A Data-Driven Decision Making Framework for Value-Based Engineering Design of Complex Network Systems

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Many applications related to fields such as transportation, energy, communication, biology, and defense, require making several strategic and tactical decisions, which includes designing a real-world complex network system and setting its operational parameters. These systems typically have high uncertainties, a lack of a master design plan, and vulnerability to system failures that could potentially have catastrophic consequences. Therefore, we need rigorous theoretical foundations for designing complex networked systems to mitigate these risks and enhance the system performance. To our knowledge, based on literature survey, there has been little to no exploration of Big Data methods and tools in value-based systems engineering in how to better formulate the value function. Moreover, to our knowledge, there has been little to no work done in the network science community to develop a value function that would enable consistent assessment of robustness and resilience. At present, metrics have been developed to guide decisions in network design, but no overarching function, such as a value function, exists to enable understanding the true benefits of network robustness and resilience for system designer and stakeholders. This research paper aims to understand the factors and attributes contributing to the value of network performance with regards to robustness and resilience; explore the strategies to design complex networked systems with Big Data analytics; bridge the gap between the network science community and systems engineering community in the understanding of system robustness and resilience; and ultimately develop a mathematically rigorous design framework for complex networked systems, such as transportation networks, for generating designs that perform optimally in the presence of uncertainties based on the preference and risk attitude of the stakeholders. Network based companies, such as air carriers, can utilize this framework in their route planning, schedule planning and fleet planning, to design new route networks or reconfigure existing ones, for maximization of profit or other preferred objectives.

I. Nomenclature

G	=	air transportation network
N	=	set of all nodes or airports in G
A	=	set of all arcs or routes in G
$\hat{C}$	=	set of all carriers operating in G
I	=	set of all possible itineraries in G with at most two stops in each way
I^c	=	set of itineraries operated by carrier $c \in \hat{C}$ in G
i, i'	=	itinerary belonging to I or I^c
i_j	=	j-th stop in itinerary i
n	=	number of airports in the design space

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a	=	number of aircrafts in the fleet
I_{od}	=	number of possible one-way itineraries with at most two stops in route o-d
R_y	=	revenue in year y
C_y	=	cost in year y
P	=	net present profit
X_{od}	=	binary variable indicating whether arc (o, d) is present in the network or not
Y_{od}	=	number of aircrafts allocated to arc (o, d)
Z_i	=	number of seats allocated for itinerary i
f_i	=	fare of itinerary i
T_i^{qy}	=	number of tickets sold of itinerary i in quarter q of year y
F_{od}^{qy}	=	flight operating cost of arc (o, d) in quarter q of year y
G_{od}^{qy}	=	ground operating cost of arc (o, d) in quarter q of year y
S_{od}^{qy}	=	system operating cost of arc (o, d) in quarter q of year y
α	=	discount factor
OL	=	operational lifetime
Q_{od}	=	quarterly frequency of flights in arc (o, d)
d_i^{qy}	=	demand of itinerary i in quarter q of year y
$D_{m\leftarrow i}^{q}$	=	total demand in origin-destination market m corresponding to itinerary i in quarter q of year y
V_i	=	value of itinerary i
K	=	number of itinerary service attributes considered in the itinerary share model
A_{ik}	=	value of attribute k in itinerary i
β_k	=	k-th multinomial logit model attribute coefficient
M_i	=	market share of itinerary i

II. Introduction

A complex networked system is a system comprising many interacting and dynamical units [1]. The interactions among these units define the connections between each pair of units and the overall network structure. In addition, the individual unit behaviors and the time-variant connections define the network dynamics, such as evolution and adaptation. Many complex networked systems, such as transportation networks, power grids, the Internet of Things (IoT), social networks, and neural networks, are an indispensable part of our daily lives. Some of the different types of networks are: scale-free networks, small world networks, random networks, network of networks, etc. Air transportation networks, which show characteristics of small-world networks and scale-free networks, are used as the research testbed for this paper.

Modeling and analysis methodologies have been investigated to study the structure and dynamics of the complex networked systems [1], which have been used to characterize the topology of the network architecture, compare system properties, and develop models to mimic the evolutionary or adaptive dynamics of a network. The most recent methodologies study node-level agent decisions with utility theory and game theory to better model the complex networked system. They provide deeper insight into network dynamics and enable the development of better surrogate models for efficient design on complex networked systems [3]. Many metrics have been identified in these modeling and analysis methodologies [4-16] to quantitatively describe the system performance under uncertainties, risks, and attacks, such as network robustness for perturbations and attacks, and network recoverability after system failures. These metrics are critical for evaluating the system performance and predicting the system behaviors based upon the current structure and design.

Unlike research on modeling and analysis of complex networked systems, approaches for designing them to achieve the optimal performance (i.e. with regards to robustness and resilience) has received little attention. Among the limited literature work on design of complex networked systems, the assessment of networked system performance, such as robustness and resilience, is inconsistent among different research communities. Some of the well-known robustness and resilience metrics are discussed in background sections A and B.

Using a combination of value-based design engineering, utility theory, and data analytics, this paper is building a design framework for complex networked systems which can perform optimally in a stochastic environment with the desired level of robustness and resilience. The following sections detail the approach used in this paper to understand the value of network performance from large-scale datasets; construct utility function for rigorous decision making; and establish a system design framework to improve value-based system performance.

III. Background

A brief review of network robustness and resilience metrics, air transportation networks, sources of data and data analytics, value-based model, sources of uncertainties, and utility theory are presented in this section.

A. Network Robustness and its Traditional Quantifications

In network science, the "robustness" of a network measures its performance in terms of tolerance under random or intentional removal of network nodes or links. If enough nodes or links are removed, the network becomes disconnected. A network is called robust if it performs well under random failures and targeted attacks on nodes and links [26-33]. Many metrics have been developed to measure network robustness, such as node connectivity, link connectivity, betweenness, centrality, degree centrality, closeness centrality, eigenvector centrality, clustering coefficient, algebraic connectivity and Laplacian energy [4-16]. Jamakovic, Uhlig and Van Mieghem [35, 36] found that the algebraic connectivity was a generic metric in the analysis of various robustness problems in three typical network models. Jamakovic and Uhlig [35] studied algebraic connectivity and network robustness in terms of node and link connectivities on three different complex network models: the random graph of Erdos-Renyi, the small-world graph of Watts-Strogatz and the scale-free graph of Barabasi-Albert. They concluded that the algebraic connectivity can be considered a measurement of the robustness in all three complex network models. Jamakovic and and Van Mieghem [36] showed that the larger the value of the algebraic connectivity, the better the network's robustness to node and link failures. Byrne, Feddema and Abdallah [37] showed algebraic connectivity can improve the robustness of the network by reducing the characteristic path length. They stated that the algebraic connectivity is the efficient network robustness measure with much less computation time for both small and large size networks. Olfati-Saber [38] showed the relationship between increasing algebraic connectivity of complex networks and robustness to link and node failures. The simulations in [39] by Sydney, Scoglio and Gruenbacher also supported the findings in [38], showing that the larger the algebraic connectivity, the more links required to disconnect a network and hence, the more robust a network. Most of the research on robustness of complex networked systems focuses on modeling and analysis using these mathematical metrics. However, these metrics are abstract and are not intuitive to support decision making during the design of complex networked system. For example, knowing that a designed complex networked system can reach the algebraic connectivity value at 14.3, tells the decision maker little about how important that number is to the system robustness performance.

B. Network Resilience and its Existing Quantifications

Modeling and analyzing the resilience of complex and large-scale systems have recently raised significant interest among both practitioners and researchers due to its role in reducing the risks associated with the disruption of systems [40]. This recent interest has resulted in various definitions of the concept of resilience. In engineering systems, the term resilience refers to the ability to withstand, adapt, and recover from the impact of system disruptions and failures [1, 2]. However, the definition of resilience is still being discussed among different research communities.

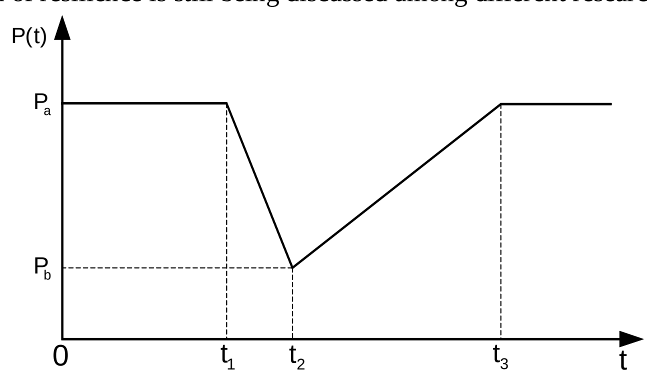

Fig. 1 Recovery of a system with time after a disruption

Figure 1 shows a system that initially operates at performance level P_a. Due to disruption, its performance starts to decline at time t_1. At time t_2 the system's performance reduces to P_b. Then the system begins to recover and eventually returns to the original performance level P_a at time t_3. In this illustration, robustness is defined to measure the system characteristic in the time range of $[t_1, t_2]$. The more robust a system is, the less performance reduction

$(P_a - P_b)$ it will have. Recoverability [33] is defined to describe the system behavior in the time range of $[t_2, t_3]$. The shorter recovery period $(t_3 - t_2)$ it needs to return to its original performance level or another desired performance level, the more resilient the system is. According to [41, 42], the concept of system resilience includes both robustness and recoverability. This resilience definition has been adopted for this research. In addition to the network robustness that measures the static network structure strength and its tolerance for innate uncertainties, external perturbations and intentional attacks, the network resilience also includes system recoverability, which measures system dynamics and its capability to adapt and recover from internal system failures and external disruptions.

In literature, the quantitative assessment of system resilience has been focused on investigating the recovery process from system failure and disruption [43], where metrics have been proposed to measure the system resilience. Bruneau et al. [42] defined four dimensions of resilience in civil infrastructure: robustness, rapidity, resourcefulness, and redundancy. They proposed a deterministic static metric for measuring the resilience loss. Zobel [44] proposed the metric specified by "calculating the percentage of the total possible loss over some suitably long time interval T^*". Henry and Ramirez-Marquez [41] developed a time-dependent resilience metric that quantifies resilience as ratio of recovery to loss. Chen and Miller-Hooks [45] introduced an indicator for measuring resilience in transportation networks. The indicator quantifies the post-disruption expected fraction of demand that can be satisfied within pre-determined recovery budgets. Janic [46] used the proposed indicator by Chen and Miller-Hooks [45] for assessing airport resilience, defined as a ratio between the on-time flights and the total number of planned flights. Enjalbert et al. [47] introduced local and global resilience assessment metrics. Francis and Bekera [48] proposed a dynamic resilience metric. These metrics are proposed to describe the system dynamics and responses after disruption. But they provide little insights to the decision maker in system design stage.

Air Transportation Networks (ATNs) operated by commercial airline companies are used as the testbeds for this research. Without exception, the performance of ATNs are also strongly affected by disruptions. The choice of nodes and edges among other design variables determines the value derived from the network. The composition and structural properties of ATNs are described in the following section.

C. Air Transportation Network

ATNs are a type of spatial network which are modeled as graphs with nodes and edges. The nodes are the airports and the edges are the flight routes between airports. They show characteristics of small-world networks and scale-free networks. A hub-and-spoke ATN [111] featuring 42 nodes in total, two of which are hubs, and 41 edges, is illustrated in Fig. 2. Such a configuration allows providing service to a large number of markets with fewer flight legs and aircrafts, resulting in significant cost savings. Typically, this cost saving is greater than the revenue loss from passengers who reject connecting service and choose a non-stop flight instead, making hub-and-spoke network more profitable than a complete point-to-point network providing non-stop service to each market.

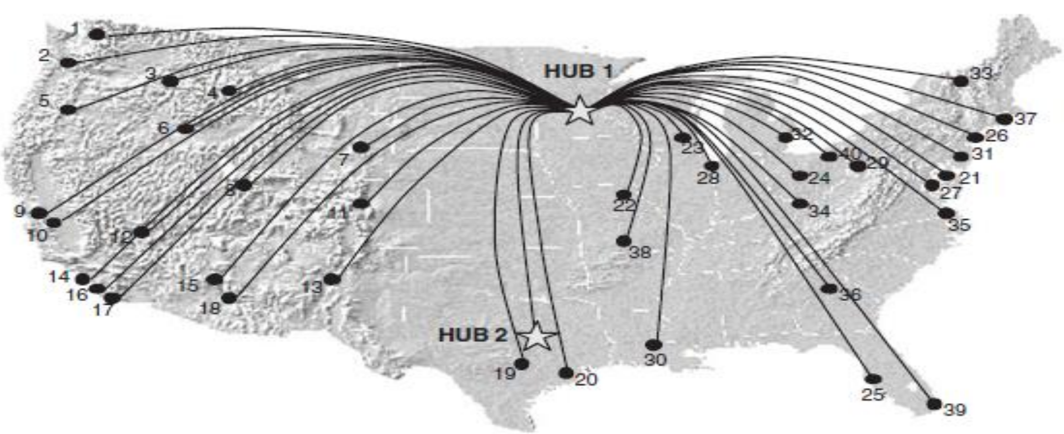

Fig. 2 An example of an ATN routing flights and passengers through a connecting hub

There are three major categories of decisions designers make during the airline planning process – route planning, fleet planning, and schedule development. In route planning, the Origin-Destination (OD) markets to be served are determined. The type and quantity of aircrafts to be acquired are decided in fleet planning. Lastly, decisions pertaining to the frequency and timing of flights are made in the schedule development part of the planning. Despite making optimal decisions in all three categories of planning, the airline company will still likely make less profit than that predicted by the airline profit model if disruptions affecting the operation of the ATN are not considered. Some of the common sources of node and link disruption are: weather, technical and mechanical problems, crew logistics, natural disasters and local anomalies. Disruptions affect airline stakeholders, airport stakeholders and passengers. A disturbance to one flight leg can have widespread disruptive effects that are seemingly unconnected to the original disturbance.

D. Big Data Analytics for Complex Networked Systems

Analyzing Big Data has become the major source for innovation behind scientific discovery and engineering applications. Big data of high volume, variety and velocity has been generated, transferred, and processed in the large-scale, dynamic complex networked systems. Research in the field of network science led to the advancement of network metrics, topology, and mathematical models that help us understand network structure, properties and relationships. Some examples of complex network systems, modeled as graphs, with significant topological features on which Big Data analytics have been applied so far are transportation, communication, energy, biology, defense and social networks. These research works were motivated by the goal of discovering patterns, analyzing trends, detecting anomalies, discovering knowledge and obtaining inferences in the complex networks. Link mining techniques such as common neighbors, Jaccard's coefficient, Adamic Adar measure, and Katz measure for predicting missing or future links [17]; graph partitioning algorithm for obtaining dense subgraphs [18]; agent-based models for understanding the effect of individual nodes on the system as a whole [19]; exponential random graph models [20, 21] for understanding formation and evolution of networks have been investigated in previous studies.

To discover strategic insights for the design and operation of ATNs, several datasets and potential machine learning techniques are currently being explored. These are enumerated in table 1.

Table 1 Datasets and potential machine learning techniques for application

Sources	Datasets	Techniques
Department of Transportation's Volpe Transportation Center	Flight trajectories and plans data	Feature extraction: PCA, Kernel PCA, linear discriminant analysis, factor analysis, autoencoders Feature selection: variance thresholds, correlation thresholds, genetic algorithm Clustering: K-Means, Affinity propagation, hierarchical/agglomerative Regression: random forest, gradient boosted tree, linear regression, nearest neighbors, deep learning Classification: support vector machines, logistic regression, random forest, gradient boosted tree, deep learning Structure learning and bayesian networks Visualization approaches
BTS	On-time performance data, OD market data, Form 41 cost data	
National Oceanic and Atmospheric Administration (NOAA)	Vertical integrated liquid, echo tops, storm relative velocity data	
Automated Surface Observing System	Airport wind data, visibility, temperature data	
High Resolution Rapid Refresh from NOAA	En-route wind data	

Using these techniques, the following key issues are being addressed: quantifying and modeling uncertainties of internal failures and external disruptions such as weather; determining the impact of delays, cancellations and misconnects on demand and hence customer loyalty and revenue; discovering hidden performance attributes of the network; and mapping system performance such as robustness and resilience to the value function. Network designers will benefit from using these insights for rigorous decision making.

Big Data has not been utilized to develop value model and capture system uncertainties for decision making in complex networked system design. Following the steps shown in Fig. 3, the large-scale data sets are analyzed to identify the key system attributes which have a statistically significant impact on value-based performance.

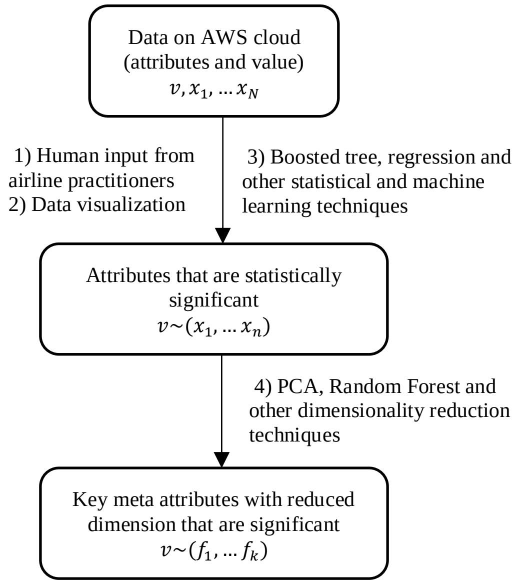

Fig. 3 The Big Data workflow to identify the key system attributes with four steps

Following the identification of the key attributes of the complex networked system, the attributes are mapped to value, thereby formulating the value function. The following section discusses Value-Based Model (VBM) and Utility Theory for Complex Networked Systems.

E. Value-Based Model and Utility Theory for Complex Networked Systems

Value-Based Modeling is a systems engineering approach that focuses on capturing the true preferences of the stakeholders involved [49]. It differs from traditional design methods where requirements are used as proxies to reflect the preferences of the stakeholders [50]. These requirements-based methods only differentiate between feasible and infeasible designs, but do not offer a meaningful guidance to rank order the design alternatives that are feasible [50]. Rather, VBM enables rank ordering of design alternatives by capturing the true preferences of the stakeholders through a single value function (an objective function) and reducing the requirements placed on the design space, thereby providing further freedom to the designer in exploring the design space [49, 51-53]. Value functions are formed as a function of system characteristics known as attributes as shown in Fig. 4. The value function has a singular unit (such as dollars or probability of mission success) that directly correlates to the stakeholders' preferences, with attributes being functions of lower level attributes and design variables. This formulation of a value function allows for a direct comparison of design alternatives from a wide range of systems that share the same set of attributes, as trade-offs are inherently captured in the value function through a single mathematical form [51]. The value function generally preferred by industry is net present profit [51, 54-56], while military or scientific applications might relate to probability of mission success [57-59]. For example, a value function might be constructed as a function of attributes such as speed, cost, range, etc., that could lead to the design of two radically different system alternatives, such as a boat or a plane. This enables the two alternatives to be compared with one another in the unit of dollars by using a value function of maximizing profit. The value of complex networked systems can be encoded using a value function, in monetary units, by assessing system performance such as robustness and resilience. This enables the designer to see a direct correlation between a change in the attributes and the value, thereby setting the stage for inherent trade-offs to be explored. In VBM, the value function is decomposed and distributed to lower level subsystems to enable more informed and consistent decision making as opposed to flowing down requirements in the traditional systems engineering processes [54, 55, 60-63]. The formulation of value functions provides a straightforward and meaningful way to compare and rank design alternatives.

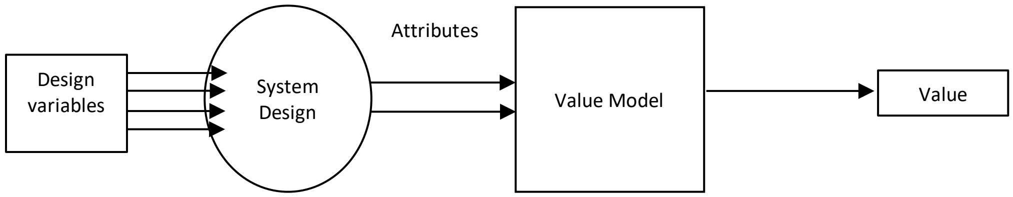

Fig. 4 The VBM process of design variables forming attributes which then feeds into the value model to give the output value

For ATNs, it is assumed that the true preference of the stakeholders is Net Present Profit, which is monetary in nature. The large-scale historical data can be used to mathematically capture the relationships of the low-level attributes with the high-level attributes - revenue and cost – which finally ties back to value (Net Present Profit) as shown in Fig. 5. The discount factor, number of year, and the operational lifetime are denoted by α,y and OL respectively.

The value function can be formulated in such a way that it captures the inherent trades present in the complex network system through attribute relationships. For instance, the number of on call flight crew members and spare aircraft are attributes that directly affect the airline operational cost. However, an increase in these two items at major airline hubs will decrease the propagate flight delays, which will increase passenger experience and passenger loyalty, and ultimately the future revenue. Since the value function is Net Present Profit, the tradeoffs due to a change in on call flight crew number and spare aircraft count can be directly measured using dollar amount. This enables a direct comparison of design alternatives in a form that is meaningful to the stakeholder.

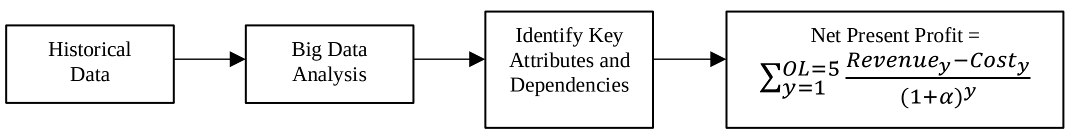

Fig. 5 The sequence of steps leading to the construction of the Net Present Profit model

Decision Theory studies the behavior of an individual making decisions under uncertainties. Normative or prescriptive decision theory is concerned with how individuals should make decisions, whereas descriptive decision theory studies how decisions are made [64-67]. Decision Analysis (DA) is a normative approach to decision theory that provides a framework for decision-making while uncertainties are present using expected utility theory [68]. Other variants exist like subjective expected utility theory, which uses subjective probabilities in the form of beliefs compared to objective probabilities in expected utility theory [69]. Some of the other normative models that are closely related to expected utility theory are causal decision theory and evidential decision theory [70-72]. On the side of descriptive decision theory, prospect theory deals with how choices are made rather than optimal choices using heuristics [73]. This research particularly uses normative decision theory as it deals with optimal choices rather than real life choices.

Expected utility theory is a mathematical method that is used to integrate probability distributions associated with uncertain outcomes into a single expected utility that is consistent with the individual's risk preferences [74]. In utility theory, the risk preference of an individual is captured using a utility function and the most preferred design has the highest expected utility [68]. Utility functions are constructed in such a way that they follow the von Neumann–Morgenstern (vNM) utility theorem [68].

F. Design of Complex Networked System for Optimal Performance

Network design is an NP-hard problem [75,76] that has been studied in past decades by many network researchers [77-86]. The design process consists of growing the network from scratch including placement of nodes [80, 81] and providing connectivity among nodes to enable services. The goal of the network design process is to improve network performance, such as robustness and resilience.

Research has shown that network optimization for robustness can be accomplished by means of rewiring links while keeping the number of links constant [39] or by means of adding new links to improve the connectivity of graphs [87]. Regarding network robustness, research has been proposed to increase algebraic connectivity. In particular, Kim and Mesbahi [88] proposed an iterative algorithm for maximizing the algebraic connectivity with a semidefinite programming solver at each recursive step. Although their algorithm has a local convergence behavior, simulations suggest that it often leads to a global optimum. Kim also studied adding a link to or deleting it from a network [89]. He proposed a computationally efficient algorithm of finding the link such that the algebraic connectivity of the new network is maximized or minimized. Sydney et al. studied link rewiring on all three kinds of complex networks and compared link rewiring to link adding [39]. In ATN robustness optimization, Wuellner et al. investigated improving network robustness by rewiring schemes [90] - among the very few research results on how to grow or maintain ATNs. Reggiani et al. proposed a decision-aid method with multi-criteria to design the strategic plans to configure airline network patterns [9]. Redondi et al. provided a tool with the simulated annealing method to evaluate the impact of new routes on the network in terms of connectivity [6]. They applied the method in a network with 467 European airports after clustering airports into modules. Vargo et al. developed the edge swapping-based tabu search algorithm to enhance air transportation network robustness [91].

Network optimization methods have been developed to maximize system resilience. Chen and Miller-Hooks [45] focus on intermodal freight transportation networks and formulate a problem of finding a strategy for maximizing the proportion of original demand that can be accommodated at a given time after a disruption, subject to an overall budget constraint for restoration activities. Faturechi and Miller-Hooks [92] introduced a multi-objective, three-stage stochastic mathematical model to quantify and optimize travel time resilience in road networks. Henry and Ramirez-Marquez [41] apply their proposed metric to a series of disruption scenarios that disable links in a transportation network in order to find restoration sequences that maximize recovery at a given time. Bocchini and Frangopol [93] formulate a bi-level optimization structure, in which flows on the network are determined by a traffic assignment computation (solution to a lower-level optimization), and decisions on a recovery strategy are identified in an upper-level optimization. Jin et al. [94] developed a two-stage stochastic programming model for analyzing the resilience of a metropolitan public transportation network. Baroud et al. [95] quantified vulnerability and recoverability of waterway network using the two stochastic resilience-based component importance measures (CIM) introduced by Barker et al. [96]. Khaled et al. [97] proposed a mathematical model and solution approach for evaluating critical railroad infrastructures to maximize rail network resilience. Vugrin et al. [98] proposed a multi-objective optimization model for transportation network recovery, where resilience is defined by the optimal recovery of disrupted links. Ash and Newth [99] attempted to optimize complex large-scale networks for resilience against cascading failures. Alderson et al. [100] proposed a mixed integer non-linear programming (MINLP) to quantify the operational resilience of critical infrastructures. Resilience is defined in terms of defense strategies with little attention given to the important recovery dimension of resilience found in most works. Sahebjamnia et al. [101] proposed a multi-objective mixed integer linear programming (MOMILP) to find efficient resource allocation patterns among candidate business continuity and disaster recovery plans while considering features of organizational resilience.

Although optimization techniques have been investigated in network science community to enhance system robustness and resilience with their identified metrics, to our knowledge, little research has been performed in engineering design to utilize Big Data analytics to develop value models for assessing system performance such as robustness and resilience, and to provide a system design framework to improve value-based system performance.

G. Capturing Uncertainties

Complex networked systems are inherently uncertain in nature, which demands for a more realistic representation of uncertainties associated with various aspects of the system including network model, inputs, link strength, node strength models, attributes, etc. The mathematical representation of uncertainties can be achieved using probability theory [108, 109], which provides a means to represent all possible scenarios associated with various aspects of the network system and not just nominal situations.

Link strength in the context of networked systems is defined through the probability of failure associated with a particular link, whereas unit strength (node strength) is defined with the probability of unit failure. For example, in an ATN, link strength can be defined with probability of flight delay, probability of flight cancellation, etc., whereas node strength represents the probability of airport shutdown, runway closure, ground stop, etc. Traditionally link strengths are quantified using weights to be represented in the calculations of robustness metrics. One of the metrics to measure robustness is called the algebraic connectivity, which is the second smallest eigen value λ_2 of the Laplacian matrix L as shown in the following equation. The higher the λ_2, the more robust the system is. In this equation, D represents the degree matrix (degree of node connectivity) and A represents the adjacency matrix that quantifies the link strength (probability of failure) using weights w_{ij} between nodes.

$$L = (D - A) = \begin{pmatrix} \deg(A) & 0 & \dots & 0 \\ 0 & \deg(B) & \dots & 0 \\ \vdots & \dots & \dots & \vdots \\ 0 & \cdots & \dots & \deg(G) \end{pmatrix} - \begin{pmatrix} 0 & w_{AB} & \dots & w_{AG} \\ w_{BA} & 0 & \dots & w_{BG} \\ \vdots & \dots & \dots & \vdots \\ w_{GA} & \cdots & \dots & 0 \end{pmatrix} \quad (1)$$

Instead of representing the link strength (probability of failure) using weights, a more realistic way of representing uncertainties is using probability distributions. These probability distributions associated with failure for both links and nodes due to several factors including internal component strength, external disruptions etc., can be modeled using statistical data. In the case of an ATN, huge volumes of statistical data are available that categorize the failure of a particular link or a node in terms of other factors that influence failure like weather events, crew shortage, airspace restrictions, government needs, airport construction, etc. The existing historical data can be analyzed using Big Data techniques to construct link strength models using probability distributions based on the factors mentioned earlier. The uncertainties in attributes like weather, crew availability, etc. can also be quantified with mean, variance and confidence level obtained from using statistical techniques on historical data.

Flight statistics data from BTS contains flight delay and flight cancellation information, which can be used to model link uncertainty in ATNs. The same dataset can also be analyzed to identify those airports that has most delay, most misconnecting passengers, or most flight cancellations, which may be a factor for node uncertainty model. Other structured data such as aircraft trajectory data from the FAA Aircraft Situation Display to Industry and meteorology data from the NOAA can be used to model link uncertainty and/or node uncertainty, which further impacts the designer's decision making. Mining the unstructured data such as social media data to find which fights and airports have been most complained about, is also being investigated to model the link and/or node uncertainty.

In this research, robustness of the network system is investigated in the context of normative decision theory [68, 109], i.e., robustness is captured implicitly using a utility function as opposed to considering robustness as an independent attribute in the value function. Robustness of a system can be defined as its potential to avoid downside consequences associated with uncertainty [110]**.** However, the term robustness is a result from decision making. For instance, Fig. 6 represents the probability distributions of value associated with two different design alternatives. As can be seen in the figure, design alternative 2 has lower uncertainty (narrower probability distribution) compared to design alternative 1. A decision-maker who is more risk averse will select design alternative 2 as the risk of uncertainty is comparatively low. However, an aggressive decision-maker who has more risk tolerance might favor alternative 1, which is more uncertain but has a potential of yielding a higher value. In this scenario, the low risk averse decision-maker is willing to accept the risk due to uncertainty with the anticipation of higher value. Robustness of a system can be directly linked to this example, where individuals with higher risk aversion prefer robust outcomes with lower uncertainty. Since the preference of individuals over robustness is subjective, the risk preferences of individuals need to be taken into account using utility functions to enable realistic and rational decision-making under uncertainty.

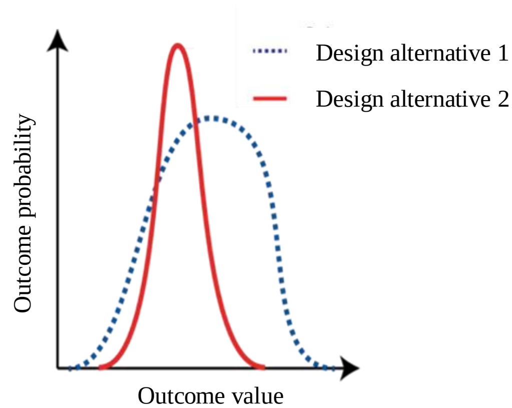

Fig. 6 Two design alternatives with different probability distributions of outcome value.

IV. Problem Formulation

For this network design research, an entrant Low-Cost Carrier (LCC), looking to set up a route network in the East Coast region of US with the goal of exploiting its busy travel corridor [112], is chosen as the stakeholder due to the emergence and rapid growth of LCCs in the past few decades [111]. The nine primary airports that are considered in the design space are: John F. Kennedy International Airport in New York, Logan International Airport in Boston, Newark Liberty Airport in Newark, Philadelphia International Airport in Philadelphia, Baltimore–Washington International Airport near Baltimore, Washington-Dulles International Airport near Washington, D.C., Hartsfield International Airport in Atlanta, Miami International Airport in Miami, Charlotte Douglas International Airport in Charlotte, Tampa International Airport in Tampa, and Orlando International Airport in Orlando. This gives rise to a total of 72 route selection design variables, denoted by X_{od}, one for each candidate city-pair market or O-D directional route. Other design variables determine the allocation of aircrafts for each O-D route and seats for each itinerary, and the fare of each itinerary, denoted by Y_{od}, Z_i and f_i respectively. The schedule of flights is assumed to be fixed to exclude schedule planning from the analysis. The number of possible one-way itineraries with at most two stops in each O-D route when the route network is a complete digraph is determined by Eq. (1). For nine airports, this equation gives 50 possible one-way itineraries for each O-D route in the network.

As described in section F, the net present profit for the next 5 years, given in Eq. (2), is used as the value function. As shown in Eq. (3), the only source of revenue considered for each year *y* and quarter *q* in any arc *(o,d)* is the sale of itinerary tickets, both one-way and round trip ones with at most two stops in each way. The number of tickets sold of an itinerary i, given by Eq. (4), is the minimum of demand and number of seats available for that itinerary. The operational cost of any arc *(o,d)* in year *y* and quarter *q* is the sum of the flight operating costs, ground operating costs and system operating costs corresponding to that arc, year and quarter, following the functional cost categorization scheme [111], as shown in Eq. (5). Average values of the cost components in per seat mile or per block hour can be calculated using the Form 41 data from the Bureau of Transportation Statistics (BTS).

It is assumed the LCC uses a single type of aircraft in its fleet – Boeing 737-700 with a seat capacity of 143 – in line with one of the major characteristics of the LCC business model. The fleet size will be varied from 10 to 100, holding it constant in each simulation, to investigate the effect on the resulting network design. The balance constraint, count constraint, and non-negativity constraint of the basic fleet assignment model [113] are applied to ensure a feasible schedule. AutoRegressive Integrated Moving Average (ARIMA) time series analysis is used to forecast the total demand for each quarter in the next 5 years for all the possible markets in G using DB1B O-D market survey data from BTS. For calculating the quarterly market shares of possible itineraries offered by the entrant LCC, a standard multinomial logit model, similar to the one in [112], is used, which computes the choice probabilities based on the following itinerary attributes: type of itinerary, travel distance, number of connections, fare, and carrier. Equations (6), (7) and (8) show how the market share, value, and demand of an itinerary are calculated respectively. Data on current itineraries and their associated attributes of different markets and airlines can be found in DB1B O-D market survey data. The logit model parameters can be estimated using the maximum likelihood technique.

The sum of the number of seats allocated to itineraries using any arc *(o,d)* must not exceed the total number of seats available in that arc in each quarter. This constraint is enforced by Eq. (9). The entrant carrier is assumed to operate all the arcs in their network in both directions with the same aircrafts flying to and fro between the nodes of the arcs, which are imposed by Eqs. (10) and (11). Equation (12) ensures that the sum of the number of aircrafts flying in the network does not exceed the fleet size.

$$I_{od} = 1 + \sum_{j=2}^{3} \prod_{k=2}^{j} (n-k) \tag{1}$$

$$\forall (o,d) \in A$$

Objective function

$$\max P = \sum_{y=1}^{OL=5} \frac{R_y - C_y}{(1+\alpha)^y} \tag{2}$$

$$R_y = \sum_{(o,d)\in A}\sum_{q=1}^{4}\Bigg[X_{od}\left\{f_{i\in I:i=(o,d)}T^{qy}_{i\in I:i=(o,d)} + f_{i\in I:i=(o,d,o)}T^{qy}_{i\in I:i=(o,d,o)}\right\}$$
$$+ \sum_{j\in N:j\neq o,d} X_{oj}X_{jd}\left\{f_{i\in I:i=(o,j,d)}T^{qy}_{i\in I:i=(o,j,d)} + f_{i\in I:i=(o,j,d,jo)}T^{qy}_{i\in I:i=(o,j,d,j,o)}\right\}$$
$$+ \sum_{j,k\in N:j,k\neq o,d} X_{oj}X_{jk}X_{kd}\left\{f_{i\in I:i=(o,j,k,d)}T^{qy}_{i\in I:i=(o,j,k,d)}\right.$$
$$\left. + f_{i\in I:i=(o,j,k,d,k,j,o)}T^{qy}_{i\in I:i=(o,j,k,d,k,j,o)}\right\}\Bigg] \tag{3}$$

$$T_i^{qy} = \min\left(d_i^{qy}, Z_i\right) \tag{4}$$

$$C_y = \sum_{(o,d)\in A}\sum_{q=1}^{4} F_{od}^{qy} + G_{od}^{qy} + S_{od}^{qy} \tag{5}$$

$$M_i = \frac{\exp(V_i)}{\sum_{c\in \hat{C}}\sum_{i'\in I^c:i'_1=i_1,i'_{last}=i_{last}}\exp(V_{i'})} \tag{6}$$

$$\forall c \in \hat{C}, \forall i \in I^c$$

$$V_i = \sum_{k=1}^{K}\beta_k A_{ik} \tag{7}$$

$$\forall c \in \hat{C}, \forall i \in I^c$$

$$d_i^{qy} = M_i \times D_{m\leftarrow i}^{qy} \tag{8}$$

$$\forall c \in \hat{C}, \forall i \in I^c$$

Constraints

$$X_{od}Z_{i\in I:i=(o,d)} + \sum_{j\in N:j\neq o,d} X_{od}X_{dj}Z_{i\in I:i=(o,d,j)} + \sum_{j\in N:j\neq o,d} X_{jo}X_{od}Z_{i\in I:i=(j,o,d)}$$
$$+ \sum_{j,k\in N:j,k\neq o,d} X_{od}X_{dj}X_{jk}Z_{i\in I:i=(o,d,j,k)} + \sum_{j,k\in N:j,k\neq o,d} X_{jo}X_{od}X_{dk}Z_{i\in I:i=(j,o,d,k)}$$
$$+ \sum_{j,k\in N:j,k\neq o,d} X_{jk}X_{ko}X_{od}Z_{i\in I:i=(j,k,o,d)} \leq 143 Y_{od}Q_{od} \tag{9}$$

$$\forall (o,d) \in A$$

$$X_{od} = X_{do} \tag{10}$$

$$\forall (o,d) \in A$$

$$Y_{od} = Y_{do} \tag{11}$$

$$\forall (o,d) \in A$$

$$\sum_{\forall (o,d)\in A} X_{od} Y_{od} \leq 2a \tag{12}$$

V. Data Analysis

Given that most of the analysis and parameter values is driven by data, which comes from different sources and many separate files for each year and quarter, a web scraper has been developed for programmatic collection and indexing of all relevant data spanning the past 20 years, which amounts to 80 quarters in total. Tables 2,3, and 4 contain snippets of OD market data, on-time performance data, and expense data. For each of the quarters, the total demand of each OD market in our design space was calculated and provided to ARIMA time series algorithm for forecasting the demand of the OD routes for the next 5 years. Figure 7a) shows a plot of the demand forecast of the Boston-Atlanta market and Fig. 7b) shows the fit of ARIMA output on historical time series demand data, where the black colored line represents the existing time series demand data and the blue line indicates the forecasted demand given by the ARIMA output.

Table 2 OD market data showing itineraries offered by different airlines in the second quarter of 2017

Itinerary ID	Origin City ID	Dest City ID	Tk. Carrier Group	Op. Carrier Group	Reporting Carrier	Tk. Carrier	Op. Carrier	Pax	Fare	Market Miles Flown
2017225	30397	30135	DL	DL	9E	DL	DL	1	312	692
2017226	30135	30208	DL:DL	9E:9E	9E	DL	9E	1	467	835
2017227	30135	30423	DL:DL	9E:DL	9E	DL	99	1	469	1505
2017228	30135	30693	DL:DL	9E:DL	9E	DL	99	1	542	906
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 3 On-time performance data showing delay statistics for flight legs operated by different airlines in April 2017

Flight Num	Origin City ID	Dest City ID	Dep Delay	Arrival Delay	Dist	Carrier Delay	Weather Delay	NAS Delay	Security Delay	Late AC Delay
1680	33192	33570	30	35	480	23	0	5	0	7
1680	30140	30194	21	33	580	5	0	12	0	16
1680	30599	32211	227	211	1618	10	0	0	0	201
1680	30194	30599	27	29	587	3	0	2	0	24
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 4 Form 41 cost data of aircrafts and airlines in the second quarter of 2017

Total Fly Ops	Total Direct Maintenance	Applied Maintenance Burden	Total Flight Equipment Maintenance	Expendable parts	Amortization Expense	Total AC operating expense	Aircraft type	Carrier
5308.93	1949.2	502.36	2451.56	101.16	80.53	8551.01	622	UA
5434.38	910.19	0	910.19	0	306.86	7011.16	698	NK
5477.83	2538.48	1451.71	3990.19	-	0	9616.35	626	5Y
5490.4	919.58	0	919.58	0	310.03	7083.44	699	NK
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .

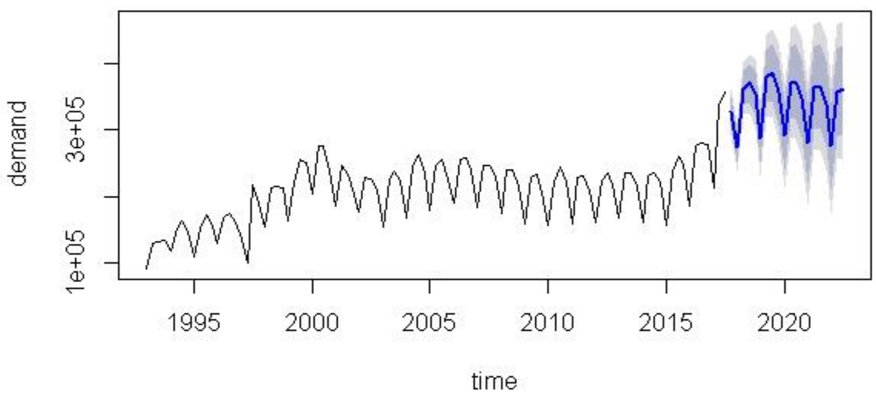

Fig. 7a) The demand forecast of Boston-Atlanta market generated using ARIMA(2,0,2)(2,1,1)[4] with drift

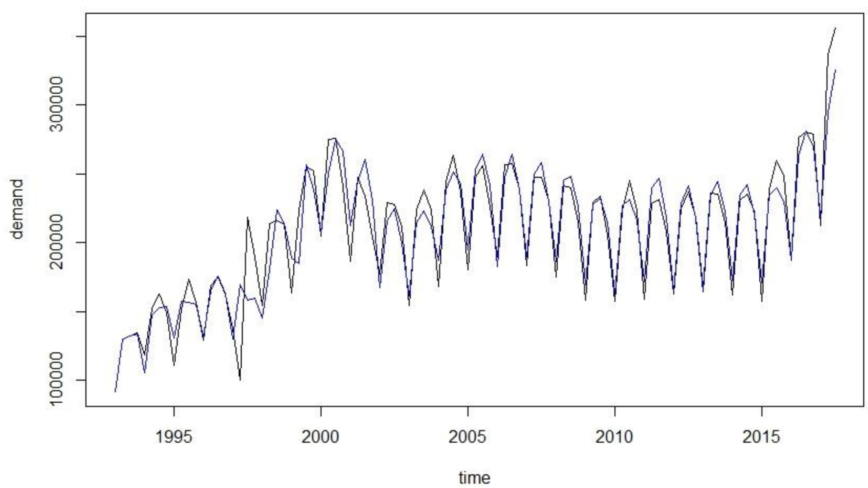

Fig. 7b) The fit of ARIMA output on historical time series Boston-Atlanta market demand data

BTS OD market survey data has been cleaned and preprocessed following standard Airlines Reporting Corporation (ARC) practices [114] to get a suitable training set for input to the logit model estimator. This involved removing multi-stop itineraries and itineraries with more than 6 legs or directional fares less than $50 or directional fares in the top 0.1% of observations.

The parameter estimates obtained for the logit-based itinerary share model using DB1B O-D market data for the second quarter of 2017 are reported in Table 5. The model was validated on DB1B O-D market data for the first quarter of 2017. The absolute error averaged across all itineraries was found to be 0.0115. The predicted itinerary shares of the entrant LCC for any given set of network design variables can be determined using Eqs. (6), (7) and (8), which can then be passed to the revenue model. The output of revenue and cost model will then be used to calculate our value function – the NPP.

Table 5 Parameter estimates of the itinerary share model

Explanatory variable	Coefficient value
Flight distance	-0.0008
Fare	-0.0009
Number of connections	-2.5512
Online itinerary	1.4805
Codeshare itinerary	-0.3334
Interline itinerary	-0.1471
American Airlines	0.7488
Southwest	0.2639
Delta	0.8479
United	0.2465
JetBlue	0.5506
Spirit	-0.8671
Frontier	-0.7479
SkyWest	-0.0002
Other airlines	0.9576

Using machine learning techniques, the following key issues are being addressed: quantifying and modeling uncertainties of fuel price, demand, and delay, and sources of internal disruptions and external failures; determining the impact of delays, cancellations and misconnects on demand and hence customer loyalty and revenue; discovering hidden performance attributes of the network; and mapping system performance such as robustness and resilience to the value function. The uncertainties will reflect the stochastic environment in which the network will operate. Plugging in these uncertainties in the NPP model will lead to a value distribution of the candidate network designs. Afterwards, a suitable utility function will be given this value distribution to determine the utility derived by the airline stakeholders. Several optimization algorithms, both deterministic and stochastic, will be tested out to find the optimal network design in our design space, which, by definition, will give the highest utility. Finally, a comparative analysis of two transportation network design approaches will be carried out: networks designed with traditional robustness and resilience metrics and networks designed using our proposed framework. Networks designed using the tools and processes described in this paper are expected to have a superior performance, with respect to the true preference and risk attitude of the stakeholders, than the metric-based ones.

VI. Conclusion

This paper aims to demonstrate that real-world network systems of any domain, such as transportation networks, can be designed to achieve optimal performance in the presence of uncertainties by planning for resilience at the system design phase based on the preference and risk attitude of the stakeholders. The proposed design framework uses VBM, data analytics, and utility theory. Using VBM, the true preference of the stakeholders can be captured. Applying statistical techniques on historical datasets allows identifying key network performance attributes; determining their interrelationships and causal relationships, and their impact on value to formulate a meaningful, holistic value function; and quantifying uncertainties as probability distributions to get value distributions. Lastly, utility theory can be used to integrate value distributions associated with uncertain outcomes into a single expected utility that is consistent with the individual's risk averseness. The value-based system resilience of the resulting complex network system can be assessed by performing a range of simulated disruption scenarios. To validate the resulting complex networked system, it can be compared with other systems designed with existing robustness and resilience metrics. The research outcomes are expected to address the inconsistencies in the traditional metric-based robustness quantification of complex network system, the challenge of capturing the desired level of robustness in the system design from the decision makers' risk attitude in the utility function, and the problem of finding the optimal recovery strategy by planning for resilience at the system design phase. This can potentially bridge the gap between the network science community and systems engineering community in the understanding of system robustness and resilience; and lead to the development of a standard methodological design framework for complex networked systems. By utilizing this framework, network designers and operators, such as air carriers, can design new route networks or reconfigure existing ones, along with planning for all other operational aspects, such as flight scheduling and fleet planning, for maximization of profit or other preferred objectives.

Future work involves the analysis and application of this framework in other domains such as designing on-demand urban air transportation networks, where airports are replaced with vertiports in a given metropolitan area, aircrafts with electric vertical takeoff and landing vehicles, and LCC with a ridesharing company like Uber.

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