Network Systems Analysis and Value-Focused Decision-Making for Regional Logistics

Megan E. Gunn, *Member, IEEE*, Megan C. Marcellin, *Member, IEEE*, Matthew C. Gunn, *Member, IEEE*, Davis C. Loose, *Member, IEEE*, Eric Jehu, Femi Popoola, Karen R. Jackson, Daniel F. Otero-León, Igor Linkov, and James H. Lambert, *Fellow, IEEE*

***Abstract*—There is a need to better understand the impacts of multimodal logistics parks (MMLPs) on freight supply chains. Through Markov decision processes, this paper examines the benefits of an MMLP in Virginia, United States for freight logistics, including for high-value electronics and consumer products. Models representing freight logistics with and without an MMLP are developed, and the optimal policies and values are compared to provide insights into the economic and operational benefits of an MMLP. An underlying freight network is created for shipping in the eastern and midwestern United States, and transport modes of road (full truckload and less-than-truckload), rail, and air are considered. Using backward induction, the shipping routes and modes that maximize the expected cumulative reward, defined as revenue minus shipping costs, are determined. For freight originating in eastern Virginia, the inclusion of an MMLP is found to increase the optimal value by approximately 15-20% depending on shipment size and market conditions. Sensitivity analyses on the network and model parameters suggest that hub utility is robust to changes in network structure, mode reliability, and shipping discount parameters. The results support decision-making for freight shipping and multimodal logistics infrastructure, strategy, and resilience.**

***Keywords*—supply chains, trust, security, freight logistics, decision analysis, systems engineering, optimal policy, stochastic decision models, Markov decision processes**

I. Introduction

Virginia, United States is positioned as a leader in logistics services due to its strategic location along major U.S. East Coast transportation routes. Nearly half of U.S. consumers can be reached within a one-day drive of Virginia, and three-quarters of consumers can be reached within a two-day drive [1]. More than 200 supply chain companies have operated in Virginia in the last ten years, creating over $800 billion in value [1]. Virginia has well-developed freight rail and air cargo networks. The state operates 16 commercial airports, including three international airports that combined ship hundreds of millions of tons of cargo annually (Dulles International, Richmond International, and Norfolk International) [1]. The freight rail network is operated mainly by two private entities, Norfolk Southern and CSX Transportation [2]. While some intermodal rail facilities exist in Virginia, the existing facilities lack flexibility, generally only providing rail to full truckload (FTL) services [3]. In contrast to FTL shipping that involves reservation of an entire truck for a single shipment, less-than-truckload (LTL) shipping refers to shared truckloads across shippers, allowing shippers to move smaller quantities of goods more efficiently. The emergence of LTL as a prominent shipping mode has highlighted a critical gap in Virginia's multimodal freight coverage. The Virginia Multimodal Long-Range Transportation Plan for 2040 predicts significant growth in the freight transportation sector through 2040, reaching one billion tons of freight shipped through the state annually [3]. With the continued growth of the freight sector, assessing supply chain resilience, flexibility, cost efficiency, and opportunities for improvement is essential for public and private entities invested in the sector [4], [5].

Multimodal logistics parks (MMLPs) have recently been adopted in India to streamline multimodal logistics. These parks span, at minimum, 100 acres and provide a centralized hub for multimodal freight aggregation across rail, air, FTL, LTL, and, in some cases, water modes [6]. In addition to freight shipping aggregation, MMLPs also provide value-added services to their customers, including customs services, warehousing, and testing [6]. India's 2017 Logistics Efficiency Enhancement Program policy highlighted the need for a national network of MMLPs,

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Megan E. Gunn is with the Department of Systems & Information Engineering, University of Virginia, Charlottesville, VA, 22904, USA (e-mail: meg9hq@virginia.edu).

Megan C. Marcellin is with the Department of Systems & Information Engineering, University of Virginia, Charlottesville, VA, 22904, USA (e-mail: mcm5ft@virginia.edu).

Matthew C. Gunn is with the Department of Systems & Information Engineering, University of Virginia, Charlottesville, VA, 22904, USA (e-mail: mcg3er@virginia.edu).

Davis C. Loose is with the Department of Systems & Information Engineering, University of Virginia, Charlottesville, VA, 22904, USA (e-mail: dcl6d@virginia.edu).

Eric Jehu is with the Virginia Economic Development Partnership, Richmond, VA, 23219, USA (e-mail: ejehu@vedp.org).

Femi Popoola is with the Virginia Economic Development Partnership, Richmond, VA, 23219, USA (e-mail: fpopoola@vedp.org).

Karen R. Jackson is with the Commonwealth Center for Advanced Logistics Systems, Petersburg, VA, 23805, USA (e-mail: karenrjackson2010@gmail.com).

Igor Linkov is with the U.S. Army Engineer Research and Development Center, U.S. Army Corps of Engineers, Concord, MA, 01742, USA (e-mail: Igor.Linkov@usace.army.mil).

Daniel F. Otero-León is with the Department of Systems & Information Engineering, University of Virginia, Charlottesville, VA, 22904, USA (e-mail: dfotero@virginia.edu).

James H. Lambert is with the Department of Systems & Information Engineering, University of Virginia, Charlottesville, VA, 22904, USA (e-mail: lambert@virginia.edu).

proposing 35 MMLPs, funded through public-private partnerships, to serve as hubs that increase highway connections [7]. The potential economic opportunities and resilience benefits of a more efficient freight network [8] motivate examining the feasibility of operating an MMLP in an industrial region of the United States.

This work aims to assess the value of a Virginia MMLP to the modern freight network. A pair of Markov decision process (MDP) models are employed to address two main research questions: (1) What decision policies emerge from an MDP-based multimodal logistics planning model that balances cost-effectiveness and resilience across uncertain scenarios? (2) Does the addition of a cost-effective MMLP in Virginia reduce costs and improve freight network resilience?

The first MDP models the currently existing freight network and determines an optimal shipping policy for a shipper seeking to send freight from one of two Virginia starting locations ("East" and "West") to a terminal location in Illinois. The second MDP follows a similar approach but models the freight network with the addition of an MMLP in Virginia. The optimal policies of the two MDPs are compared to determine the impact of the MMLP on both freight costs and mode-route choice.

II. Literature Review

Recent research has applied MDPs, integer linear programming, deep learning, Q-learning, neural combinatorial optimization, and proximal policy optimization to multimodal and intermodal freight logistics problems such as defining shipping networks, selecting transportation modes, dispatching vehicles, managing fleets, operating autonomous delivery vehicles, sorting and storing containers, and forecasting demand [9], [10]. Farahani et al. proposed an online deep reinforcement learning (DRL) approach to determine whether a freight container was transported by truck or train to minimize expected cumulative transportation costs [11]. Assuming that the cost to ship by train was always lower than by truck, [11] essentially sought to maximize the number of containers assigned to trains subject to constraints on train departure, arrival, and capacity. Two heuristics for container assignment order were compared: first in first out (FIFO) and earliest due date first (EDF) [11]. Compared to re-optimization and greedy heuristic approaches, the DRL approach achieved comparable or superior results [11].

Building on the model developed in [11], [12] considered uncertainty in freight container arrival and departure times. Arrival uncertainty was simulated by assigning each container a probability of being late according to the system-wide uncertainty level [12]. If the assigned train was infeasible based on the container delay, then the container was shifted to a truck, which had a significantly higher cost than the trains [12]. Expanding on the previous formulation, four heuristics for selecting the next container to assign were compared: FIFO, EDF, FIFO with EDF for containers arriving the same day, and EDF with FIFO for containers arriving the same day [12].

Considering only truck-based freight logistics, [13] defined the dynamic stochastic temporal bin packing problem for the allocation of freight containers to company-owned and outsourced trucks with a one-month planning horizon. The containers had the same starting location but different destinations, requiring different truck resources (e.g., transport duration). Uncertainty was considered through two scenarios with different probabilities of container delays [13]. The formulation enforced on-time arrival of all containers while minimizing expected total transportation costs [13]. To address dimensionality issues for more realistic problem sizes, two approaches were compared: proximal policy optimization and rolling-horizon two-stage stochastic programming [13].

The previous approaches only considered a single mode of transportation for the entire journey. Zhang et al. described a Q-learning approach with a multi-objective MDP for multimodal freight routing that optimized a weighted sum of transport and mode switching costs, transport time, and emissions-related costs [14]. To address uncertainty in transport time, the transport time for each node-mode pair was defined as a random variable [14]. Case studies applied the approach for networks with 16 to 17 nodes and mode choices of rail, air, and road [14].

The described approaches assumed that all freight shipments were of the same size (full container) and were not permitted to be divided, which precluded LTL. Given the prominence of both container-level and sub-container-level shipping in and through Virginia, there is a need for a model that accounts for shipment size and incorporates both LTL and FTL when determining optimal transport routes and modes. Although some of the approaches include multimodal nodes in the freight network, the operational benefits of adding multimodal nodes were not examined. This paper novelly contributes an MDP-based approach that integrates optimal multimodal routing with evaluation of a multimodal hub to provide insights for logistics and infrastructure decision-making.

III. Model

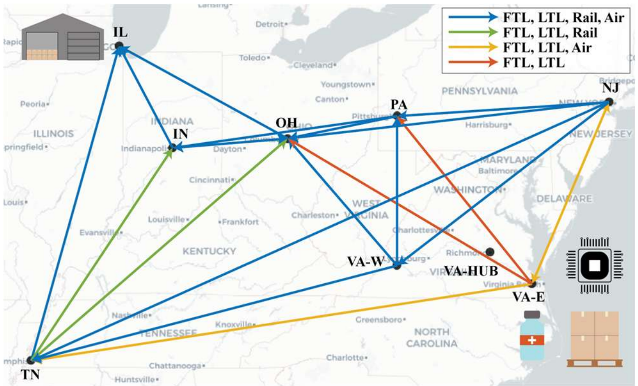
This paper introduces a two-model approach to assess the impacts and economic and operational benefits of a new MMLP in Virginia. Markov decision processes model sequential decision-making in stochastic systems. MDPs include sets of states, actions, rewards, and transition probabilities that follow Markovian dynamics. At each decision epoch, a subset of actions may be taken according to the current state, and the policy prescribes the specific actions taken from each state. Optimal policies may be identified through methods such as backward induction.

Two MDP models were defined, one without an MMLP and one with an MMLP, and the differences in optimal policies and values were compared. The approach represents freight flow from two starting locations in Virginia (eastern and western locations in the state) to Chicago, Illinois via several intermediate nodes in the northeast, southeast, and midwestern United States. The freight system was characterized as a network of nodes, representing shipping locations and facilities, and arcs, representing shipping paths between nodes. Apart from Virginia, shipping locations were abstracted at the state level, with one node per state.

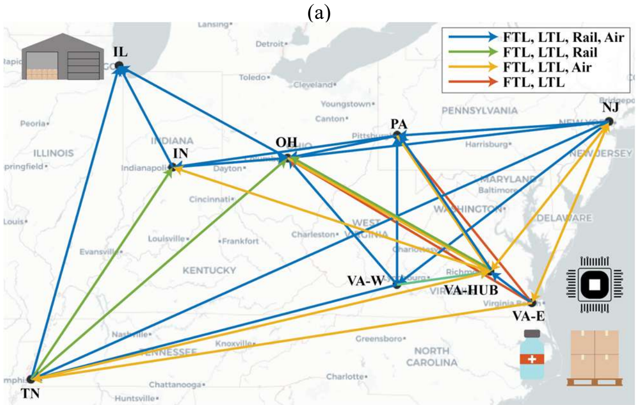
The two MDP models include: 1) a baseline model with eight nodes (the "no hub" model), and 2) an extended model that includes an additional node representing an MMLP in Virginia (the "with hub" model). Fig. 1 shows the network representations of the two models.

A. Data

The nodes of the networks were strategically chosen to represent major freight shipping paths between the eastern and



(a)



(b)

Fig. 1. Network representations of the "no hub" (a) and "with hub" (b) models where nodes represent shipping facilities and arcs represent multimodal routes connecting nodes.

midwestern United States. The start and terminal nodes, specifically, represent common origin-destination pairs for domestic goods originating from Virginia and internationally sourced goods arriving to Virginia.

In the absence of access to proprietary data directly from shippers, publicly available data from the U.S. Bureau of Transportation Statistics (BTS) were leveraged in the models. The BTS Freight Analysis Framework (FAF) provided data on the value of commodities shipped by origin-destination-mode for 2024 [15]. These values, collected across all commodities, were used as a proxy for shipping costs between nodes in this model. These data also provided insights into which modes (rail, air, and/or road) were active between nodes. The U.S. BTS Freight Transportation Services Index (TSIFRGHT) provided freight output index by month for 2020-2025, which served as the basis for the market cost scenario transitions in the models [16]. The TSIFRGHT is an economic indicator that reflects trends in the freight sector and overall economic activity. The monthly observations were categorized as either above or below the five-year median, representing a "high" or "low" market cost scenario state, respectively. The frequency of transitions between the monthly market cost scenarios were used to populate the transition probability matrix.

The reliability rates, representing full and on-time delivery for origin-destination-mode combinations, were synthetically generated and cross-checked to confirm that the values were reasonable. In line with industry observations, air was considered the most reliable mode (95-98% reliable), followed by FTL (88-95%), LTL (78-90%), and rail (70-90%).

B. *Model Definitions*

The epochs, $t = \{1, 2, 3, \dots, 10\}$, for both models were defined as the legs of the shipping journey, starting from either $VA\text{-}E$ or $VA\text{-}W$ and ending when reaching the terminal node, IL. The states are 3-tuples of the current node, the current market cost scenario, and the current freight quantity:

$$X_t = (n_t, d_t, f_t) \tag{1}$$

where

- $n_t \in N = \{VA\text{-}E, VA\text{-}W, PA, TN, OH, NJ, IN, IL\}$ is the current node at epoch t. For the "with hub" model, $n_t \in N \cup \{VA\text{-}HUB\}$.
- $d_t \in \{high, low\}$ is the market cost scenario at epoch t.
- $f_t \in \{small, large\}$ is the freight quantity at epoch t.

The actions available from a state, s, are 3-tuples of the next node, the shipping mode, and the shipment size:

$$A_t(s) = (n_{t+1}, m, z) \tag{2}$$

where

- n_{t+1} is the next node along the shipping path; feasible next nodes are restricted according to the structure of the freight network.
- $m \in \{FTL, LTL, rail, air\}$ is the shipping mode; feasible shipping modes between n_t and n_{t+1} are restricted according to the structure of the freight network.
- z is the shipment size; for s with $f_t = large$, $z \in \{small, large\}$. For s with $f_t = small, z = small$.

Stochasticity was introduced into the model through the network-level transitions between high and low market cost scenarios. Equation (3) shows the cost scenario transition matrix, $\boldsymbol{P}$, which was calculated using the TSIFRGHT by determining the frequency of monthly transitions between "high" (H) and "low" (L) cost scenarios:

$$P = \begin{array}{c} H \\ L \end{array} \begin{bmatrix} 0.72 & 0.28 \\ 0.26 & 0.74 \end{bmatrix}. \tag{3}$$

Node and inventory level transitions are deterministic based on the action a. The immediate rewards, $r(s, a)$, are equal to the shipping revenue, R, minus the expected shipping costs, $E[ship\ cost]$. Shipping revenue is specific to the shipment size z and is recognized only upon shipping to the terminal node, IL:

$$R = \begin{cases} 0, \text{if } n_{t+1} \neq IL \\ 30, \text{if } n_{t+1} = IL \text{ and } z = small \\ 50, \text{if } n_{t+1} = IL \text{ and } z = large \end{cases}. \tag{4}$$

Expected shipping costs are calculated as in (5):

$$\begin{aligned} E[ship\ cost] = \Big(& y_{n_t, n_{t+1}, m} c_{n_t, n_{t+1}, m, d_t} \big(1 \\ & + (h-1) \mathbf{1}_{\{n_t = VA-HUB\}} \big) \\ & + \big(1 - y_{n_t, n_{t+1}, m}\big) p c_{n_t, n_{t+1}, m, d_t} \big(1 \\ & + (h-1) \mathbf{1}_{\{n_t = VA-HUB\}} \big) \Big) q_z \end{aligned} \tag{5}$$

where

- $0 < y_{n_t, n_{t+1}, m} \leq 1$ is the reliability rate of shipping from node n_t to node n_{t+1} by mode m.

- c_{n_t,n_{t+1},m,d_t} is the cost of shipping from node n_t to node n_{t+1} by mode m under market cost scenario d_t.
- $0 < h \leq 1$ is a hub discount factor applied to the cost of shipping from node $VA\text{-}HUB$.
- $\mathbf{1}_{\{n_t = VA\text{-}HUB\}}$ is an indicator function that equals 1 when $n_t = VA\text{-}HUB$, and 0 otherwise.
- $p \geq 1$ is a cost penalty factor for unreliability.
- q_z is a cost scaling factor based on shipment size, z.

The Bellman equations for the model are defined in (6):

$$V_t(s) = \max_a \{r(s,a) + \textstyle\sum_{s'} P(s'|s,a) V_{t+1}(s')\}. \quad (6)$$

The Bellman equations were solved through backward induction to determine the optimal policy, and the corresponding policy values were calculated. Using standard workstation resources, the optimal policy and values were calculated in less than one second for each model.

C. *Assumptions*

The models make several assumptions to calculate the shipment cost between nodes, c_{n_t,n_{t+1},m,d_t}, in (5). The BTS FAF dataset includes information on tons of shipment between nodes and total dollar value. The model aggregates these values to a single value, shipping cost per ton, between nodes for a specific modality, $c_{n_t,n_{t+1},m}$, independent of market scenario. The model incorporates a cost premium for high market cost scenarios through a proportional market cost multiplier, with a default value of 1.15; that is, shipment cost between nodes during periods of high market cost is calculated as $1.15c_{n_t,n_{t+1},m}$. Additionally, the BTS FAF dataset does not distinguish between FTL and LTL shipments, including only an aggregated truck shipment modality. Since FTL shipments comprise most of the shipment volume, the model assigns the BTS FAF values to FTL shipment costs and assumes a proportional LTL multiplier to determine LTL shipping costs. The reliability of a shipment, $y_{n_t,n_{t+1},m}$, is assumed to affect shipment costs proportionally through a purely cost-based multiplicative reliability penalty, p, with a default value of 2.0. Sensitivity analyses were performed on the values of the LTL multiplier and reliability penalty and are discussed in Section IV.

IV. Results

A. *Optimal Policy*

The optimal policy for shipping to Illinois from all nodes was calculated using backward induction. Given the focus on economic and operational impacts of an MMLP for Virginia, the analysis centered primarily on the optimal policy when starting in Virginia ($VA\text{-}E, VA\text{-}W$), assessing how the optimal policy changed with the addition of the MMLP ($VA\text{-}HUB$). Fig. 2 displays the complete optimal policy routes and modes. The optimal policies always indicated shipping the maximum shipment size for the given freight quantity, i.e., when $f_t = small$, $z = small$, and when $f_t = large$, $z = large$.

In the "no hub" model, the optimal policy starting from $VA\text{-}E$ was to ship to PA via LTL or FTL, for small or large shipments, respectively, then from PA to IN via rail, and finally from IN to IL via rail. Similarly, the optimal policy starting from $VA\text{-}W$ was to ship to PA to IN to IL, all via rail. In the "with hub" model, the optimal policy starting from $VA\text{-}E$ changed to first ship to $VA\text{-}HUB$ via rail, then from $VA\text{-}HUB$ to PA via rail, before shipping to IN and IL via rail. The optimal policy from $VA\text{-}W$ was the same as in the "no hub" model. In general, the optimal policies primarily indicated shipping via rail. The addition of the MMLP facility in Virginia was utilized for shipments starting in $VA\text{-}E$, but not those starting in $VA\text{-}W$.

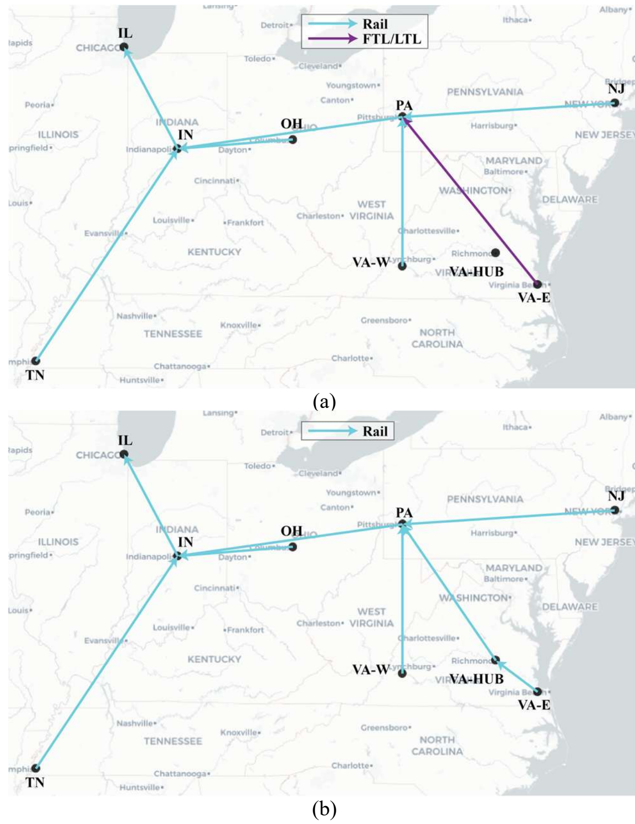


Fig. 2. Optimal policy routes and modes from each location for the "no hub" (a) and "with hub" models (b).

B. *Optimal Values*

The optimal policy value is the expected total reward when following the optimal policy. To assess the impact of the inclusion of an MMLP on policy value, the policy values of the "no hub" and "with hub" MDPs were compared. Table I summarizes the optimal policy values for each starting state-model combination. The addition of the hub increased the optimal policy value from all $VA\text{-}E$ starting states. The increases in value ranged from 14.8% for low market cost and large freight quantity to 20.8% for high market cost and small freight quantity. However, there was no change in the optimal policy value starting from $VA\text{-}W$ as the optimal policy itself did not change.

C. *Sensitivity Analysis*

1) *Removing IN*

All optimal policies routed Virginia shipments via Pennsylvania (PA) and Indiana (IN). Given the unanimous use of these intermediate nodes (PA and IN) in the optimal policies, the impact of removing one of these nodes from the network was assessed. This removal can represent a severe disruption of operations at the node, such as those caused by extreme weather or a labor disruption, resulting in the inability to ship to or through the node. The IN node and all its connecting arcs were removed from the network, resulting in a revised node space, $N' = \{VA\text{-}E, VA\text{-}W, PA, TN, OH, NJ, IL\}$ for the "no hub" model and $N' \cup \{VA\text{-}HUB\}$ for the "with hub" model. All actions shipping to and from the IN node were removed from the feasible action space.

TABLE I. VALUES (REVENUES MINUS EXPECTED SHIPPING COSTS) OF THE OPTIMAL POLICIES FROM VA-E AND VA-W

Starting Location	Market Cost	Freight Quantity	Model	Value	% Change with Hub
VA-E	High	Small	No hub	21.99	20.8%
VA-E	High	Small	With hub	26.57	
VA-E	High	Large	No hub	36.41	18.5%
VA-E	High	Large	With hub	43.14	
VA-E	Low	Small	No hub	22.87	16.9%
VA-E	Low	Small	With hub	26.74	
VA-E	Low	Large	No hub	37.87	14.8%
VA-E	Low	Large	With hub	43.48	
VA-W	High	Small	No hub	27.33	0%
VA-W	High	Small	With hub	27.33	
VA-W	High	Large	No hub	44.65	0%
VA-W	High	Large	With hub	44.65	
VA-W	Low	Small	No hub	27.52	0%
VA-W	Low	Small	With hub	27.52	
VA-W	Low	Large	No hub	45.03	0%
VA-W	Low	Large	With hub	45.03	

The removal of the intermediate IN node resulted in a re-routed optimal policy for both the "no hub" and "with hub" models. For the start node $VA\text{-}E$ in the "no hub" model, shipments were re-routed to IL via NJ and OH, removing both PA and IN from the optimal shipping path. Similarly, for the start node $VA\text{-}W$ in the "no hub" model, shipments were re-routed to IL via OH and included a shift from exclusively rail modes to mixed rail and road modes. Starting from node $VA\text{-}E$ in the "with hub" model, the intermediate path of $VA\text{-}HUB \rightarrow PA \rightarrow IN$ was replaced by $VA\text{-}HUB \rightarrow OH$. Starting from node $VA\text{-}W$ in the "with hub" model, the revised optimal policy routed shipments first to $VA\text{-}HUB$ before routing to OH then IL. Notably, the removal of the IN node resulted in the utilization of $VA\text{-}HUB$, which was not utilized in the original optimal policy. This result indicates that the addition of the $VA\text{-}HUB$ node provides benefits to system resilience as it provides a cost-effective replacement for other high-use nodes facing disruption.

2) Hub Discount

The hub discount factor, $0 < h \leq 1$, is applied to the shipping costs, c, originating from $VA\text{-}HUB$. The model considered a default value of $h = 1$, representing no discount on shipping costs from the MMLP. However, optimal policy results were compared across the range of possible values of h. For all values of $h > 0.1$, the optimal policy remained consistent with the original result. For values of $h \leq 0.1$, $VA\text{-}HUB$ utilization increased due to the extreme cost effectiveness of shipping from the hub. Considering a more reasonable discount factor of $h = 0.5$ did not change the optimal policy and resulted in only a small (2%) increase in policy values for both small and large freight quantities. Applying the discount factor for shipments *to* the hub, in addition to those *from* the hub, also did not result in changes in the optimal policy.

3) LTL Multiplier

The models considered a default LTL multiplier of $l = 1.15$, representing a slight cost premium on LTL shipping per unit relative to FTL. However, this multiplier is influenced by factors such as commodity type and private contractual terms and may differ by application. As a result, the effect of different LTL multipliers on the optimal policies and values was examined. In the "with hub" model, neither LTL nor FTL modes were utilized in the optimal policy, so increases to the LTL multiplier had no effect on the optimal policies or values. For the "no hub" model, the optimal policies remained consistent for increased LTL multipliers within a reasonable range (e.g., $l \leq 5$). In the optimal policy, LTL shipping was only used between $VA\text{-}E$ and PA for small shipments. As no rail routes originate in $VA\text{-}E$, the only other available mode is air, which is 30 to 100 times more expensive than LTL. Thus, the LTL multiplier must be unrealistically high to affect mode choice in the optimal policy. Increasing the LTL multiplier to reasonable values of $l = 1.25$ or $l = 1.5$ reduced the optimal policy values by about 2% or 7%, respectively, for small quantities originating from $VA\text{-}E$. Optimal policy values for large quantities originating from $VA\text{-}E$ and both freight quantities from $VA\text{-}W$ did not change.

Conversely, consideration was given to the possibility that LTL shipping may unlock cost savings by reducing fixed costs for shippers. Multiplier values greater than 0.7 resulted in no changes to optimal policies. Some policy changes occurred for $l = 0.7$ in both models, shifting shipments between intermediate nodes from rail to LTL. However, these policy changes did not affect the routes from the Virginia starting nodes. Reducing the multiplier even further to $l = 0.4$ resulted in both route and mode shifts to the optimal policy starting from $VA\text{-}E$: small shipments from $VA\text{-}HUB$ were sent directly to IN by LTL instead of routing through PA and IN by rail.

Overall, the optimal policies demonstrate a high level of resilience to changes in the relative cost of LTL shipping. For reasonable values of the LTL multiplier, the optimal policies for $VA\text{-}E$ and $VA\text{-}W$ were unaffected. As a result, shippers in the network experience few impacts from volatility in LTL pricing.

4) Reliability Rates

As the optimal policies relied heavily on rail as the predominant transport mode, the effects of changes in rail reliability were assessed. The original rail reliability rates range from 70% to 90%, depending on the origin and destination nodes. Optimal policy results did not change when reducing reliability by up to 50%. For reductions of 50% or more, some mode shifts occurred between intermediate nodes, but the optimal routes from $VA\text{-}E$ and $VA\text{-}W$ were unaffected. This lack of an effect on the optimal policies reflects that the significantly lower leg costs for rail outweigh the consequences of unreliable shipments in the current model formulation.

5) Reliability Penalty

To further investigate reliability-related sensitivity, larger values of the reliability penalty were tested. The default reliability penalty of $p = 2$ implies that it is twice as expensive to transport a shipment if it initially fails, but the value may be significantly higher in practice depending on the application.

Reasonable increases in the reliability penalty ($p = 5$ or $p = 10$), resulted in large shipments from OH to IN being transported by the more reliable FTL. However, the optimal policies from Virginia were unaffected. When the penalty was more extreme, in both the "no hub" and "with hub" models, the optimal policies shifted to sometimes send small shipments from large freight quantity states, an action that was not taken in the original optimal policies. Although the reliability penalty is most impactful for rail transport (the least reliable mode), extreme values of the penalty are necessary to offset the low shipping costs of rail and affect the optimal policy for $VA\text{-}E$ or $VA\text{-}W$.

Realistic changes in the rail reliability rates or reliability penalty individually did not appear to have significant impacts on optimal policies for $VA\text{-}E$ or $VA\text{-}W$ in the current models, however, simultaneously varying both within realistic ranges did induce optimal policy changes. For example, setting the reliability penalty to $p = 10$ and reducing the rail reliability rates by 30% caused small and large shipments from $VA\text{-}HUB$ to be routed differently. While small shipments traveled by rail to PA, large shipments were transported by rail to OH when market cost was high and by FTL to IN when market cost was low. With the addition of the hub, the optimal values for $VA\text{-}E$ increased 111%, 69%, 41%, and 27% for small quantities under high market cost, small quantities under low market cost, large quantities under high market cost, and large quantities under low market cost, respectively. The results emphasize the potential economic and resilience benefits of including a hub under scenarios with decreased reliability and greater consequences for unreliable shipments.

V. Conclusion

This paper defines and solves a pair of MDP models to evaluate the benefits of adding an MMLP in Virginia. The resulting optimal policy routed shipments through the MMLP when starting in $VA\text{-}E$, but the MMLP was not used when starting in $VA\text{-}W$. The addition of the hub improved optimal policy values for shipping between $VA\text{-}E$ and IL by about 15-20% depending on freight quantity and market cost scenario. Through sensitivity analyses, the utility of the MMLP was found to be robust to node removal, mode reliability, and hub and LTL discount factors. These results provide evidence for benefits to shippers of an MMLP hub for some, but not all, Virginia locations. From a government and policy planning perspective, additional analysis is needed to determine whether investing in an MMLP in Virginia would provide sufficient benefits and attract new business to the state. The infrastructure start-up and construction costs, which are not considered in this model framework, would play a significant role in this decision.

The size of the model was limited, including only eight (or nine, including the hub) nodes, which may limit generalizability. Future work will expand the model, considering nodes at a more granular, sub-state-level scale. The limited nature of publicly available route and cost data suggests further refinement for improved applicability of the results. Future work will consider incorporating commodity-specific shipment costs for more nuanced and representative modeling. Regional demand and market condition fluctuations will be considered in future work through node-specific market cost scenarios. Additional sensitivity analyses can test more complex scenarios involving multiple disruptions to the freight network. Finally, the methods could be extended to compare the benefits of other MMLP locations, finding an optimal location that best serves the Virginia freight sector.

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