The resilience of the system is evaluated using a methodology consistent with the definitions presented in this paper. We have implemented the ability of defining a set of events where each event is specified as loss of capacity on a desired set of arcs at a particular time t for a specified duration Δt. At time t, infrastructure investment is turned off, so that only operational decisions are optimized during the specified time interval Δt. A reference case is run with no capacity decrease at all. Resilience for each event is computed as the operational cost increase over the time interval Δt relative to the reference case. System resilience is computed as the average of the operational cost increases across all events.

The remainder of this section addresses the modeling of the energy and transportation systems within the cost minimization linear program in NETPLAN. A more detailed description can be found in Ibanez (2011a; 2011b).

The energy system

We consider the national energy system to be the group of networks that together satisfy the country's energy needs. This includes energy sources (e.g., coal mines, natural gas wells), storage (e.g., natural gas underground storage), conversion (e.g., power plants, petroleum refineries), energy transport (e.g., natural gas and oil pipelines, electric transmission) and consumption.

Mathematically, a generalized network flow transportation model (Quelhas, 2007) is used to model the energy system, 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 (MBTU/month) and extraction cost ($/MBTU/month). Petroleum, coal, natural gas, and uranium have finite capacities, while renewables have infinite capacities. All sources have finite maximum extraction rates. Conversion and transportation are endowed with: capacity (MBTU-capacity/month), efficiency (%), operational cost ($/MBTU-flow/month), investment cost ($/MBTU-capacity/month), component sustainability metrics (e.g., CO_2 tons/MBTU-flow), and component resilience (e.g., reliability).

The transportation system

The U.S. transportation network is a broad and diverse system comprised of hundreds of thousands of miles of roads, railroads, and waterways. This complex structure of movements is responsible for moving millions of passengers and tons of freight on a daily basis. The transportation system can be succinctly defined in terms of its five primary components: commodities, fleet, infrastructure, freight, and passengers.

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 (BTS, 1997) 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 the transportation formulation and that of the energy formulation. Whereas the energy problem 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).

Mathematical model overview

The mathematical formulation used to co-optimize investments in the energy and transportation systems is thoroughly described in Ibanez (2011a; 2011b). A brief overview is provided here, capturing the meaning of the main equations involved.

Figure 5 showes that at the multi-objective optimization relies on multiple cost minimization solutions. The optimization model is described in (2-8). The objective to be minimized is the sum of operational and investment costs (2) for the energy and transportation systems. The energy system must be able to meet its demand (3). Said demand comprises fixed demand (e.g., residential and industrial natural gas demand) and also energy demand derived from the transportation system (e.g., gasoline demand for traditional vehicles or electricity due to electric trains). Likewise, the transportation system must be able to meet its fixed demand (4) (e.g., cereal grains transported between two states) and the demand created by “energy commodities”, which are commodities whose final use depend on the energy system (e.g., coal).

Energy flows along the system are constrained by the maximum capacity (5) (e.g., generation fleet nameplate capacity or rated capacity for a transmission line). These capacities can be augmented, but doing so increases the investment costs in the energy system. The transportation flows on the other hand are assumed to be affected by two levels of capacity constraints (6,7). First, flows are constrained by available fleet (e.g., trains, trucks) and, second, by the available infrastructure (e.g., rail lines, highway capacity), which is used by the fleet to transport commodities. As it was the case with the energy network, the model may increase these capacities and takes into consideration investment costs.

Finally, there are additional constraints that are considered (8). Examples of these are DC power flow equations for electric transmission, and equations to ensure that the peak load in a given year can be covered with an specified capacity margin.

$$\textit{Minimize}\ \ (\textit{Op. Cost} + \textit{Inv. Cost})_{energy} + (\textit{Op. Cost} + \textit{Inv. Cost})_{transportation} \tag{2}$$

Subject to:

$$\textit{Meet energy demand} \tag{3}$$

$$\textit{Meet transportation demand} \tag{4}$$

$$\textit{Energy flows below maximum capacity} \tag{5}$$

$$\textit{Transportation flows below fleet capacity} \tag{6}$$

$$\textit{Transportation flows below infrastructure capacity} \tag{7}$$

$$\textit{Other operational constraints} \tag{8}$$

5 Numerical example

The following numerical example allows us to demonstrate some of the capabilities described in this paper. Although NETPLAN allows for a comprehensive representation of the energy and transportation systems, this example will focus around the U.S. However, the natural gas production and distribution network, and the railroad system, vital in the delivery of coal around the country, were represented.

The model includes different mix of generation technologies including traditional and renewable. Generation fuels include coal, natural gas, nuclear and oil, as well as renewable sources (hydro, wind, solar, and geothermal). The production and distribution of the first two by state is considered as part of the model, while the supply of other two is considered unlimited.

For coal production, prices (EIA, 2009a) and mine capacity (EIA, 2009b) by state are collected, as well as heat content and emissions (EIA, 2009c) for the different types of coal. Natural gas wells for each state are given their respective production capacity (EIA, 2009d) and price (EIA, 2009e). The interstate gas pipeline system is also represented (EIA, 2009f) along with the storage facilities (EIA, 2009g) that help regulate the flow throughout the year. Imports from Canada through the different points of entry (EIA, 2009h) and natural consumption for non-electric purposes (EIA, 2009i) are also included.

The electric system is represented using the 13 electric regions in the continental United States from the National Energy Modeling System (EIA, 2009j). Initial available capacities (EIA, 2010a) and power demand (EIA, 2010b) by region are available from different sources. Some of these sources include Canadian provinces, but these were dismissed for this example. A 2% growth rate in electrical demand is assumed for each region, while the retirement of existing capacity is projected using the actual years that each generation unit has been active. We consider a penalty cost of \$10 per kWh of electric energy not served.

A total of fourteen technologies are included from which the model selects to replace retirements and satisfy demand growth. These include pulverized coal, integrated gasification combined cycle (IGCC), inland wind, off-shore wind, solar photovoltaic, solar thermal, nuclear, oil, integrated pyrolysis combined cycle (IPCC), natural gas combined cycle (NGCC), combustion turbine (CT), geothermal, tidal, and oceanic thermal energy conversion (OTEC). Operation and investment costs of each technology have been obtained via an extensive literature search (Gifford, 2011). With the exception of tidal and off-shore wind, all the technologies are assumed to be available throughout the country. The capacity factors of wind and solar power varies geographically depending on the availability or suitability of resources.

Three objectives are considered during the optimization. The first two are total cost (investment and operational), and total CO_2 emissions for the 40 year simulation period. There were no costs or caps associated with CO_2. For the resilience objective, fourteen events were defined and each one consisted of the total failure of each generation technology at year $t = 25$, with duration $\Delta t = 1$ year. The consequence of each event was measured as the increase in operational cost in the system during said year. Table 1 provides the 20 Pareto optimal solutions from the NSGA-II algorithm after 93 generations.

Table 1 Pareto Optimal Solutions from NSGA-II

Sol. No	Cost (10^9 \$)	CO_2 (10^9 sh. ton)	Resilience (10^9 \$)	Sol. No	Cost (10^9 \$)	CO_2 (10^9 sh. ton)	Resilience (10^9 \$)
1	4366	53.2	336.56	11	5934	46.1	8.74
2	4379	52.7	319.95	12	5994	44.4	7.94
3	4427	52.5	362.82	13	6051	45.1	7.33
4	5105	50.7	13.37	14	6107	44.2	7.95
5	5126	51.2	13.25	15	6171	42.4	7.20
6	5180	50.2	13.68	16	6314	43.1	6.42
7	5243	50.5	12.71	17	6369	41.6	6.68
8	5369	49.1	11.63	18	6393	39.7	6.29
9	5560	48.4	10.78	19	6475	38.0	5.95
10	5629	47.9	9.86	20	6521	40.3	5.32

The comparison of the three objectives can be done through Figure 6, which includes all the possible combinations of objectives. The plots can be interpreted by noting that all the plots in the first column have cost in the horizontal axis. Likewise, all plots in the first row have cost in the vertical axis, and so on.

The series of two-dimensional plots helps us to gain valuable insight about the Pareto front in the multi-objective solution space. There is a significant negative correlation between cost and CO_2 emissions, which indicates that more sustainable solutions have a higher system cost. When considering resilience, there are three cases that show highly abnormal values with respect to the rest. The remaining solutions present a negative correlation with respect to cost. Thus, the system is more resilient with greater installed capacity, which causes cost to rise.

Figure 6 Pareto front of solutions

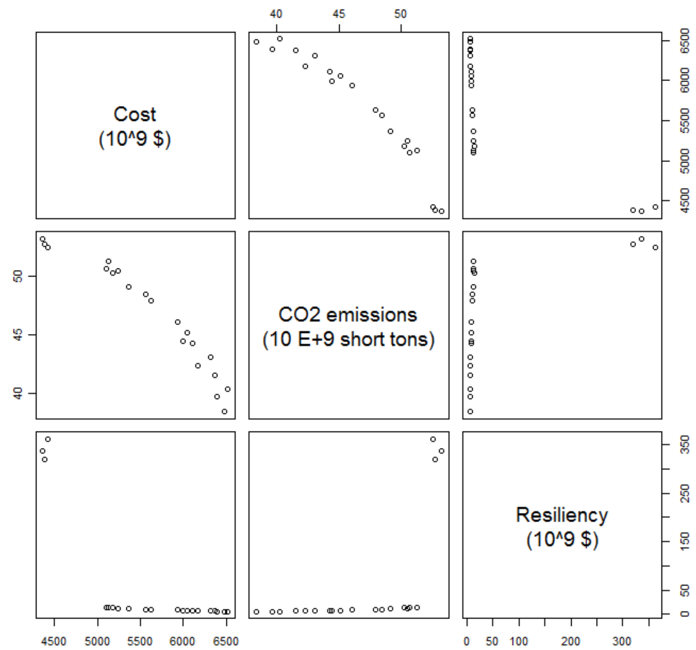


Figure 7 shows the resilience measures under all the 14 events considered (one per generation technology) for the solutions with best and worst overall resilience objectives and an intermediate value. These solutions correspond to solutions 20, 3, and 10 in Table 1, respectively. The resilience metric above is calculated as the average of the values shown in Figure 7. According to this figure the event corresponding to removing the entire nuclear fleet at year 25 causes the maximum impact, followed by the events corresponding to removal of geothermal and pulverized coal, respectively. Nuclear energy is a preferred investment when cost alone is being minimized, as shown in Figure 8 which shows capacity investments by technology. Thus, the loss of this type of generation in portfolios that are not very diversified creates load curtailment, which in turn results in the high consequence observed in the graph of Figure 7. This is true for all three cases with unusually high resilience consequence in Figure 6.

Figure 7 Resilience measure under various generation events for best, medium and worst resilient solutions

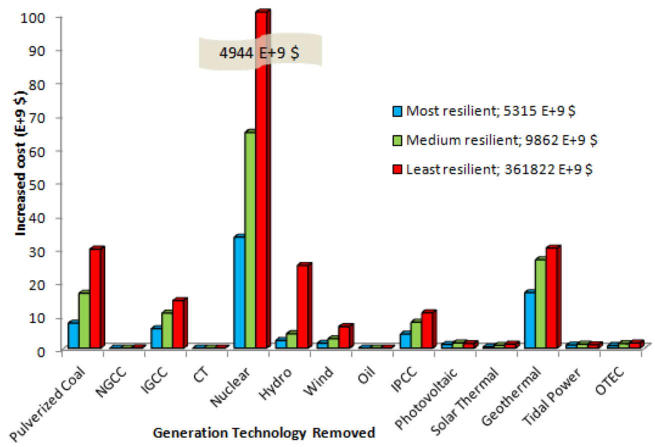


Figure 8 Investment in various generation technologies for most, medium and least resilient solutions

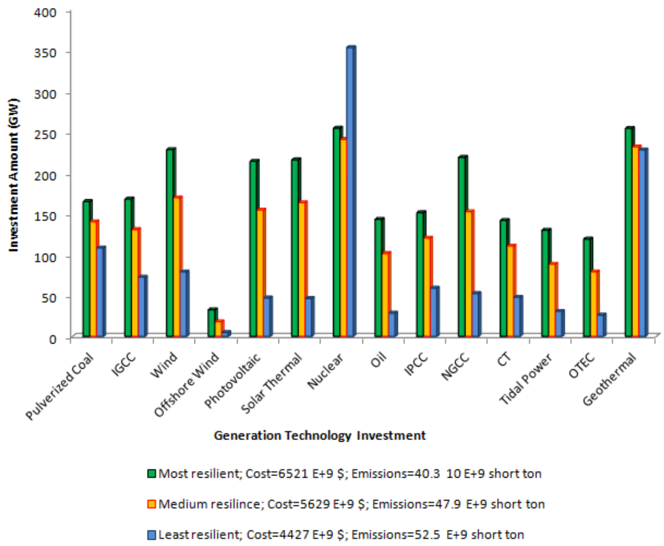
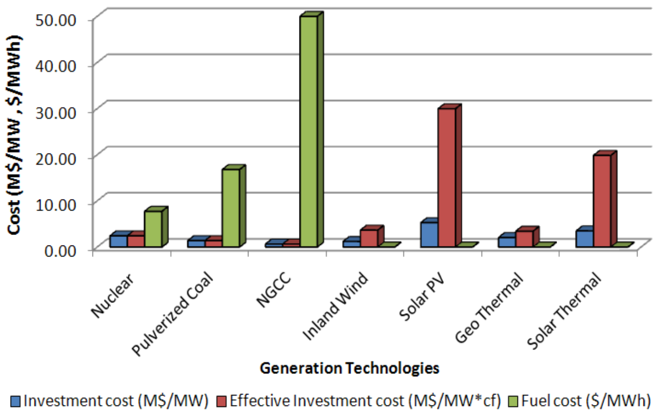


Figure 9 presents the cost data for some of the technologies, where “Effective Investment cost” represents the investment cost per MW of effective capacity (obtained by dividing investment cost by capacity factor). So even though the actual investment cost of renewable technologies, especially wind is lower compared to geothermal and nuclear, the effective investment cost of wind is higher due to its variable nature and low capacity factor. This explains why in Figure 7, the low cost (and thus high emission) solution has nuclear and geothermal predominating over other renewable technologies.

Figure 9 Cost data for generation technologies



Figures 10 and 11 present the yearly investment in terms of various technologies (represented by solid areas) and the yearly CO_2 emission (shown as a solid black line) over the entire planning horizon of 40 years, for the least and most resilient solutions respectively. We can observe that the investments for the least resilient solution are significantly smaller than in those in the most resilient solution. The former is composed mainly of new nuclear power and geothermal, which correspond to the most economical options as seen in Figure 9, while the latter shows a balanced mix of all types of generation. The diversity in generation along with the higher level of generation available make the system better suited to withstand failure for all types of generations and events of bigger magnitude. In addition, since there are more renewable resources available in the most resilient solution, greenhouse gasses are significantly reduced with respect to the first solution. In both solutions we see an initial decrease in generation because existing coal units are being retired and replaced mostly by nuclear energy and renewables.

Figure 10 Yearly generation investment and CO_2 emission for the least resilient solution

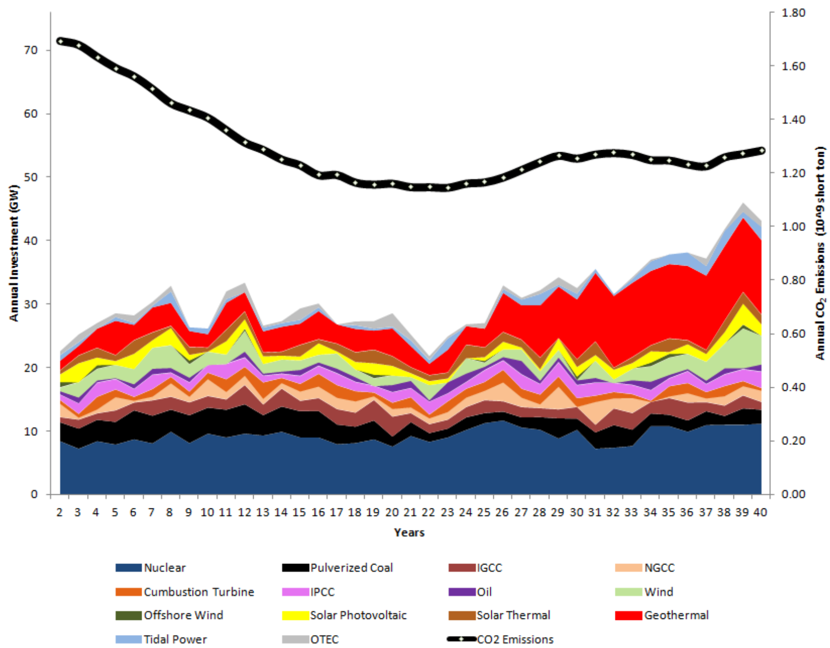
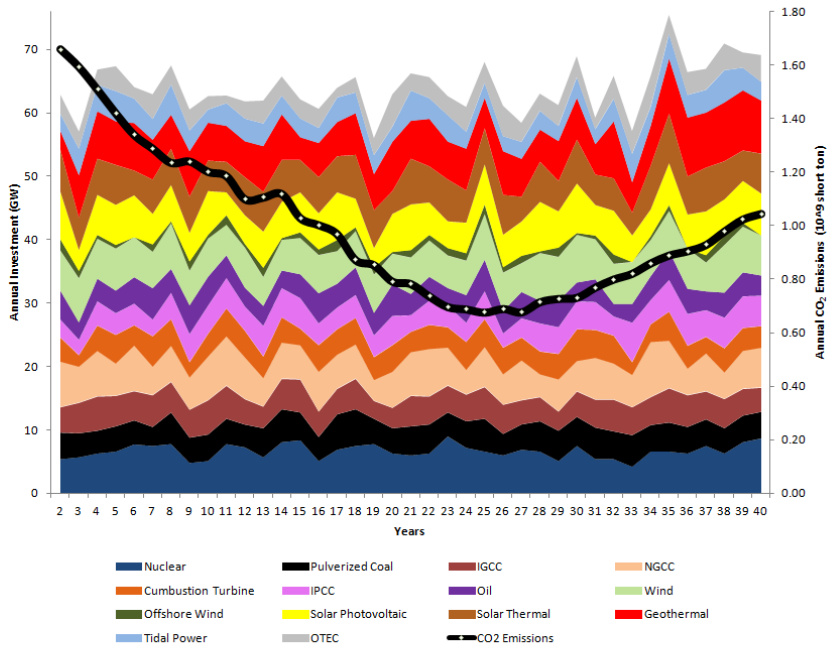


Figure 11 Yearly generation investment and CO_2 emission for the most resilient solution



Even though a single state was defined for this numerical example, we can observe in Figure 7 that the most resilient solution also presents the smallest spread across all 14 events. Hence, in this case, the more resilient solutions are also the most robust.

We will derive a case in which the most resilient solution is not necessarily the most robust. Let us assume that we solve the same problem but using only events for the four technologies included in Table 2 and that the 20 solutions above are still part of Pareto front. The table includes the consequence when each technology is removed as well as the resilience measure and the standard deviation. Solution 20 is still the most resilient, but both 18 and 19 present lower standard deviations. If we were to judge robustness based on said number we would determine that solution 19 is the most robust while solution 20 is the most resilient.

Table 2 Alternative resilience and robustness calculations

Sol. No	Geothermal (10^9 \$)	Hydro (10^9 \$)	IGCC (10^9 \$)	IPCC (10^9 \$)	Resilience (10^9 \$)	St. Dev. (10^9 \$)
18	17.15	2.76	5.98	5.99	7.97	6.31
19	17.00	2.88	5.84	5.31	7.76	6.30
20	16.65	2.32	5.82	4.19	7.25	6.43

6 Discussion on event selection

An analyst or designer, in using simulation to consider resilience, must choose a set of events to simulate. This choice should be made based on the objective of the study. The Katrina and Rita hurricanes mentioned earlier in the paper represent a good example of such an event, where a large amount of natural gas production was constrained for several weeks simultaneous with significant reduction of Mississippi River barge traffic and loss of many electric generation and transmission facilities in the area.

Other events that could be simulated to assess resilience of the national energy and transportation systems include:

- Six month loss of rail access to Powder River Basin coal,
- One year interruption of 90% of Middle Eastern oil;
- Permanent loss of U.S. nuclear supply (SC, 2010);
- Six month interruption of Canadian gas supply;
- Earthquake in St. Louis (STC, 2010) with major loss of transmission, rail, oil, and gas pipelines, and extended interruption to Mississippi River barge traffic;
- One year loss of U.S. hydro resources due to extreme drought,
- One year loss of U.S. wind resources due to climate change effects;
- Sustained flooding in the Midwest that destroys crops, reducing the availability of biofuels, and interrupts key corridors of the east-west railroad system.

Another important characteristic to take into account when selecting events following the methodology presented in this paper is that their effects are typically exacerbated by congestion. Recent effort has identified congested regions on the nation's electric transmission system, as illustrated in Figure 12 (DOE, 2009). Figures 13 (FHA, 2007) and 14 (AAR, 2007) compare current and forecasted future congestion of highway and railway, respectively, with orange-colored links in each map indicating highly congested paths.

Events which include failure of such paths are much more susceptible to produce large consequences with relatively small failures. Congestion does also not only depend on geography, but also time. For example, it is common to observe peak demands for the electric system both in the summer and in the winter as well as a higher degree of passenger traffic during the summer and holiday seasons.

Figure 12 Congested areas for the Western and Eastern interconnections

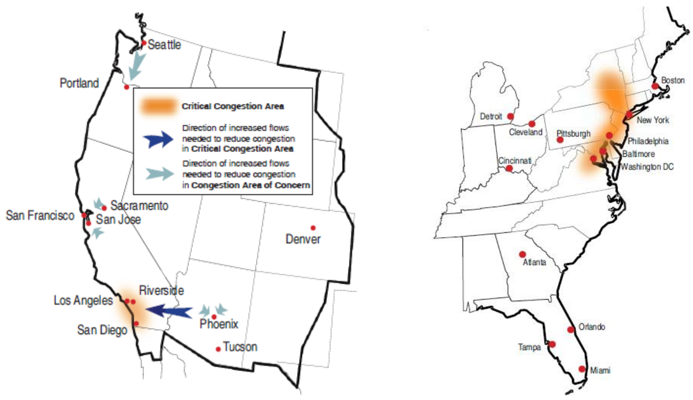
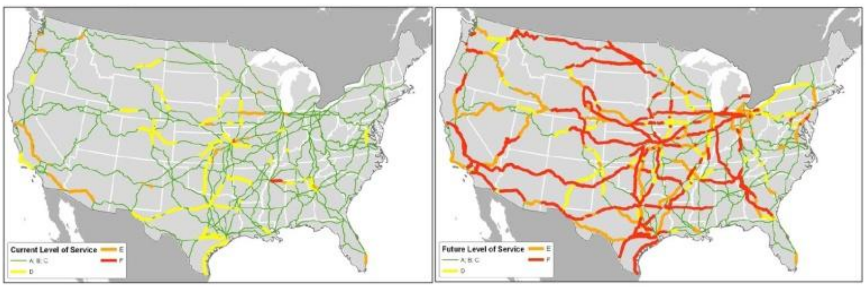


Figure 13 Predicted levels of highway congestion in 1998 and 2020

Figure 14 Predicted levels of rail congestion in 2005 and 2035



7 Conclusions

In this paper, we presented the concept of resilience with respect to the national energy and transportation systems based on the notions of states – the system topology and operating conditions, events – the representation of large-catastrophic Katrina-like failures or changes in the system, and consequence – the measure of the effect of an event. Robustness is defined in terms of variability in cost-consequence across states with respect to a set of events. We have developed a computational model called NETPLAN that optimizes cost, resilience, and sustainability for energy and transportation infrastructure investment over 40 years at the national level. The model allows exploration of how different objectives affect long-term investment portfolios. A numerical example was presented where resilience is measured via averaging one-year operational cost increases resulting from 14 different events, and we observed the interactions between the total cost of the system, greenhouse gas emissions, and the resilience measure. For this particular example, we found that that investment and operational costs, sustainability and resilience are competing objectives and we analyzed the difference between solutions with different levels of resilience. We conclude that the proposed resilience measure is a reasonable measure to use in designing long-term investment portfolios for national multi-sector infrastructures. The events for resilience assessment were selected to most clearly illustrate the method; other more realistic (and more complex) events could be defined for this purpose as well, and we have provided examples of such events.

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