Modeling Resource, Infrastructure, and Policy Cost Layers for Optimizing Renewable Energy Investment and Deployment

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Abstract— *This paper presents a framework for creating a common spatial canvass that can bring together considerations of resource availability, infrastructure reliability, and development costs while strategizing renewable energy investment. We describe the underlying models and methodologies that annotate an investment plan for potential sites over a time-period with costs and constraints which may be imposed on distance from infrastructure, system impact on infrastructure, and policy incentives. The framework is intended as an enabler for visualization, optimization and decision making across diverse dimensions while searching for lucrative investment-plans.*

1. INTRODUCTION

The grand challenge of reducing fossil fuel dependence by shifting to clean-energy technologies in the next few decades has posed the following questions: how many, what kind (wind, solar, geo-thermal, etc.), when, and where should one invest to accomplish the desired energy production goals and environmental-impact objectives. Addressing aspects of such a grand challenge, researchers from the Oak Ridge National Laboratory (ORNL) and Lockheed Martin Corporation (LMC) have developed an end-to-end integrated tool to assess, prioritize, and plan renewable energy investment options and production scenarios. The integrated tool is called *GSPEIS* - short for Geo-Spatial Planner for Energy Investment Strategies.

GSPEIS consists of three main components, namely: (i) *Geo-Fuser* which is a geo-spatial resource management interface; (ii) cost *Simulator* which implements an agent-based modeling approach that provides a systematic and coherent methodology to include installation and equipment costs along with feasibility constraints for energy production and distribution; and (iii) *Optimizer* which implements the genetic algorithm. In a related paper [1], we explain how the *Geo-Fuser* processes resource layers of wind, solar-potential, and land-use maps to help identify geographic regions for renewable energy investments. We also show that when the output regions from the *Geo-Fuser* are annotated with specific costs, the *Optimizer* can search for lucrative investment plans simultaneously streamlining cash flows and maximizing return-of-investment. In this paper, we describe models and methodologies used within the cost *Simulator* to evaluate grid-integration related costs to complement the spatial-resource filter implemented into the *Geo-Fuser* and the financial feasibility evaluation capability of the *Optimizer*.

The layers within the cost *Simulator* include seemingly hidden costs that are specific to integrating new renewable energy generation in addition to the land, equipment, and installation costs. An example of such an indirect construction-time cost arises from the need for new transmission lines to transport renewable energy from the site to the electric grid. Another hidden but significant cost is the infrastructure stability cost to counter transmission line thermal-overload and bus voltage out-of-range contingencies while adding new power to the existing infrastructure. The need to include such costs in the planning phase cannot be ignored [2, 3]. In addition to the power system related costs, we have addressed the challenge of including governmental policy incentives and regulations into GSPEIS. We have developed a baseline approach to quantify policy considerations by structuring an ensemble of rather vague and disparate policy specifications into a parameterized input space, amenable to precise quantitative analysis [30].

By bringing together such diverse yet relevant dimensions, of investment constraints and incentives we present GSPEIS as a:

- framework that can assemble and optimize across diverse cross-domain models of resource availability, development costs, environmental impacts, system reliability, governmental incentives, energy-demand forecast etc.,

- decision-support tool for investors and energy planning experts to evaluate *what-if* configurations for renewable energy investment and deployment,

- spatial canvass that enables visualization, optimization, and decision making for renewable energy investment related queries.

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2. Background and Related Work

The ability to include renewable sources into the energy portfolio has been a global desire [4-6] in the last few decades. Some countries attribute climate-change concerns as the motivating factor behind their clean-energy ambitions while other countries have expressed the shift to renewable sources as a futuristic defense strategy [7]. Recently, the United States Federal Government set forth the ambitious vision of achieving 15% wind penetration by 2020, and 25 % renewable penetration by 2025 to meet future energy demands.

Inspired by this vision, we began a literature survey of key methods and models addressing the renewable energy integration challenge. We soon realized that the renewable-energy investment-strategy space requires cross-cutting expertise in the following key areas:

1. Power systems – Developing cost models for new infrastructure (transmission [8], storage [9], distribution and contingency planning [10])
2. Social and environment impacts – Providing environmental cost quantifiers based on the expected reduction in carbon footprint from renewable energy production [11].
3. Geo-spatial data collection and search – Segmenting out suitable regions for solar, wind installations and computing distance-related costs for integrating renewable energy to existing infrastructure [12].
4. Government policy - Quantifying rules, regulations and incentives [13].
5. Optimization - Pruning the feasibility space while considering dynamic factors such as siting dependencies and population growth over time [14-17].
6. Investment econometrics - Motivating investment while minimizing the risk on the return-of-investment in renewable energy projects.

Several efforts have addressed the challenge of optimizing over costs generated by the diverse set of renewable-energy related models while planning energy production. Tools like WinDS [19], NEMS [20], MARKAL [21], and AMIGA [22] have inspired Ding and Somani [16] who propose a long term investment planning model for integrating renewable resources with new thermal and nuclear power plants. Such software tools that implement models for supply–demand prediction, seasonal forecast, geo-spatial optimization, and emission estimation are available both in the commercial and the open-source market. Conolly et al. present a comprehensive survey of these software tools in [18].

Our survey also helped us contrast and compare the siting results from multi-attribute decision analysis [14], multi-objective site-search [15], linear programming [16], and the evolutionary genetic algorithm based strategies [17]. We choose the genetic algorithm approach for GSPEIS over other optimization techniques because genetic algorithms allowed customizable fitness functions of diverse independent dimensions (with linear and non-linear constraints).

We note that most of the existing efforts are implemented as decision-support tools for government agencies that strategize the future road map for energy production by formulating policy guidelines. With GSPEIS, we pose and address the problem from an investor's perspective. We include several of these cross-domain models and interpret the governmental regulations and incentives. Our motivation is to help an investor test feasibility of business plans while minimizing the risks involved with the investments. In other words, we have developed GSPEIS as a tool that will allow the user/investor to choose and configure a desired investment space, use realistic models to annotate the chosen investment space with costs and constraints and thereby, analyze *what-if* scenarios to maximize investment-returns.

3. Proposed Approach

GSPEIS follows the workflow illustrated in Figure 1 towards answering the question of how many, what type, when and where should one invest on renewable energy technologies. We present an example of a process flow through the illustrated pipeline and explain the models implemented into GSPEIS in this Section.

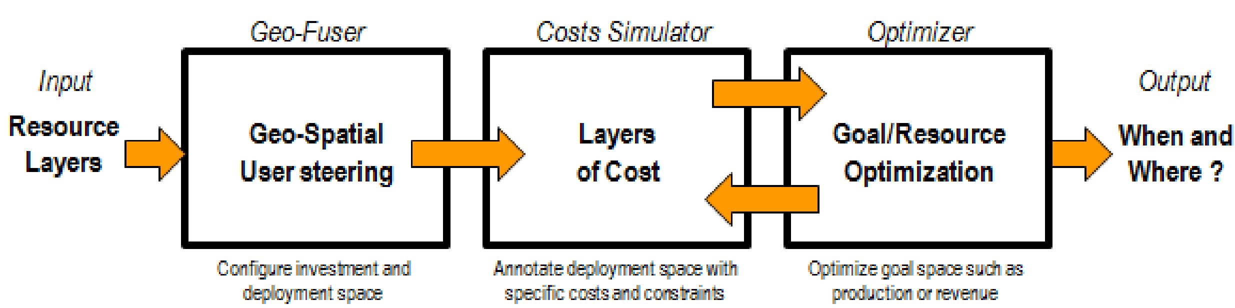


Figure 1 - Block diagram of the GSPEIS tool that takes renewable resource related input layers and outputs an optimal space-time investment plan for renewable energy investment and deployment.

Resource Layer Fusion

GSPIES takes input layers such as solar-potential, wind availability, land costs, and the grid infrastructure to prune the geographic feasibility and later segment out potentially profitable regions for investment. In Figure 2, we illustrate the idea of bringing together several maps on a spatial canvass like Google Earth and show the regions of interest as pink polygons. These polygons were selected by filtering wind-potential and land cost input layers using the *Geo-Fuser* interface. The output from the *Geo-Fuser* is the latitude and longitude locations of the sites along with the electricity generation expected from each of these sites. We will leverage this wind-energy case-study example as the investment/deployment space to explain different functionalities of GSPEIS throughout this paper.

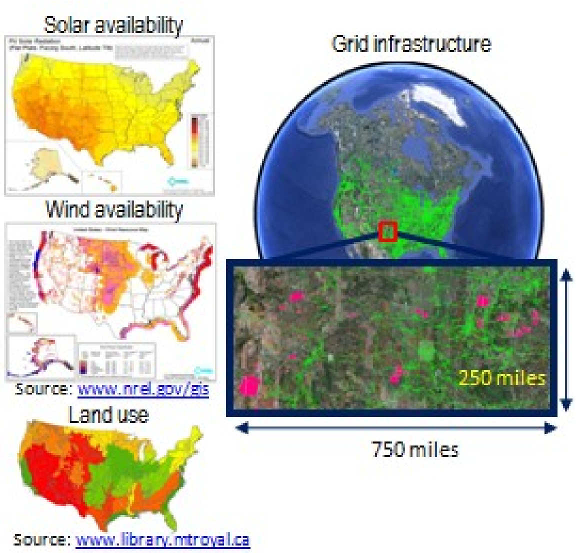


Figure 2 - Resource layers like wind availability, solar potential, and land use are input to the *Geo-Fuser*. The *Geo-Fuser* interface can filter out spatial regions based on user-specified thresholds on each input layer.

Spatial Analysis of Sites

As the next step, we try to understand the spatial organization of potential sites with respect to the existing electrical infrastructure. This is significant because the distance to existing energy transmission interconnects can become a key factor when we attempt to transport the power generated from such sites of resource abundance. We note that transmission line costs of \$1 million for a mile of 345KV line [8] (\$400,000 for a mile of 138 KV line) can be a significant financial burden on the budget.

We recall the *Geo-Fuser* output of potential sites **S** = { s_j; $j = 1,2..,N_s$} considered for investment in a region overlapping Texas, Kansas, Colorado, New Mexico, and Oklahoma. The input that our approach requires in addition to sites of interest for renewable energy is the topology of the existing electric grid. We represent the grid network as a network graph **G** = < **V**, **E**> where **V** is the (vertex set {v_i}) of sub-stations/generators geographically associated with a latitude and longitude pair (x_i, y_i) . **E** (the edge set) is the set of transmission line links between generators and sub-stations. We compute and store the distance in miles between each site and the nearest bus in **V** (Equation 1). We used the specifications in [23] to convert the latitude and longitude data to a Cartesian system of three-dimensional (3D) co-ordinates. The function *d* in Equation 1 is the Euclidean distance between two points in the transformed 3D space. $N_b(s_j)$ is the nearest bus to a site of interest s_j and $d_{N_b}(s_j)$ is the distance to the nearest bus.

$$d_{N_b}(s_j) = \min_{v_i} d(s_j, \mathbf{V}) \tag{1}$$

$$N_b(s_j) = \arg\min_{v_i} d(s_j, \mathbf{V}) \tag{2}$$

Although some sites in **S** can already be eliminated from consideration if the physical distance challenges electric transmission requirements, we learn from experiments that it may be more beneficial to cluster potential sites when the intra-cluster distances are small compared to the bus and cluster-center distance. We show an illustration of such a scenario in Figure 3 and argue that what may be an expensive proposition for electric transmission as an individual site can turn cost-effective when considered as a group of sites. We contrast the two configurations in Figure 3a and 3b. In the figure, the green squares represent potential sites, dotted red lines are proposed transmission lines, blue circles are proposed bus stations, solid black lines represent existing transmission lines and yellow circles are existing sub-stations.

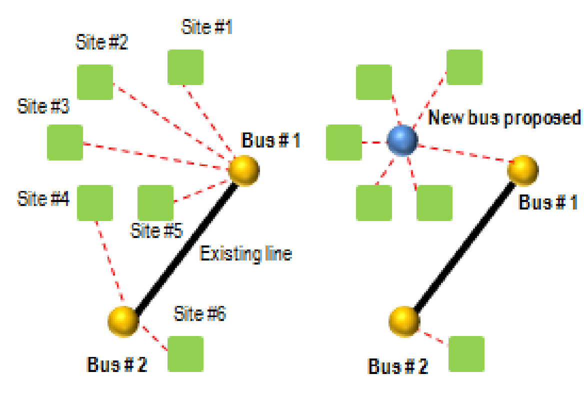
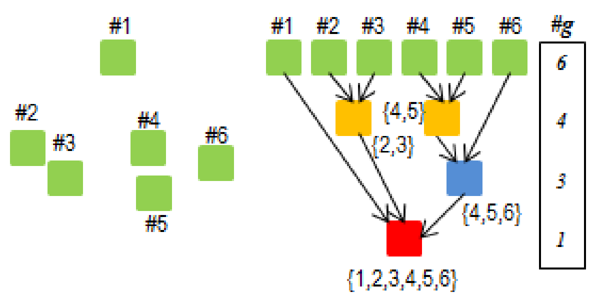


Figure 3 - Understanding the spatial organization of potential sites to estimate the investment required for new transmission lines. (a) A configuration connecting potential sites to the nearest bus can be redundant and expensive. (b) A clustering of the sites can reveal more cost-effective solutions.

We group sites using an agglomerative hierarchical clustering algorithm similar to the one specified in [24] to associate a group number and an effective transmission distance with each of the potential sites under a cluster-configuration. Thereby, when we later evaluate possible investment options using the *Optimizer*, we can consider group costs wherever possible instead of individual transmission line costs to the nearest bus. We illustrate the result of hierarchical clustering on a toy example in Figure 4 below. The algorithm begins by first considering potential sites as belonging to an independent cluster. Two or more sites are then merged into a single group iteratively. The choice of which clusters to merge or split is determined by a linkage criterion. The linkage criterion usually is a function of pair-wise distances between observations. We used the Euclidean distance for illustrative purposes in Figure 4 to show that this approach provides a tree structure that can be queried for clusters based on a specific distance threshold. In the toy example, the linkage criterion organizes the six sites into 4 levels of 6, 4,3 and 1 cluster-groups respectively.



(a) (b)

Figure 4 - Hierarchical cluster representation of potential sites. (a) Potential sites before cluster assignment. (b) Cluster assignment using the Euclidean distance between sites.

However our interest is not to cluster sites based on their separation from each other, but to cluster them based on the effective distance from the grid infrastructure. Instead of using the standard Euclidean distance as the parameter for inter-cluster separation, we define an 'effective-transmission-distance' measure as shown in Equation 3. This measure favors site clusters that reduce the cost of new transmission lines and proposes configurations similar to Figure 3b.

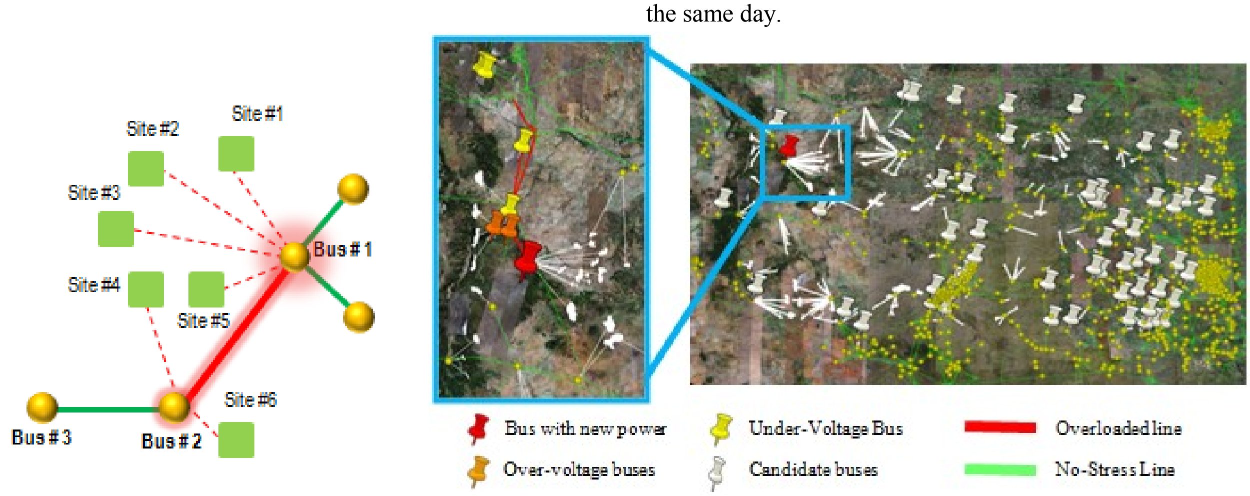
$$d_{eff}(s_j) = \min\left(n_{cl} * d_{N_b}(s_j), \sum_{k=1}^{n_{cl}} d(s_j, s_k) + d_{N_b}(s_j) \right) \qquad (3)$$

where n_{cl} is the number of sites in each cluster-group at each level of the hierarchical representation.

We also compute answers to three other questions, namely: (1) How many buses are within a specified radius of s_j to accept extra power? (2) What is the nearest bus with a voltage rating of more than 200 kV? (3) Which state does the site belong ? We will revisit the annotated answers in the power-system and policy modules of GSPEIS.

Power-System Cost Annotation

The power-system related costs arise from the fact that a typical transmission bus is designed for operation between ± 6% of its voltage rating [25]. Exceeding or falling below the range must be avoided as it may severely damage company and customer equipment. We illustrate this need in Figure 5 and emphasize that before adding new power into the transmission network we have to make sure that expected line and transformer loadings are upgraded to handle new renewable energy without violating ratings of the installed equipment. We also have to accommodate for the fact that there may be several days in a year when the energy production falls below expected production efficiency and times with spurts of higher than expected production within the same day.



(a) (b)

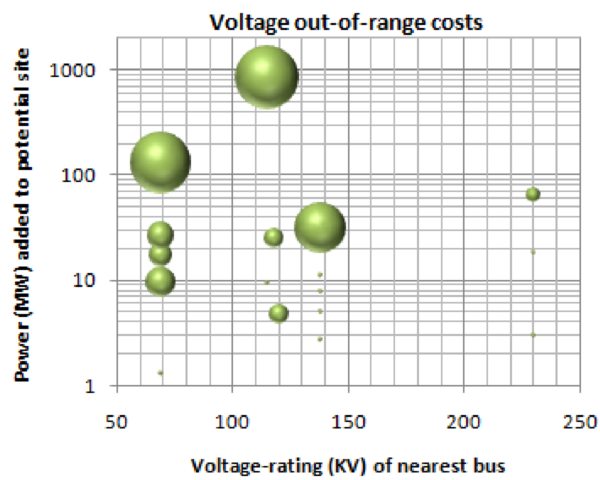
Figure 5 - Computing power-flow related costs. (a) An illustration that shows that including renewable energy can affect existing buses and transmission lines. (b) The result from a power-flow simulation showing voltage out-of-range buses and thermally overloaded lines when 831 MW of power is injected to the existing grid infrastructure.

We recall that candidate sub-stations to receive the generated power for each of the potential sites was identified during the proximity analysis. We also leverage the topology of the entire U.S. electric grid consisting of approximately 850 GW total generation, 10500 generators, 37500 loads, 65000 buses, and 85000 branches (transmission lines and transformers) used in the proximity analysis for the power flow analysis. We treat the renewable energy site as a new generator added to the grid and study the impact of the new power on the existing infrastructure. An iterative numerical solver (Newton-Raphson method) is employed to compute the power-flow, voltage magnitude, and phase angle at each bus within the interconnect along with the real and reactive power flows in transmission lines and transformers. The results presented in this paper are based on the power-flow solver provided as part of the Power World simulator [26]. Other power-flow solvers like Siemens PSS/E [27] and ORNL's THYME [28] can be used, but we chose Power World solver for its simplicity and functionality in providing base-case overloads with contingency analysis considerations.

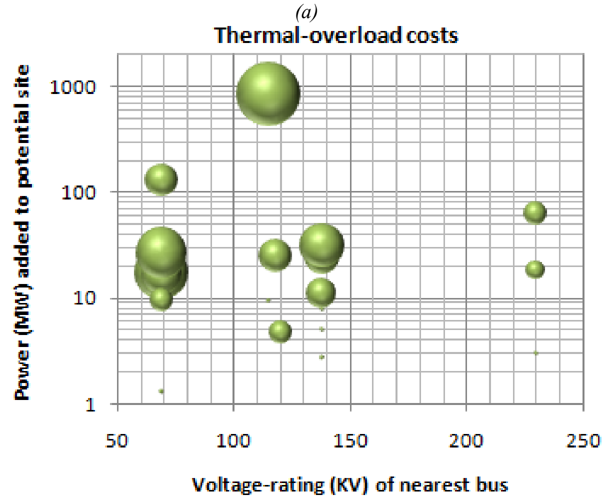
The effect of adding extra power to existing infrastructure, and henceforth the number of violations, depends on many factors such as the amount of added power, the network topology, locations of generators and loads, equipment specifications and ratings, etc. The power-flow analysis helps us identify buses that would be forced to operate over or under-voltage as well as transmission lines operating beyond their thermal limits. We showed one example in Figure 5b that resulted in 8 under-voltage, 15 over-voltage buses and 24 over-loaded lines (not all of them visible in the figure). This was a hypothetical experiment where we added 831 MW of new power into the grid to a 115 KV bus from a clustering of 12 potential sites to emphasize the need to quantify infrastructure-related costs.

In Figure 6, we summarize the results of power-flow analysis on 20 sites. The expected power from each potential site used for these experiments is a function of capacity factor, wind potential, typical equipment capacity and, the area of the site. We have plotted the voltage-rating of the nearest bus, the amount of power added to that bus from a potential site and the cost required for upgrading existing bus nodes and transmission lines. Figures 6a and 6b show the bus voltage out-of-range costs and thermal overload costs on transmission lines respectively. The area of the circular bubbles represent costs associated with upgrading existing infrastructure at the point of the "tap" to sustain the electrical and thermal limits of the newly injected power for each of the 20 sites of interest.

As one would expect, we observe an increased number of violations (both overloaded transmission lines and out-of-range voltage buses) while adding extra power to low capacity sub-stations. These graphs also appear to suggest if a site or a site cluster is adding more than 10 MW of new power we either have to inject the power to the nearest bus with 200 KV or more voltage rating or build new sub-stations capable of handling 10 MW of power. This is the reason why we specifically extracted information about the nearest sub-station with more than 200KV capacity during the spatial analysis. We also included the number of sub-stations within a specified radius to evaluate the contingency that several short-distance transmission lines to low-capacity sub-stations may be more economical and feasible than a long transmission line to the nearest high-capacity sub-station. The spatial analysis and the power-flow analysis modules are designed to interact within the GSPEIS framework enabling simultaneous consideration of proximity and power-flow validity/feasibility. This interaction is necessary to automatically hypothesize and test different configurations within an investment plan for feasibility.



(a)



(b)

Figure 6 - Based on the power-flow costs computed on 20 sites of interest we see that both sub-stations and transmission lines need attention before injecting new power. (a) Bus-voltage out-of-range costs. (b) Transmission-line thermal-overload costs.

State-Wise Governmental Policy Annotation

In the two previous sections, we discussed potential grid-integration costs for the investor while building renewable energy farms. In the following paragraphs, we try to include state-wise governmental policy incentives and regulations on renewable energy. As of May 2010, close to 30 states across the United States of America have mandated a renewable portfolio standard - a regulation that requires increased renewable energy production. Several of these states encourage and attract investment by providing creative tax breaks and incentives on the purchase of renewable energy equipment, installation, and production. Such policy incentives can be significant to the commercial investor, especially when investing on large scale farms. However, there are few methods in the literature that can quantify these incentives and disincentives (regulations, etc.) and make them amenable to a uniform optimization framework. Our approach here is to take the first steps in this direction and show how state incentives may be quantified to feed into the integrated processing (visualization, optimization, etc.) along with the other cost layers.

We have constructed a computational module - a rule-based system - to evaluate state incentives and their impacts on renewable energy investment. Leveraging the excellently compiled Database of State Incentives for Renewable Energy (DSIRE) [29], we have developed computational scripts and interfaces to query the database based on user inputs of an investors plan. Figure 7 is a Google Earth visualization of the renewable policy landscape within the United States. Typical inputs to the policy quantifying module are equipment costs, installation costs, property tax, sales tax, expected energy output, etc. We recall that the spatial analysis module annotated potential sites with their respective states. We use this information to recommend and compute eligible incentives for each site of interest. In other words, our rule-based system is designed to answer a query like: If an investor is ready to invest \$X to generate *s* KWh of solar, *w* KWh of wind energy and *r* KWh of other renewable energy, how much encouragement (in the form of incentives) from each site can he expect for that renewable energy investment?

We presented a detailed description of the computational policy module in a different paper [30] and concluded that state incentives can be significant if an investor is able to invest with long-term return-of-investment goals and large-scale farms. Evaluating hypothetical cases, we learnt that some states offer as much as 10% of the investment in the form of tax breaks and incentives.

Evolutionary Optimization

The *Optimizer* component of GSPEIS [1] implements the multi-dimensional search functionality. In Figure 8, we present screen shots of the Optimizer showing the potential sites identified from the *Geo-Fuser*. The *Optimizer* interface allows both manual user-steered selections and automated random selections of the investment space. The user then chooses a desired optimization objective from options such as energy production, profits or return-of-investment.

In our genetic algorithm based *Optimizer*, an investment plan is encoded as a chromosome as shown in Figure 8. The chromosome is a sub-set of the list of potential sites from the *Geo-Fuser* output scheduled along a time-line (6 years in the example shown in the Figure). We begin with a sufficiently large population of chromosomes (randomly generated investment plans) as our initial search space and query the spatial analysis, power flow and policy modules to annotate costs for each chromosome in the population.

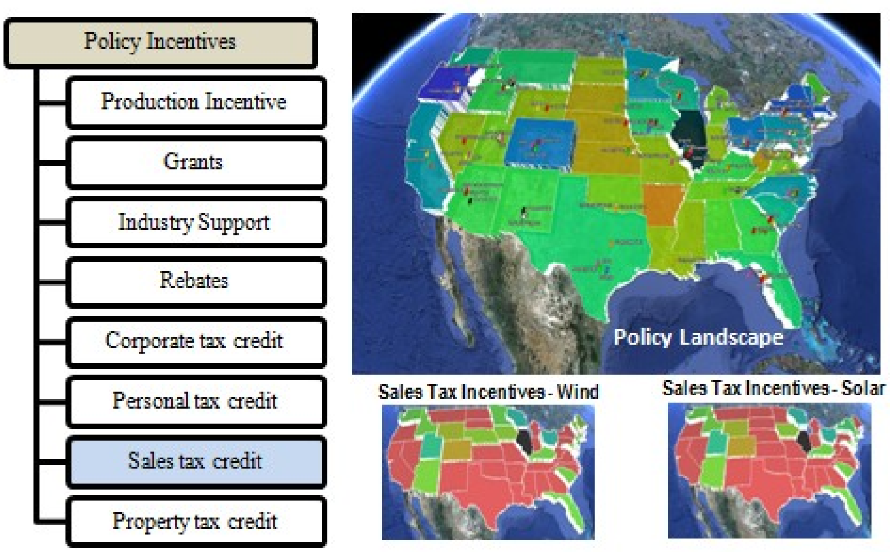


Figure 7 - Visualization of our computational policy module using Google Earth shows the encouraging incentives offered by different states within the Unites States. Incentive-friendly states are represented as tall blue or green bars.

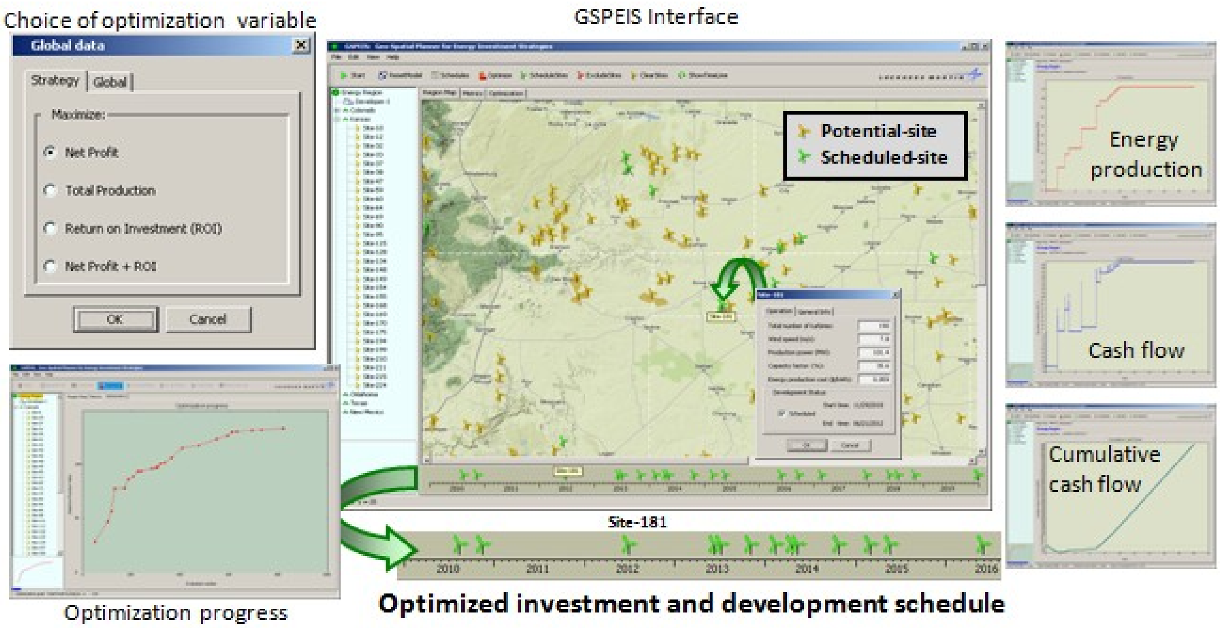


Figure 8 - Screenshots of the *Optimizer* interface within GSPEIS.

The chromosome encodes the spatio-temporal aspect of an investment plan and the construction of the fitness function (user-desired objective function) brings together diverse dimensions of renewable energy investment. One iteration of the genetic algorithm on a randomly selected initial population helps us identify a few cost-effective investment strategies. We iterate over several thousands of chromosomes that are generated by retaining the best chromosomes from the previous population along with several mutations and crossovers of chromosomes [31] before converging to a profitable investment plan. New chromosomes in each iteration are annotated with the configuration-specific costs by executing the different models implemented within the *Simulator* and evaluated for fitness. After several iterations of evaluating chromosomes, the optimality of the converged solution can be visualized as stream-lined cash-flows, increased energy production and as profits over the timeline.

4. SUMMARY AND FUTURE DIRECTIONS

The joint effort of ORNL and LMC has brought together power and energy-grid systems expertise and market research on renewable energy deployment to build realistic, implementable cost/profit models that would assist both entrepreneurial investors and energy policy decision makers. Specifically, our integrated tool has a user-steering component that enables analysts and decision makers to: (i) configure the investment and deployment space by choosing geographic-interest regions; (ii) execute underlying models to annotate the deployment space with specific costs and constraints; and (iii) optimize across the goal space for different objectives such as production, revenue, and return-of-investment. We showed how the diverse dimensions such as distance from infrastructure, system impact on infrastructure, and policy incentives may be brought into a single framework that enables visualization, optimization, and decision making.

We note that GSPEIS can be extended beyond the current focus of renewable energy investment to include traditional coal-based thermal or nuclear energy generation options. With additional resource layers such as seismic zones, water availability, geo-spatial forecast of energy demand, and the transportation grid, the agent-architecture design underlying GSPEIS can help us seamlessly transition GSPEIS into a nation-wide energy planning tool. We understand that for the scale both in size and energy demand for a country like the United States, an energy planning tool that thinks ahead by a few decades will have to evaluate a really large number of alternatives. The layered approach within GSPEIS and the genetic algorithm based optimization is well-suited for such ultra-scale computations leveraging computer clusters and parallel-processing super-computers.

ACKNOWLEDGEMENT

This manuscript is authored by employees of UTBattelle, LLC, under contract DE-AC05-00OR22725 with the U.S. Department of Energy. Accordingly, the United States Government retains and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes.

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