

OPTIMIZING FRIEGHT TRANSPORTATION POLICIES FOR SUSTAINABILITY

A Simulation-Based Investigation of Freight Transportation Policy Planning and Supply Chains

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ABSTRACT

Regional freight transportation policy planning is a difficult task, as few policy-planners have adequate tools to aid their understanding of how various policy formulations affect this complex, socio-technical system. In this paper, we develop a proof-of-concept model to simulate the impacts of public policies on freight transportation in a simulated region. We use the techniques of multi-disciplinary system design and optimization to analyze the formulation of regional freight transportation policies and examine the relative effects of policies and exogenous forces on the region in order to provide insight into the policy-planning process. Both single objective and multi-objective analysis is performed to provide policy-planners with a clear understanding of the trade-offs made in policy formulation.

INTRODUCTION

Regional freight transportation policy planning is a difficult task, as few policy-makers have adequate tools to aid their understanding of how various policy formulations affect this complex, socio-technical system [Sussman, Sgouridis, and Ward 2004] The impact of regional freight transport is far-reaching, impacting the regional economy, environment, and society through many interactions with complicated effects. The effect of a policy meant to improve one aspect of a freight transportation network is not always known *a priori*, and the interactions of that policy with other policies in the portfolio are seldom understood well. Additionally, there are

not always clearly-defined objectives that all policy planners use. While some regions may prefer to cater to business in an effort to boost the economy, others may be more concerned about environmental impact, or have other region-specific concerns when formulating regional policies. As a result, regional freight transportation planning is often more of an art born of experience and politics than a science.

Our goal in this paper is to develop a proof-of-concept model of a regional freight transportation system, extended to include a region's product supply chains and consumer markets, which can be analyzed with multidisciplinary system optimization techniques to provide insight to policy-makers by comparing the relative effectiveness and interactions across policies. To our knowledge, this is the first time this approach has been applied in strategic transportation planning. The model that we have developed for this paper is not based on an actual region, as even small, relatively closed regions can encompass a multitude of industries and can quickly become complex models beyond our scope. Such multi-disciplinary, high-fidelity models of entire regions can become the subject of large, well-funded studies involving many system experts.

Our model is based on an imaginary region with three primary industries. The majority of the population is located in a single large urban area which is landlocked and served by truck-based freight transportation. We have chosen realistic inputs into this model based on typical figures found in similar regions.

Once the model was developed and tested, we performed different multidisciplinary system optimization techniques on it. Our effort aimed to better map the tradespace of all possible policy portfolios, the interactions and behaviors of the portfolios, and to understand and quantify tradeoffs that must be made when choosing a final policy portfolio to be implemented.

MODEL IMPLEMENTATION

Our model is based on a view of a regional transportation network represented simplified in Figure 1. In this model, represented using causal loop diagramming from system dynamics [Sterman 2000], supply chains extract raw materials and create products, while importing and exporting goods. Created products are circulated in use for a certain time, and then they are discarded or recycled.

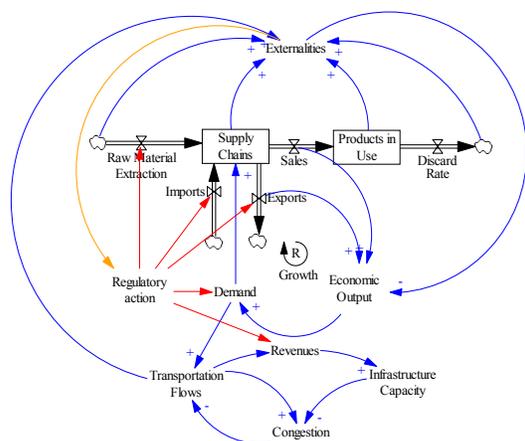


Figure 1 – A high-level overview of a Regional Freight Transportation Network

On top of this basic flow of goods and resources there are many variables that affect and are effected by these flows such as economic output, infrastructure capacity, transportation flows, product demand, traffic congestion, and environmental externalities in the form of greenhouse gas (GHG) emissions from production and transportation and landfill waste from discarded products. In this view of the world, transportation is but one key element among others in the larger regional area.

Transportation planners can weigh the relative cost-effectiveness of their policy alternatives and through cooperation across agencies provide

recommendations for regulatory action to decision-makers with more system-wide authority. They can affect change in this regional system through the application of policies that either mandate certain behavior in the system or increase prices in the system, allowing the market to react and reflect these changes. In our model, we seek to alter the behavior of our system in just this way, identifying regulatory action that can be taken to modify the behavior of the network in a desired direction.

As can be seen from the view in Figure 1, our regional freight transportation model must encompass many disciplines in order to provide useful data to policy planners. In addition to the more apparent disciplines such as transportation engineering and policy planning, a good model must consider the regional economics, supply chain management, and environmental assessment.

To address these issues, we developed a modular model that encompasses the disciplines listed above. At the highest level, we have a regional module that contains regional parameters, such as the total amount of environmental externalities, the state of the regional economy, and the total flow of traffic (both freight and passenger) on the transportation network. At a lower level, we have multiple industry modules that model a particular industry from raw material extraction throughout the product lifecycle. With minimal work, additional modules can be added into this model.

We chose to model three contrasting industries in our mock region—an automotive industry, an electronics industry, and a food distribution network. Each one of these industries has fairly different freight demands, and creates revenue and impacts the environment in different ways and at different rates, allowing for increased insight into the effects of policies on highly differentiated industries.

Modeling Environment

For our modeling environment, we chose to use a relatively new piece of software called AnyLogic[®], Version 5.2 [XJtek 2005]. The primary benefit of AnyLogic is its ability to create models using several modeling methodologies, including discrete event

modeling, system dynamics, agent-based modeling, physical modeling, or even Bayesian network modeling. These methodologies, created using both object-oriented visual tools as well as Java code, can be used together in a single, integrated model. Any model can be customized using custom code to extend its capabilities. Since the application is written entirely in the Java language, the resulting model can be exported as a cross-platform Java applet with a user-defined interface that can then be given to policy-makers to use.

AnyLogic comes packaged with the OptQuest[®] optimization engine [OptTek 2005]. The interface between the two packages is integrated inside the AnyLogic application, making new optimization experiments easy to set up and run.

Modeling Methodology

The original intent for our regional model was to model large scale regional behavior using a system dynamics based model taking advantage of the methodology's causal loop structure, while using a discrete event based model for the supply chains, product flows, and freight flows to simulate the discrete flow of trucks and products throughout the network. Due to delays in obtaining a license for the software, we were not able to complete the discrete event portions of the model before our first deadline, so we instead developed a system dynamics based model of the industry supply chains in its place, which we then used throughout the further development and simulation of our model.

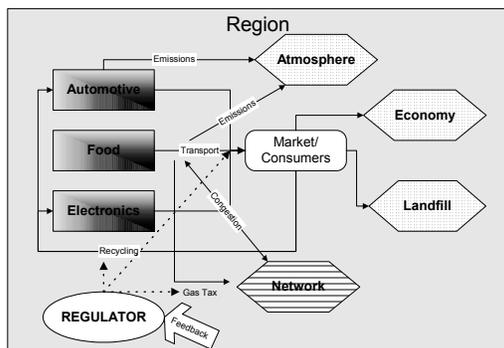


Figure 2: Module Hierarchy

As shown in Fig. 2, each industry is modeled using a standard supply chain model module that we developed. We created three instances of the

module and then developed several parameters describing the product size, weight, costs, initial conditions, and distances between suppliers, manufacturers, and the urban area to calculate the parameters needed by our regional model in calculating our region-wide objective functions.

Each industry supply chain module iteratively determines its production costs based on flows, demand, and regulation, adds a profit margin, and then determines the new demand based on the price of its product. Based on the condition of the region, the regional module may then inform the industrial supply chain modules to change their output.

The interactions among the modules are summarized in the N^2 diagram of Fig. 3.

N^2 Diagram

	Regulator	Economy	MFG	Transport	Land Use	Environment
Regulator			1	1	1	
Economy	1		1			
MFG		1		1		1
Transport			1			1
Land Use				1		1
Environment	1	1				

Figure 3: N^2 Diagram for Module Interactions

Model Characteristics/Assumptions

Our model is based on assumptions that were made to allow for simplicity and yet would still give enough fidelity to make the model behavior informative and realistic.

Economy. A prominent assumption made in the model was to recreate a demand driven economy rather than a supply driven competitive one. Profit margins are held constant for each industry. If there is demand in excess of capacity then the profit margin is increased, but if there is a limit in production capacity or if the price becomes excessive then the manufacturers are required to sell at a maximum price which may induce losses. In this model profits are not re-invested in capacity unless required by increases in demand.

Costs. In the supply chain module, costs that are attributed on a per product basis include raw material costs, manufacturing costs, externality costs (carbon emissions tax), transport costs (flat fee for truck and distance-based fuel cost), and inventory costs (both in transit and in storage).. The consumer price is the sum of these costs plus the profit margin, multiplied by the product tax.

Transportation and land use. Because our model uses system dynamics rather than discrete event modeling, the distances between the nodes of the network (raw material sources, production sites, warehouses, and retailers) are based on averages. The capacity of the network is given as a total including a passenger component (dependent on population and economic vitality). The use of the transportation network reduces its capacity over time while the influx of gas taxes is used to maintain and expand it. If transportation demand approaches the capacity of the network then both the speed of the vehicles is reduced (increasing travel time) and excess demand is unsatisfied. Finally, the vehicles operating in the model are of a single type and single mode (although variants can be implemented using the current structure). The capacity of the vehicles can be limited either by weight or by volume.

Model Design Variables and Parameters

The design vector for our model consists of regulatory actions that could be implemented to influence change in the regional network. The five design variable we chose are shown in Table 1, along with the acceptable range of values used in our model for each variable.

We should note that even though some of the ranges seem unrealistic we wanted to allow substantial room for the variables to capture the nuances of the model.

Table 2: Design Variable

Design Variable	Values (range)
Gas tax	\$0 - \$5 / gallon
Truck Weight Limit	50,000 – 160,000 lbs.
Recycling Mandate (where applicable)	0-100%
Product Tax	0-100%
Carbon Emissions Tax	\$0 - \$5 per kg CO ₂

We used more than one hundred individual parameters to represent a range of real-world characteristics typically beyond the control of transportation planners, ranging from the efficiency of the vehicles used to the demand curves for individual products. Some important model parameters are shown in Table 2.

Table 3: Parameters and Indicative Values

Network	Values (Initial)
Network Capacity (total)	60.000 vehicles
Nodal Distances	Varying (~20 miles for warehouses to retailers)
Vehicles	
Emissions / mile (base)	0.5 kg CO ₂ / mile
Empty truck weight	30.000lbs
Speed	55 mph (less if congested)
Economy	
Fuel Cost	\$1/gallon
Externality Costs	\$1 / kg CO ₂ \$0.5 / lbs of waste
Demand Curves	Varying
Population	1.000.000
Supply Chain / Production	(these values are for the automotive SC)
Product weight and volume	Var.(Auto 3000lbs, 12/truck)
Production Emissions	Varying (Auto 100kg/unit)
Manufacturing Costs	Varying (Auto \$4000/unit)
Material/Recycling Costs	Varying (Auto \$2000/unit)
Profit Margin	Varying (Auto 20%)

Figure 3 shows our model’s “dashboard” with all the major design variables and parameters represented as sliders that the user can change in order to investigate their effect on model’s objective function. Important variables in the model are tracked and graphed as the model runs.

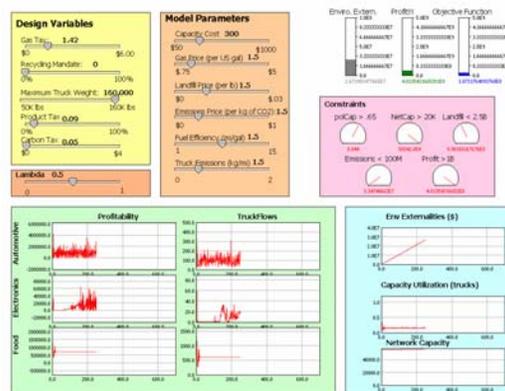


Figure 3: “Dashboard” view of the model.

Model Validation

The current model is sufficiently nuanced to exhibit complex behavior but the simplifying assumptions discussed previously, such as a “cost plus” economy, single mode of freight transportation, and limited number of industries render the model’s fidelity far from satisfactory.

For the reasons above, only the most general comparisons with real-world behavior can be made rather than exact model validation. We verified the model’s consistency of behavior through sensitivity analysis and time step by time step examination of results. We performed multiple runs examining outputs across the board and ensuring that the outcomes matched our expectations.

OPTIMIZATION

Design of Experiments

After our the completion of our model, we first explored the design space using a Design of Experiments L_{18} orthogonal array for our 5 design variables, using a high, medium, and low setting for each variable.

We found that for our five design variables, the combination favored by the design of experiments was a medium gas tax (\$1/gal), the smallest possible trucks (50,000 lbs), and no taxes or regulations of any kind. We did not do further investigation with design of experiments, however, because we know that there are very high interaction effects between our design variables, which diminishes the value of the main effects.

Selection of Optimization Algorithm

We originally hoped to be able to test the effectiveness of several different optimization algorithms on our model, including a variety of gradient-based and heuristic algorithms. Unfortunately, we were not able to get AnyLogic to interface with Matlab or any other optimization engine within our schedule constraints, although we know that this is possible to do. Instead, we chose to use the built-in OptQuest optimization engine.

Gradient-based optimization algorithms would have had difficulty on our model, as the design

space we discovered has many local optima that could trap this class of algorithms. Our design variables are poorly scaled, and would have required scaling if gradient-based methods were used.

The OptQuest optimization algorithm is a heuristic based algorithm that is based on Tabu search with a neural-network backend used to guide the search path. It has been compared to other more popular algorithms, such as genetic algorithms, and has been found to outperform them on several problems by a fairly wide margin, both in terms of accuracy and evaluations necessary to find an optimum [Glover, Kelly, and Laguna 1999].

Unlike genetic algorithms or simulated annealing, there are few parameters that need to be tuned in OptQuest. The few tunable parameters that are available relate to the criteria used to determine when the algorithm should stop, such as the minimum objective precision and the model time precision.

A separate choice to be made was to allow the algorithm to determine when it should stop based on its own internal algorithm, using a predefined minimum change in the objective function over a specified number of trials, or a simple number of trials that must be completed for each design combination. After experimenting with these options on our model, we determined that the auto-stop feature as well as the minimum change thresholds were not effective at determining where to stop. It was not uncommon for the optimizer to find a new best design after up to 1000 design trials that were not better than the previous best. While previous work detailing the efficiency of OptQuest suggests that for many problems, the algorithms should need two orders of magnitude less function evaluations[Glover et al. 1999], we found that OptQuest needed a large number of evaluations (~4000) before we were satisfied with the design it had found but we have not benchmarked it against other approaches.

Single Objective Optimization

We began the optimization analysis of our model using a single objective as the basis of optimization. We selected this single objective to reflect the task of the regional planner with

long-term sustainability in mind: to maximize the economic output of their region while minimizing its impact on the regional environment. We captured this objective as

$$f(\mathbf{x}) = \text{Profits} - (\text{Emissions Externalities} + \text{Landfill Externalities})$$

In order to directly compare the economy with the impact it has on the environment, we determined appropriate values to monetize the pollution caused by both emissions and landfill in dollars per kilogram. The choice of these values can be politically sensitive as they can bias the relative impact of policies as discussed in the Sensitivity Analysis section. We tried to choose values that were fairly moderate, but recognize that they play a significant role in the value of our objective function.

We also chose to run our model for two years as the basis for our optimization. We chose this time period to both minimize the time required for a model evaluation while allowing enough time for interesting effects, such as the impact of increased traffic on the transportation network, to have an effect on our model.

Constraints. The constraints in this experiment were chosen to represent a minimum acceptable standard in the region in terms of economic well-being, pollution from landfill and emissions, and roadway capacity. Acknowledging the political nature of many of our design variables and the anticipated resistance to radical change and increases in taxes by the general population we introduced the idea of a “*political capital*” constraint that limits the total amount of regulation that can be placed on a system such that a politician could hope to gain support for. Each type of tax or regulation carries a weight, analogous to its public visibility and is compared to the amount of change from a nominal value for that variable. Olsonian vs. Stiglerian [Oye 1994] considerations can also affect this weighting. Even in the case that the region would be better off with major changes on all five design variables, we consider this policy infeasible since decision-makers are rarely able to pull-off major changes without mounting opposition from the status-quo and interest groups. Instead, it is may be more practical to focus on one design variable or spread small changes across many. We found that in practice,

this constraint is often active, as verified by experience where it is always ‘easy’ to theoretically increase regulations and taxes, but this is rarely realized.

Below is the formulation of our optimization problem written in standard form, including the actual values we used for our constraints. We determined these constraints such that they would be challenging to simultaneously meet, in an effort to push the abilities of our optimizer.

Table 4: Optimization Problem in Standard Form

<p>Minimize $f(\mathbf{X}) = - \text{Profits} + (\text{Emissions Externalities} + \text{Landfill Externalities})$</p> <p>Subject to: $g(\mathbf{x}_i) =$ Emissions Externalities < \$100 M Landfill Externalities < \$200M Profits > \$1B Political Capital > .65 Infrastructure Capacity > 20,000 EV units</p> <p>Design Vector $\mathbf{X} = [\text{Gas Tax, Maximum Truck Weight, Recycling Mandate, Product Tax, Carbon Tax}]$;</p>
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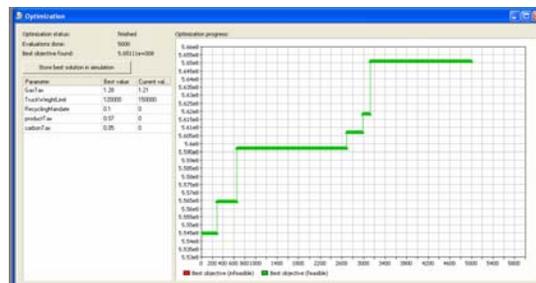


Figure 4 – The OptQuest Interface

When run, the optimizer graphs the value of the current objective function value for the best design at each function evaluation so that the user can see the progress of the optimizer. See Figure 4. The value of the design under consideration along with the values of the best solution are shown in the table the upper left side of the window. Feasible designs are indicated in green, while infeasible designs are indicated by red.

The experiment run in Figure 4 was set to stop after 5000 function evaluations. As can be seen from the chart, the optimization algorithm was trapped at a local maxima for over 2000 function

evaluations before finally escaping to a much higher optima later.

In this case the optimizer converged to the solution

$$X = [1.28, 120,000, 0.1, 0.07, 0.05]$$

$$f(X) = 5.65e8$$

which compares favorably with the results obtained using the design of experiments.

Sensitivity Analysis

To understand how sensitive our design variables and model parameters are at the optimal solution, we performed a sensitivity analysis at this point. We used central differencing to estimate the Jacobian, ∇J , at the optimal solution, and then normalized these values such that they show the percentage change in the objective function that occurs to a 1% change in the design variable or parameter. See Figure 5.

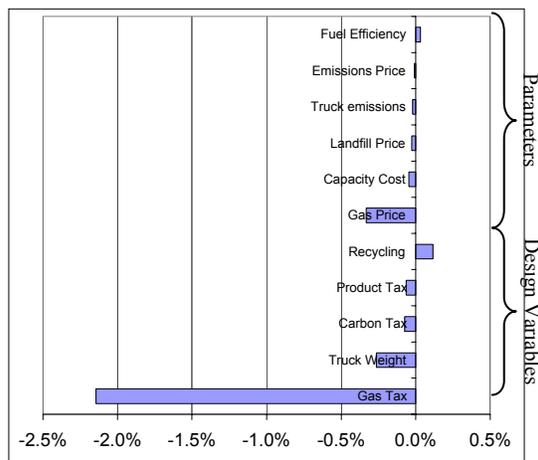


Figure 5 – Sensitivity Analysis of design variables and model parameters at X*.

As can be seen in the figure above, the variables and parameters that have the most significant effect are those that directly affect the market price for gasoline. This parameter impacts prices throughout the economy, and therefore has a large effect. The only two parameters that have a positive impact are recycling and fuel efficiency. It makes intuitive sense that increasing the fuel efficiency would have a beneficial effect. The reason recycling remains positive is because the design vector in this case was constrained by the political capital constraint, limiting the amount of change

allowable in the system. Surprisingly, the model parameters emissions price, average truck emissions, and landfill price do not have a significant effect. This is probably due to the scale difference in the two components of the objective function (profit is about two order of magnitude greater than environmental impact), as we discuss in the next section. If the environment had a strong impact on the objective function, these values would become more influential.

Multi-objective Optimization

Since the single objective optimization requires a monetization of the externality costs, the choice of those parameters can be open to controversy and political manipulation. Alternatively, multi-objective optimization allows for an exploration of the design space that gives relative valuations of multiple objectives. In our case, we chose two objectives as the basis for our multi-objective optimization: economy and environmental externalities. This mirrors the original single-objective closely, logically dividing the economy, which should be maximized, and the environmental externalities of landfill and emissions, which should be minimized.

For purposes of multi-objective optimization, we chose to use a weighted sum approach [Stadler 1984] to find the Pareto Front in our tradespace. The size of our design space was such that a full-factorial exploration would have been prohibitively large. We used the weighting factor λ to control the weight given to each of the two parts of our objective function. The formulation of $f(X)$ in the multi-objective case was:

$$f(X) = \lambda * \text{Profits} + (1-\lambda) * (\text{Emissions Externalities} + \text{Landfill Externalities})$$

We varied the parameter λ initially from 0 to 1, using a step size of 0.05 for a total of 20 points in the tradespace. The values 0 and 1 represent our anchor points—designs corresponding to optimizing strictly for minimizing environmental externality and maximizing profits, respectively. After looking an initial plot of the tradespace, we determined that there were large gaps for low values of λ , and ran a second run on the same data set, varying λ from 0 to 0.3 in steps of 0.01.

Pareto Front Analysis

Both sets of resulting design points are shown in the tradespace in Figure 6. The solid line indicates the apparent Pareto Front. As can be seen, many points found using the weighted sum optimization approach are dominated, especially as λ is increased to higher values and it seems that the economic gains reach an upper bound.

Despite the addition of data with finer λ step sizes, there is still a significant unpopulated section along the Pareto Front. For very low values of λ (< 0.03) designs are found near the lowest anchor point. As λ is increased, it quickly jumps up to a higher curve that slowly approaches the upper anchor point.

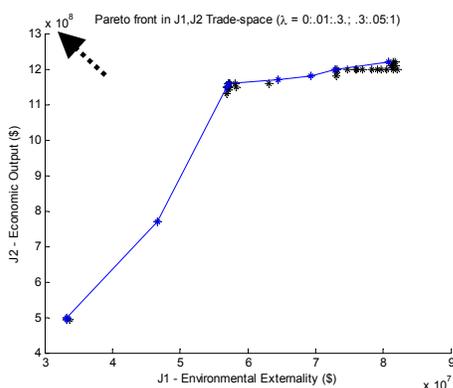


Figure 6 – Multi-objective Pareto Front. The points not on the line are dominated solutions. (The utopia point is in the upper left hand corner.)

The reason for this large jump is because our two objective functions are poorly scaled—the scale for environmental externalities is approximately two orders of magnitude lower than the economic scale. Because these scales are both in dollars, we feel that the objectives should be directly comparable and should not have scaling applied to them in order to get a smoother front.

The implication of this is that designs that wish to have a significant impact on the environment must heavily emphasize the environment at the expense of the economy. Looking at Figure 5, there is a knee in the curve at $\lambda = 0.15$. At this point, further reductions in emissions come at great expense to the output of the economy. Above this point, however, only modest gains

can be made for the economy by relaxing design variables that favor the environment.

Another interesting feature of our Pareto Front is that upon investigating individual point designs, we discover that often times very different designs can be very close together in the tradespace. For instance, near $\lambda = 0$, there were two major designs that lead to designs with minimal environmental externalities: extremely low gas taxes, which lead to a very poor infrastructure with limited capacity, and extremely high taxes which drove up the price of goods, causing the market to limit the quantities purchased. The latter method tended to be much better for the economy, but not quite as good as the case using a degraded infrastructure.

Designs along the Pareto Front. To understand how designs change as we move along the Pareto Front, we plotted three characteristic designs on a radar plot, corresponding to values of λ of 0, 1, and 0.15, which are the anchor points and the knee of the curve, respectively. See Figure 7.

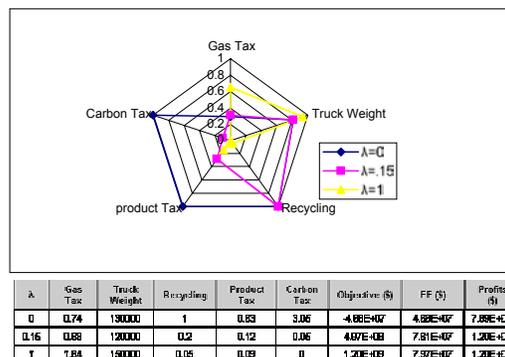


Figure 7 – Radar plot of three characteristic designs along the Pareto Front

The first design, corresponding to $\lambda = 0$, favors the highest possible carbon emission tax, product tax, and a 100% recycling mandate for all possible recyclable materials. It favors a medium-large truck size that reduces the number of trips necessary to haul freight, although larger trucks tend to have a higher impact on both emissions and the transportation infrastructure. Interestingly, the gas tax favored by this design is fairly low, which runs counter to the observations made on other taxes. Upon investigation, the reason for this is that the gas tax is used to maintain the transportation infrastructure. If the tax is low, the transportation network's carrying capacity and average speeds

in the network are lowered, leading to decreased traffic flows and emissions at the expense of the economy.

The second design, corresponding to $\lambda = 0.15$, is the design at the knee of the curve of the Pareto Front. Here, the recycling mandate is kept high, while taxes on emissions and products are lowered to promote the economy. The design, like others, favors a medium-large truck. The gas taxes are lower in comparison to other cases, but it is higher than in the first case.

The last design corresponding to $\lambda = 1$ favors almost the exact opposite set of design variables from $\lambda = 0$. Here, taxes are reduced to minimum possible levels to ensure that constraints are met. Again, trucks are at a medium large size, close to the sizes found by other designs, which minimizes fuel costs because fewer trips are needed, balanced against the impact they have on the transportation network.

CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER WORK

In this paper, we have presented a proof-of-concept model of a regional freight transportation network and supply chains, and shown how using multidisciplinary optimization techniques can help to yield insight into creating regulations to affect the region.

At fundamental odds are motivations to improve the economy while minimizing the damage that is done to the environment in the process of creating goods and services. We have seen that there is a sharp knee the Pareto Front, where the front transitions from a region where great gains can be had for limiting environmental damage while only marginally decreasing the economy, and another region where only marginal decreases in environmental impact can be realized while having a great effect on the economy. A regional planner that is interested in long-term stability would ideally want to focus on creating a portfolio of policies that lies in the vicinity of the knee, which offers a good compromise between minimizing environmental impact while maintaining a strong economy.

Our work has shown that gas taxes are a very sensitive policy lever, and the impacts of

changes in the gas tax should be carefully considered before making any changes to it. Other taxes, such as product taxes and emissions taxes should be kept at low levels that are just sufficient to achieve environmental goals, as these taxes when raised high have a significant negative impact on the economy with a comparatively smaller beneficial impact on the environment. Across a broad array of cases, freight truck size should be kept fairly large for achieving significant economies of scale by consolidating loads.

On the other hand we have to point out that these recommendations are only indicative of the capabilities of the method and should only be regarded after validation of a higher fidelity regional model.

Further Work

Because our model is modular, it would not be difficult to plug in additional modules to capture additional industries or to add increased model fidelity by adding in interfaces to traffic flow models or land use models. We also aim to design and implement a discrete event model for the supply chain to see how this would affect the results of our model. Additional characteristics, like more than one region, or different types of modes are possible to implement but they require structural changes in the model.

A very important next step in this model would be to apply it to an actual region for purposes of benchmarking. This would be difficult to do without first modifying the model to take into account market economies, global markets, and to allow for multiple modes of freight transportation and for imports and exports from other regions. A first region to model would ideally be somewhat isolated to minimize market transactions beyond the regions boundaries while having sufficient size that the impacts of distances in a freight transportation network could be felt. Additionally, the modeled region would have to have a manufacturing based economy, as service industries cannot be represented in our model without substantial modifications that would quickly grow the model well beyond its scope.

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