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Pricing and Product Mix Optimization in Freight Transportation

Michael F. Gorman
University of Dayton, mgorman1@udayton.edu

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Pricing and Market Mix Optimization in Freight Transportation

We propose improved pricing and market mix can improve the profitability of the freight transportation provider through the reduction of equipment repositioning costs. We hypothesize that because of complexities surrounding pricing and equipment repositioning costing, existing pricing strategies in freight transportation fail to fully consider these costs. We test this hypothesis in an applied setting in which Monte Carlo simulation captures the stochasticity of market conditions inherent in the problem. We use a heuristic to improve the nondifferentiable, discontinuous objective function. Our results from test cases show with high confidence that current prices are not optimal, as indicated by a strong correlation between recommended increases and decreases in market prices and the internalized repositioning costs. Our hypothesis is further supported by a high confidence that the obtained profit level distribution is significantly (statistically) higher than the current profit levels.

by Michael F. Gorman

The objective of this paper is to evaluate the hypothesis that an individual freight transportation company tends to implement pricing strategies that underrepresent the cost of empty equipment repositioning. By fully incorporating these costs into pricing strategies, freight carriers can vastly improve profitability in their network of service offerings, or market mix, through full consideration of equipment repositioning costs into their price offerings.

In order to test this theory, we propose an approach that addresses the three key components of developing an integrated network pricing strategy for a freight transportation company.

(1) Regardless of market structure, market demand conditions for each market in the network must be observed.

(2) Nodal equipment imbalances and repositioning costs must enter into individual loaded traffic market pricing and market mix decisions.

(3) Market condition uncertainties over future demand levels and price sensitivity must be included in order to assure a robust and useful model solution in an applied setting.

The solution employs a heuristic, which strives to maximize the nonlinear, discontinuous network profit function. The heuristic considers market conditions for all markets in the network and fully incorporates repositioning costs into pricing decisions through incorporating a transportation problem into the network profit function. To account for uncertainties in the product markets, we ran Monte Carlo simulations of the demand conditions to gain a level of confidence in the model solutions and to test them for sensitivity to changing market conditions.

We find that in our test cases in intermodal rail, a focus on the profitability of individual markets leads to pricing behavior that treats empty equipment repositioning costs as an externality, suboptimizing the

network. If these costs are in fact externalities to the product pricing decision, internalizing these costs into the pricing decision leads to greater network-wide profitability. As the costs of repositioning are considered, some markets prices are discounted while others are raised to achieve a better-balanced network. Statistical tests of the change in profit levels and correlation of recommended price changes with externalities show support for our hypothesis.

FREIGHT PRICING

Freight transportation provides the service of moving goods between numerous geographic locations, which are identified as origin-destination pairs. A directed arc connecting an origin and destination node in a network diagram represents a freight market (or product) that is characterized by a price and quantity as governed by the demand conditions facing the firm. The number of markets a freight transportation company participates in and the quantities offered in each of those markets measures its market mix.

When the difference of the sum of the quantities in inbound and outbound markets at a location does not equal zero, the equipment used in providing transport becomes unbalanced in the network and costly equipment repositioning must rebalance the network. Thus, the market mix impacts the cost structure for the transportation company through equipment repositioning costs the transportation company must incur to rebalance its equipment. An enlightened transportation company would recognize and try to encourage markets that reduce this cost and discourage business that increases this cost to the extent these markets are profitable.

Despite this relationship, pricing decisions are often limited to a market (arc) focus, ignoring or discounting equipment imbalances and repositioning requirements which exist by location (node). While the direct

costs of the market (such as fuel and crew) affect market profitability in a clear way, node imbalances affect individual market's network-level profitability through complicated interactions with other markets. Thus, the total cost of repositioning is neither fully nor accurately included in pricing decisions for individual markets; some markets are more profitable than they would appear on the surface, while others are less so. In economic terms, repositioning is a positive or negative externality to each individual market, but a fully internalized cost in the network of products provided by the transportation company.

Taking a network pricing perspective on product pricing is a daunting challenge. The best way to address a costly imbalance at a particular location in the network depends on both the market conditions for all markets in and out of that node as well as the imbalances at locations adjoined by the markets (which are themselves affected by all markets they face). Because numerous markets affect the imbalance at each location, and each of the markets affects two locations in the network, it is difficult to effectively identify the best markets for price changes to maximize the profitability of the network. Further, as market conditions change continuously, the network should be regularly reevaluated for pricing opportunities. The speed of price publication and proliferation of spot-market pricing made possible by the Internet makes the ability to create on-the-fly precision pricing with a network wide perspective all the more pressing.

LITERATURE REVIEW

No work has been published based on intra-firm externalities in pricing transportation products, but work from related areas applies to some aspects of the problem.

Considerable work has taken place in the area of rail equipment repositioning, as in Crainic, et al. (1993). It is important to note

that this work focuses on pricing strategies to reduce network imbalances and required repositioning (equipment imbalances), not optimal repositioning strategies given those imbalances.

The most prolific publishing in the literature on interrelated markets deals with the interactions of numerous product markets. Samuelson (1952) provides a general framework to spatial price equilibrium in numerous markets. It accurately argues proper analysis requires a multi-market view. Dafermos and Nagurney (1989) introduce spatial separation to network market models with fixed transportation costs. It focuses on the shipper's multiple products rather than the multiple transportation products provided by the carrier, as is the case here.

Hurley and Peterson (1994) and Friesz, Gottfied and Morlok (1986) discuss optimal freight market pricing from the carrier's perspective. These works concentrate on the shipper-carrier relationship given the impacts of large shippers and the optimal setting of volume price breaks in an oligopolistic setting. This study differs in that it assumes the carrier sets price on a market-wide basis, not by individual shipper, as is the case when a large number of small shippers make up the market. This study includes inter-carrier interaction only insofar as it is represented by the demand curve facing the carrier; it is concerned with characterizing intra-carrier multiple product interactions.

Other studies have considered multiple product interactions within the firm. Beije and Groenwege (1992) lead a qualitative discussion of the inadequacy of single-market analysis when multiple products are usually produced by a firm in cooperation with a number of suppliers facing an array of input and output market conditions. Dillon and Roberts (1993) provide an empirical analysis of cross-product input market impacts in the agriculture industry, which estimates the interrelationships of input and output markets. Both of these studies only characterize firm behavior; neither presents a quantitative, prescriptive model for optimal behavior for a firm producing multiple inter-related markets.

PROBLEM DESCRIPTION:

The firm's objective is to maximize network profit (Π^n) across all markets M_{ijk}:

$$(1) \quad \Pi^n = \Sigma_i \Sigma_j \Sigma_k (TR_{ijk} - TC_{ijk}) - \Sigma_k (TRC_k),$$

where i and j are indexes for origin and destination nodes in the network, and k is an index for equipment type. Any particular node in the network can act as either an origin or a destination for a market or both.

We assume the firm faces a downward-sloping demand curve, and thus has some price-setting capability. The quantity sold in each market, q_{ijk}, is given by

$$(2) \quad q_{ijk} = f(p_{ijk}, \mu_{ijk}, \varepsilon_{ijk}),$$

where p_{ijk} is the price charged in the market which is driven by ε_{ijk}, the price elasticity of demand facing the firm in the market. μ_{ijk} represents any number of exogenous demand-shift variables.

We experimented with numerous functional forms for the potential demand curve facing the firm, including constant slope (linear), constant elasticity (log linear), and kinked at the current market price (non-linear). The search methodology performance was unaffected by the functional form of the demand curve. In both the stylized example and the case study presented below, we found the linear demand curve represented the problem well and suited our needs.

We assume the firm does not price discriminate and charges only one price for all units shipped in a market such that total revenue, TR, is the product of price, p, and quantity, q, in each market. To the extent that some price discrimination may be possi-

ble, p_{ijk} may be interpreted as the mean of the prices charged in a market without affecting model validity.

Let the total cost function be represented by $\psi(q_{ijk})$. The model allows for any non-decreasing total cost function. We tested quadratic (increasing marginal costs), linear (constant marginal costs), and nonlinear (discontinuous costs based on discrete, train-level volumes of service), and hard capacity constraints. Because the search methodology makes no assumptions on functional form, instead evaluating improvement computationally, it is unaffected by the choice. For simplicity, we use a linear total cost function for our stylized example. We found a constant marginal cost function in our case study adequately depicted the cost of service in the quantity ranges under consideration in the case study.

Thus, given demand curve and cost functions, the direct market profit disregarding network repositioning is given by:

$$(3) \quad \Pi^d{}_{ijk} = p_{ijk} * q_{ijk} - \psi(q_{ijk})$$

COST ALLOCATION

In order to determine total network repositioning costs and allocate them across markets, a classic transportation problem is solved to address all imbalances in a way that minimizes Total Repositioning Cost (TRC) and to determine the total network repositioning costs.

$$(4) \quad TRC = \Sigma_k \, Min \, TRC_k = \Sigma_k \Sigma_i \Sigma_j \, RC_{ijk} \, R_{ijk}$$

$$\text{subject to } \Sigma_j R_{ijk} - \Sigma_j R_{jik} = I_{ik} \quad \text{for all } j.$$

Where the imbalance I at a node i for equipment type k (I_{ik}) is equal to the difference between the total market flows into (q_{jik}) and out of (q_{ijk}) the node i for each equipment type, k.

$$(5) \quad I_{ik} = \Sigma_j q_{jik} - \Sigma_j q_{ijk} \qquad \text{for all k.}$$

The market quantities directly impact the repositioning flows, R_{ijk}, the total repositioning costs, TRC, and thus the network profitability function.

When repositioning costs are introduced into the profit function, they are no longer external to the individual market profit function and the total service costs become interdependent. They are tied through the required repositioning implied by imbalances at the nodes, I_{ik}, in the network. The network transportation problem is solved for all surpluses and deficits in the network and the total repositioning costs are subtracted from the profits of the individual markets. Optimal prices cannot be derived by analytical methods that cannot capture the complicated cost interdependencies across markets that arise from repositioning. At the boundaries of dual sensitivity ranges, marginal costs are discontinuous and total costs are nondifferentiable. Thus, other methods must be used to find optimal prices.

The dual values, D_{ik}, on the balance constraints in the transportation problem indicate the dollar value of reducing or expanding a surplus or deficit at a single location in the network. For a market, which affects two locations in the network, the Marginal Externality Cost, MEC_{ijk}, of an additional unit moved is difference of the duals between origin and destination nodes in the market:

$$(6) \quad MEC_{ijk} = D_{ik} - D_{jk}.$$

The MEC indicates the relative dollar value of equipment at each location. A positive MEC_{ijk} indicates an equipment move to a more desirable location, and TRC_k, is reduced (a "bonus") through reduced repositioning; TRC_k is increased if MEC_{ijk} is negative (a "penalty"). The network repositioning costs resulting from market quantities are internalized to individual markets through the equation:

(7) $\Pi^n_{ijk} = TR_{ijk} - TC_{ijk} + q_{ijk} * MEC_{ijk}$

Note that for each equipment type, k, all repositioning costs are allocated to the various markets.

(8) $TRC_k = \Sigma_i \Sigma_j MEC_{ijk} * q_{ijk}$

ALLOWING FOR DEMAND UNCERTAINTY

When testing our theory in an applied setting, we must account for the single most ubiquitous form of pricing inefficiency, market demand uncertainty. Market uncertainty affects pricing two ways. First, existing network price shortcomings may be a reflection of market uncertainty that can create the inability to price optimally. Second, reckless pricing strategies that aggressively attempt to reduce nodal imbalances could have highly negative profitability impacts due to demand uncertainty. Because of the nature of the problem, the objective function has a sharp peak at its optimum where the bonus becomes a penalty (a change in sign of MEC). For example, using price reductions to reduce an equipment surplus at an origin node could create a deficit at the origin because of unpredictable customer behavior. In this case the market profitability is hurt two ways: through the lower market price as well as the increased repositioning costs into the origin that has become a deficit location. In order to have a fair comparison against current pricing practices, and to introduce market risks to the model search, it is critical to search for potential price improvements in the presence of market uncertainties.

Two forms of demand uncertainty shroud the successful application of the algorithm: uncertainty of price elasticity of demand, ε_{ijk}, (customer responsiveness to price changes) and of shifts in demand, μ_{ijk}, (external economic impacts on the markets). We found a trapezoidal, or truncated triangular, distribution as depicted in Figure 1 best met our sampling needs for these variables. Within the expected range for demand and elasticity levels, observations were distributed uniformly. Outside the expected range, a linear degradation of probability of occurrence is applied out to the best case and worst case possibilities for each sampled variable.

We must estimate price elasticity of demand to price effectively; however, the responsiveness of customers to a change in price is typically difficult at best to estimate. Given the general lack of precision in price elasticity estimates typically produced through statistical methods (Tellis, 1988), we develop a nonstatistical methodology which is consistent with current market pricing behavior (Gorman, 2000).

Pricing strategies that are not robust to varying demand conditions are not useful in an applied setting. We avoid relying on a single point estimate of elasticity of demand by sampling ε_{ijk} as shown in Figure 2a (adapted from Gorman, 2001). We ran the optimization routine multiple times, each from a different random draw from a distribution of elasticity estimates to generate recommendations that hold for a wide range of customer price responsiveness.

Exogenous factors create shifts in the demand curve that can upset pricing strategies geared towards maximizing profits by managing nodal imbalances. To introduce the market risk associated with demand shifts, we conducted Monte Carlo sampling of the stochastic demand level, μ_{ijk}, as shown in Figure 2b. We sample demand shifts within the search, producing a risk-adjusted measure of expected profit for each market with each iteration. Sampling from a distribution within the optimization module bases decisions on expected values of the profit function, and creates model output that is a distribution of optimal prices under a wide variety of demand conditions. We forego point solutions in favor of less precise but more robust

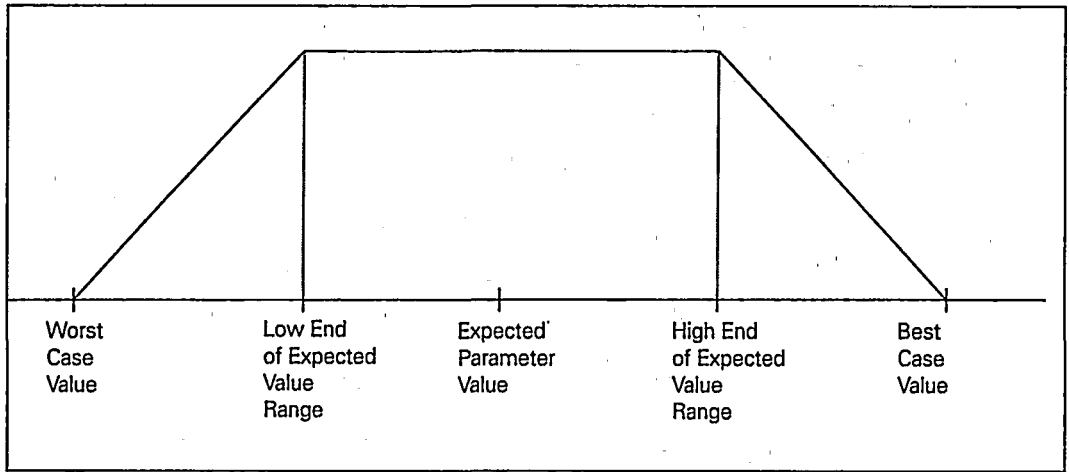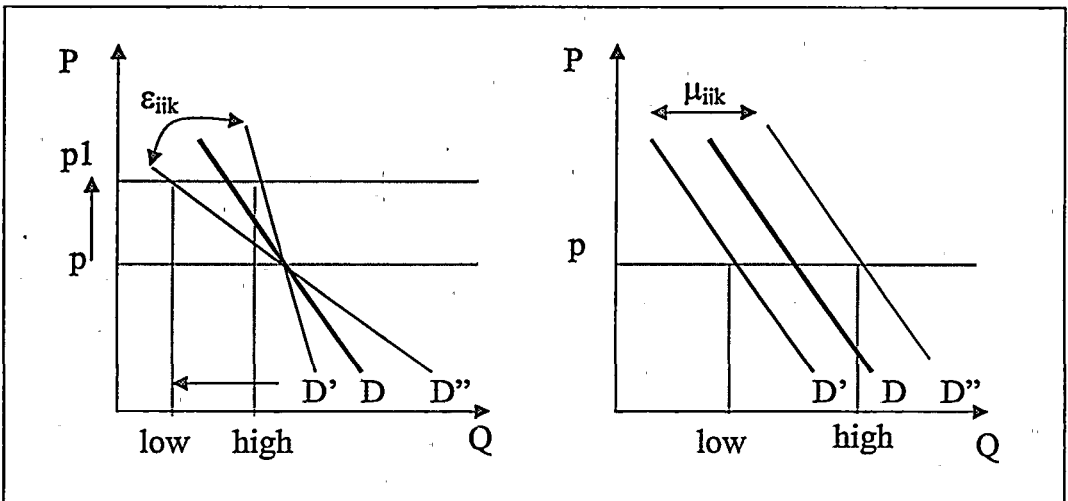**Figure 1: Trapezoidal Probability Density Function Used for Demand Parameters ε_{ijk} and μ_{ijk}.**

Worst	Low End	Expected	High End	Best
Case	of Expected	Parameter	of Expected	Case
Value	Value	Value	Value	Value
	Range		Range	

Figure 2a: Demand Elasticity Sampling (ε_{ijk}).   **Figure 2b: Demand Shift Sampling (μ_{ijk}).**

recommendations based on the expected value of the objective function.

In the stylized example presented below, we did not perform any elasticity or demand sampling for ease of illustration. In our case study, sampling distributions for demand shift and price elasticity sensitivity are based on market study and expert opinion. For the demand shift sampling, in order to be conservative we used double the range of actual market quantities experienced by BNSF for the past four quarters. For the elasticity sampling, we used from one-half to two times the point estimate generated from the methodology in Gorman (2000). We validated this range with a survey of BNSF market managers who were most familiar with these markets. The sampling range employed fully encompassed most survey responses received.

SOLUTION ALGORITHM

No standard method exists to solve the problem in equation (1) to optimality because of the discontinuous, nondifferentiable profit function with numerous local optima. Additionally, because of the combinatorial attributes of setting prices in multiple markets, the problem size grows exponentially with the number of markets. Thus, we focus on quickly finding price improvements over existing pricing strategies as evidence of the presence of externalities, rather than search for optimal prices. We found a heuristic for finding price improvements was effective for testing our hypothesis. We felt that more exact and time-consuming search methods were unwarranted given the uncertainty of market demand parameters.

The algorithm uses a computational gradient technique to improve network prices. Parameters to the search—the set of starting prices $\{P^0\}$, the initial step size, Δp^0_{ijk}, final step size, Δp^{min}_{ijk}, and the rate of reduction of the step size, α—are derived experimentally. We found solution speed and quality to be negligibly affected by these parameters, but the implications of the analysis hold whatever the parameter choices. The quantity of sampling of elasticity and demand shifts each affects model solution speed linearly; usually 10 samples of each were enough to gain confidence the model was producing regular and stable results in the face of uncertainty.

Throughout the algorithm description, the denotation " ' " indicates the value of the variable set (P', Q', D', p'$_{ijk}$, q'$_{ijk}$, $\Delta p'_{ijk}$, $\Delta \Pi'_{ijk}$) in the current iteration.

The algorithm proceeds as follows.

(1) For n sets of price elasticity samples:

(1.1) Sample market price elasticities, e_{ijk} for all markets under consideration.

(1.2) Set $\{P'\} = \{P^0\}$; Set $\{Q'\} = \{Q^0\}$; Set $\Delta p'_{ijk} = \Delta p^0_{ijk}$

(2) While $\Delta p^{min}_{ijk} < \Delta p'_{ijk}$,

(2.1) Calculate the set of market quantities $\{Q'\}$, given the current best set of $\{P'\}$, as in equation (2).

(2.2) Calculate direct profits Π^d_{ijk} given the set of prices $\{P'\}$ and quantities $\{Q'\}$ as in equation (3).

(2.3) Calculate imbalances I_i given $\{Q'\}$ for all nodes in the network as in equation (8).

(2.4) Solve the total repositioning cost linear program TRC as in equation (4).

(2.5) Update the duals $\{D'\}$ for all points in the network as indicated by the solution to TRC.

(2.6) Calculate the marginal externality cost (MEC$_{ijk}$) of all markets as in equation (6).

(2.7) Calculate the network profits generated by each market (Π^n_{ijk}) as in equation (7).

(2.8) For m samples of demand shift parameter μ_{ijk}:

(2.8.1) Calculate q'_{ijk}, for $p'_{ijk} = p'_{ijk} \pm \Delta p'_{ijk}$ as in equation (2).

(2.8.2) Generate expected change in total market profit estimates:
$$\Delta \Pi'^n_{ijk} = \Delta TR_{ijk} + MEC_{ijk} * \Delta q_{ijk} \qquad (9)$$

(2.9) Let $p'_{ijk} = p'_{ijk} \pm \Delta p'_{ijk}$, for $\Delta \Pi^n_{ijk} > 0$. (Update value of p'_{ijk}.)

(2.10) If $\Delta \Pi'^n_{ijk} <= 0$ for all markets, then $\Delta P'_{ijk} = \Delta P'_{ijk} * \alpha$. (Update value of $\Delta P'_{ijk}$.)

(3) $\{P^*\} = \{P'\}$ given this sample of ε_{ijk}. (Save the current values of P'.)

(4) Save distribution of $\{P^*\}$ for all n samples of e_{ijk}.

The algorithm returns a distribution of price change recommendations {P*} and a distribution of expected profit levels given samples from various market conditions (ε_{ijk} and μ_{ijk}).

STYLIZED EXAMPLE

For pedagogical reasons, we adapted a simple three-node, six-market, single equipment type network adapted from Gorman (2001) as shown in Figure 3 to demonstrate the concepts of this model. The network is solved without sampling for ease of presentation.

In this network, the flows in the six product markets result in equipment deficits and surpluses at the three end points which must be balanced via equipment repositioning at the transportation provider's expense. Table 2 shows the market profits from the customer moves, the corresponding repositioning costs, and the resulting network profits before the optimization algorithm is applied to the network. Table 2 also shows the corresponding steps in the algorithm that generate the calculated figures.

Based on the results of the empty repositioning linear program, TRC, dual values are used to create MEC(0) (the initial value of MEC given initial values in the network), which is shown in Table 3. The initial step size is set to $\Delta P_{ijk} = \$50$ and $\alpha = .75$. The search stopped when $\Delta P_{ijk} < \Delta P^{min}_{ijk} = \$1$. After 21 iterations of the algorithm on this simple network without demand shift sampling (Step 2.8), the model finds no further improvements in network profitability (Steps 2.9 and 2.10) and converges on the final results in Table 3.

The total network profits in Table 3 and the change in network profits in Table 4 both demonstrate an opportunity to overcome the resulting 6% reduction in market profit due to price changes with an 85% reduction in empty repositioning costs, resulting in a 23% network profitability increase. The results are particularly dramatic in this example because of the small network, which allows for few low-cost repositioning alternatives.

It is interesting to note that the FW-CH market is originally priced as a negative-

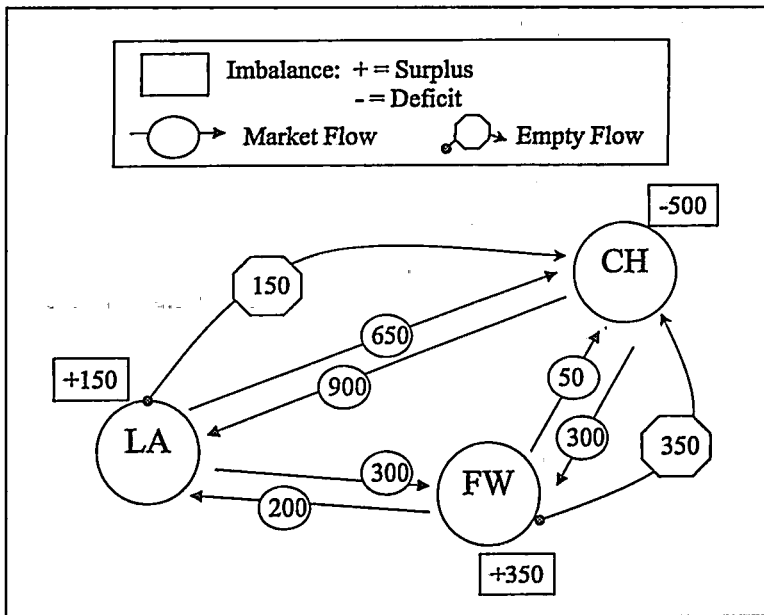Figure 3: Sampling Illustrative Network

Table 1: Variable Glossary

Market Pricing Problem Variables:

i = Origin node index for any node in the network acting as an origin

j = Destination node index for any node in the network acting as a destination

k = Equipment type index

q_{ijk} = Total quantity shipped by the carrier in the market from i to k for equipment k

p_{ijk} = Price charged in the market from i to j for equipment type k

Π^d_{ijk} = Direct profit associated with the market from i to j for equipment type k

Π^n_{ijk} = Network profit associated with a market, including repositioning cost impact

Π^n = Total network profit; equals the sum of Π^n_{ijk}

TR_{ijk} = Total revenue generated from a market

TC_{ijk} = Total direct costs of a market

Repositioning Problem Variables:

TRC_k = Total network repositioning cost

R_{ijk} = Repositioning flow from node i to node j for equipment k

RC_{ijk} = Repositioning cost from node i to node j for equipment k

MEC_{ijk} = Marginal externality cost of the last unit moved in a market, q_{ijk}

D_{ik} = Dual of balance constraint at node i for equipment k

I_{ik} = Imbalance at node i for equipment type k

Stochastic Demand Parameters:

μ_{ijk} = Exogenous factors causing shifts in the demand curve of a single market

ε_{ijk} = Price elasticity of demand in a single market

Sampling Parameters:

m = Number of samples taken of μ in each iteration of each price search

n = Number of samples taken of ε, also the number of price searches

Search Parameters:

α = Factor for reducing the step size of search in P_{ijk} , $0 < \alpha < 1$

$\{P^*\}$ = Final set of recommended prices from price recommendation search

$\{P^0\}$ = Initial set of prices to start recommendation search

Δp^0_{ijk} = Initial step size in price search

ΔP^{min}_{ijk} = Minimum step size to be considered in price search

profitability move when looking at only the direct market profit. The only rationale for this pricing is to encourage additional volumes in this market to reduce surpluses thereby reducing deficits at FW and CH. The model does not suggest a change to this price; rather, to address these imbalances it shuts down the CH-FW market. Thus, although repositioning costs had been accounted for to some degree in initial pricing, correct incorporation of repositioning costs into pricing decisions results in a large impact on network-based pricing.

CASE STUDY RESULTS

We test our hypothesis in applications from 201 to 462 markets of six equipment types in intermodal freight rail at Burlington Northern Santa Fe Railroad to test for the presence of equipment repositioning externalities in an applied rail setting. The model only applies to rail-controlled equipment, for which railroads are responsible for shouldering repositioning costs. (Shippers manage and pay separately for the repositioning of privately owned fleets.) We applied the problem to six of eight different

Table 2: Starting Prices and Quantities for the Network in Figure 3

	Step 1.1	Step 1.2	Step 2.1		Step 2.2
Market	Elasticity	Price	Quantity	Cost/Load	Market Profit
CH-LA	7.5	$1,200	900	$650	$495,000
LA-CH	4.0	$750	650	$650	$65,000
CH-FW	2.3	$600	300	$500	$30,000
FW-CH	6.0	$350	50	$500	($7,500)
FW-LA	3.4	$850	200	$600	$50,000
LA-FW	7.0	$700	300	$600	$30,000
Total:			2,400		$662,500
Step 2.3	Network Imbalance:		CH -500	FW +150	LA + 350
Step 2.4	Repositioning		Quantity	Cost/Empty	Total Repo Cost
	LA-CH		150	$500	$75,000
	FW-CH		350	$300	$105,000
	Total Repositioning		500		$180,000
Step 2.5	Dual Values:		CH +300	FW -300	LA -500
Step 2.7	Total Network Profit: (Market Profit - Total Repositioning)				$482,500

Table 3: Final Network Prices and Quantities

	Step 2.6	Step 3.			
Market	MEC(0)	Price	Quantity	Cost/Load	Market Profit
CH-LA	$800	$1,211	866	$650	$485,826
LA-CH	($800)	$738	723	$650	$63,624
CH-FW	$600	$700	0	$500	$0
FW-CH	($600)	$350	50	$500	($7,500)
FW-LA	$200	$861	190	$600	$49,590
LA-FW	($200)	$689	333	$600	$29,637
Total			2,162		$621,177
Repositioning			Quantity	Cost/Empty	Total Repo Cost
LA-CH			0	$500	$0
FW-CH			93	$300	$27,900
Total Repositioning			93		$27,900
Total Network Profit:					$593,277

Table 4: Change in Network Prices and Quantities

Market	Price	Quantity	Market Profit	Price/MEC(0)
CH-LA	$11	(34)	($9,174)	1.4%
LA-CH	($12)	73	($1,376)	1.5%
CH-FW	$100	(300)	($30,000)	16.7%
FW-CH	$0	0	$0	0.0%
FW-LA	$11	(10)	($410)	5.5%
LA-FW	($11)	33	($363)	5.5%
Total		238	($41,323)	5.1%
LA-CH		(150)	($75,000)	
FW-CH		(257)	($77,100)	
Total Repositioning		(407)	($152,100)	
Total Network Profit:			$110,777	

intermodal equipment types, which are vans and containers of different lengths.

The initial prices and quantities are set to current market conditions. The initial step size is set to $\Delta P_{ijk} = \$50$ and a = .75. The search stopped when $\Delta P_{ijk} < \Delta P^{min}_{ijk} = \$1$. The demand shift parameter, μ_{ijk}, is sampled for m=30 times for each price change; price recommendations are based on sampling for n=30 different ε_{ijk} elasticity draws. As a test, we ran the model with other search parameters and found similar results.

Precise optimization in this setting cannot be assured nor was aspired to, given market uncertainties. Our objective was to find high confidence of improved pricing strategies despite market uncertainty, as evidence that repositioning costs are external to individual market pricing within the transportation firm.

The solution algorithm produced intuitively plausible solutions for both nodal imbalances as well as market prices. While creating a more balanced network, no rec-

ommended market price changes generate an expected reversal of a nodal imbalance. The introduction of uncertainty of demand to the solution algorithm creates high costs of aggressive attempts to balance the network, driving a risk-averse behavior in the price search that reduces the likelihood of overly aggressive pricing. We found individual market price recommendations to be plausible. For example, no corner solutions (such as market shut down) are generated, primarily due to the quadratic nature underlying the profit function.

Our hypothesis is that equipment repositioning costs are an externality, or are under-represented, in current prices. We tested this hypothesis in two ways. First, we looked at the correlation of MEC and recommended price changes. A positive correlation is evidence that these costs are not fully reflected in current pricing. Second, we looked at the distribution of revised profit levels after recommended prices are implemented. If a high confidence is achieved that proposed prices

deliver improved profitability despite market uncertainties, then the improvements attained are delivered despite market uncertainties.

Our findings support the hypothesis that empty repositioning costs are externalities to individual markets in this case study. We found a high correlation between recommended price changes and MEC in each market. Recommended price changes in 90% of the markets studied were positively correlated with the introduced externality cost for that market, MEC_{ijk}. The other 10% of the markets experienced no recommended change in price. The correlation holds true regardless of direction of recommended price change; 46% of the price changes were price increases, 44% were price decreases. We found no examples in which price moved in the opposite direction of MEC. Similar results were realized in our stylized example, in which five out of six market prices moved in the same direction as MEC, while the last was unchanged.

Despite the strong correlation of the change in price and MEC, we noted that the size of the price changes was only 14% of the MEC, which is a smaller ratio than initially anticipated. Similarly, in the stylized example, the average ratio of price change to MEC was only 5%. We hypothesize three reasons for the small price changes. First, the repositioning costs are, to some degree, already considered in existing market prices; the MEC is not an external cost in its entirety. Second, uncertainty in market parameters discourages more aggressive price changes. Both in practice and in this model, demand shifts can cause otherwise valid network-balancing prices to become undesirable. Third, the simple algorithm finds an improvement less than the true optimum, and prices change less than optimally given MEC in each market.

Based on our results, there is a high level of confidence that current prices produce suboptimal profit levels, as is visible in Figure 4. Despite the introduction of a wide range of market fluctuations, in all applications tested, the distribution of expected profit levels after optimization has almost a 95% confidence level that revised prices produce improved market mix and network profitability. Across all markets studied, the model proposed an average of a 2.94 percent improvement in network wide profitability.

Profit improvements found by the model were driven primarily by the reduction in required repositioning after pricing modifications. In fact, direct market revenues and profits both fall in every case examined, but are more than offset by reduced repositioning. In one example (Gorman, 2001), a 3.5% increase in network-wide profits was realized through a 61% reduction in empty equipment repositioning costs. These gains could only be realized by accepting a 1.4% reduction in revenue and a 4.1% reduction in direct market profits. We observe this as further evidence that the focus tends to be on optimal pricing based on the primary markets' costs and revenues, and that the repositioning costs are largely underrepresented in pricing decisions.

These results also imply that the current level of equipment repositioning in the transportation network studied is above optimal. In every case examined, we found a 50-70% reduction in repositioning with model recommended prices. By introducing MEC to the pricing decision, the network-wide repositioning is drastically reduced. Reduced repositioning frees up otherwise unproductive equipment time and makes it available to provide additional revenue, effectively expanding the fleet's effectiveness and reducing shortages through a market mix that is complementary with respect to equipment utilization.

EXTENSIONS

In this analysis, we take a centralized view of cost allocation and equipment repositioning for the freight transportation carrier. We set

Figure 4: Distribution of Projected Savings Based on Model Results
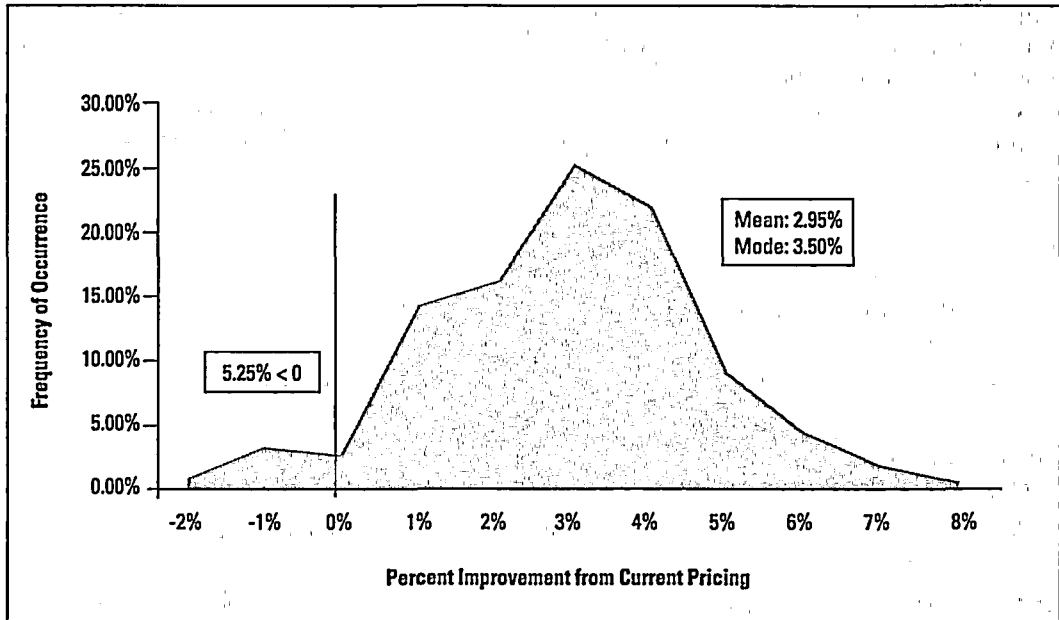
a combination of market prices that strive for network profitability given an externality. The same efficiency gains could be realized via a different mechanism: a market-based approach to externality internalization. If liquid trading markets were devised for buying and selling the rights to empty equipment at the network nodes, prices for the equipment would result that parallel the duals calculated in TRC. By this method, instead of including repositioning considerations while pricing in the primary market, the freight transportation price may be split into two separate components: one for the direct shipment of the goods, and one for the acquisition and disposal of the empty. In this way the pricing decision in the primary transportation market is simplified to include only the direct factors of shipment; repositioning costs are handled in their own markets. These secondary markets have the potential for removing the task of allocating externality costs from the primary markets by distributing them to secondary markets, thereby untangling the equipment repositioning considerations from

the primary market pricing. The advantage to this approach would be more responsive and dynamic secondary market pricing for equipment repositioning. While the approach is different, the implication would be the same: the cost of empty repositioning must be fully considered within the transportation provider's market mix strategy.

CONCLUSION

We hypothesize equipment repositioning costs are treated as an externality to the freight transportation pricing decision. We propose a methodology that allows us to capture these externalities in the individual market pricing decisions. Monte Carlo simulation accounts for marketplace demand and price sensitivity uncertainties to produce a robust solution in an applied setting. A simple heuristic generates objective function improvement quickly despite the nondifferentiable, discontinuous nature of the objective function. The approach succeeds in resolvi147ng empty equipment repositioning

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externalities and identifying market-pricing opportunities in a case study in freight rail. Our results confirmed our hypothesis; we observed a strong positive correlation of price change and externality when the cost is introduced to the pricing decision. Further, we observed almost a 95% confidence that the level of net profits is increased through our methodology. We concluded freight transportation companies must take an optimal market mix perspective when establishing pricing policy rather than focusing on the performance of their individual products.

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Michael F. Gorman is currently the director, Supply Chain Solutions at Burlington Northern Santa Fe Railway. Previously, he has held positions in eBusiness, Operations Research, Service Design, Marketing and Finance at BNSF. He is also currently an adjunct faculty member at Southern Methodist University. Gorman has published and refereed research in topics such as asset management optimization in a rail setting, pricing theory and practice, and inventory strategies and business cycle dynamics. He has received numerous recognition awards at BNSF for his work, and has won teaching awards from Indiana University. He has recently chaired the Rail Applications Special Interest Group of INFORMS. He has a Ph.D. in Business and Economics from Indiana University, M.S. in Economics from Indiana University, and B.S. in Computer Science and Economics from Xavier University (Cincinnati).