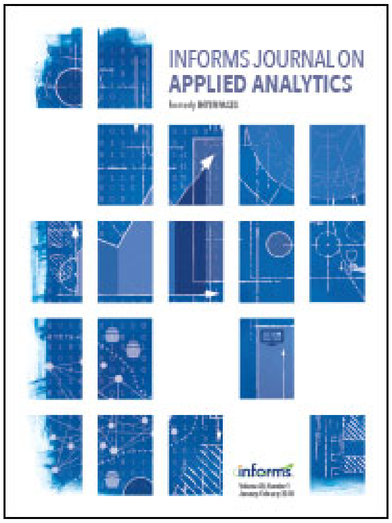

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Abstract. The Verizon Global Supply Chain organization currently manages thousands of active supplier contracts. These contracts account for several billion dollars of annualized Verizon spend. Managing thousands of suppliers, controlling spend, and achieving the best price per unit (PPU) through negotiations are costly and labor-intensive tasks handled by Verizon strategic sourcing teams. Verizon engages thousands of suppliers for many reasons—best price, diversity, short-term requirements, and so forth. Whereas managing a few larger spend suppliers can be done manually by dedicated sourcing managers, managing thousands of smaller suppliers at the tail spend is challenging, can often introduce risk, and can be expensive. At Verizon, a unique blend of descriptive, predictive, and prescriptive analytics, as well as Verizon-specific sourcing acumen was leveraged to tackle this problem and rationalize Verizon's tail spend suppliers. Through the creative application of operations research, machine learning, text mining, natural language processing, and artificial intelligence, Verizon reduced spend by millions of dollars and acquired the lowest PPU for the sourced products and services. Other benefits Verizon realized were centralized and transparent contract and supplier relationship management, overhead cost reduction, decreased contract execution lead time, and service quality improvement for Verizon's strategic sourcing teams.

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Keywords: global procurement • strategic sourcing • supplier rationalization • business process outsourcing • spend analytics

1. Introduction

Verizon is a multibillion-dollar telecommunication and media company with global operations and diverse product offerings such as Huffington Post, FiOS, AOL, Yahoo!, and Visible; more than 150,000 employees worldwide; and 2,300 retail stores in the United States. Verizon is a pioneer in commercializing 5G Internet services and operates the world's largest cellphone network, covering personal, residential, and business customers. To be able to run the world's fastest telecommunications network and provide a world-class customer experience to its customers, Verizon uses the latest and most advanced technologies available in the market. As a result, partnering with global telecommunication equipment manufacturers has been a successful business strategy for Verizon to deliver its services across the globe.

Because delivering quality services at the lowest possible price to customers is Verizon's corporate strategy, Verizon implemented world-class intelligent systems within its global strategic sourcing teams, leading to significant cost reductions in acquired network equipment and services, managing redundancies and improving its cost-to-serve (CTS) model.

Operating a network with millions of subscribers calls for strong risk avoidance strategies. A small disruption in supply of network equipment or maintenance components might lead to a drop in network services and significant customer losses. Therefore, Verizon avoids single sourcing its telecommunication equipment and services from its suppliers and instead engages multiple suppliers per category for its required products and services. Supplier diversification programs, which were implemented by Verizon's strategic sourcing teams in the early 2000s, allow competitive pricing, as well as risk and supply disruption management. Although these programs were successful at the beginning, they increased Verizon's supplier network to approximately 47,000 suppliers worldwide over time, leading to significant contract management, supplier negotiations, and overhead costs for the sourcing teams to the point that these costs were exceeding the programs' benefits. As a result, in late 2017, Verizon decided to transform its sourcing operating model and initiated one of the largest public business transformation efforts in the history of the telecommunications industry.

Deciding on the right number of large and small suppliers is a challenging business decision for any organization with global sourcing operations. Conducting multiple requests for proposal (RFPs) and several rounds of supplier negotiations often takes thousands of supplier business attributes into consideration, creating opportunities to leverage advanced analytics techniques and transforming traditional decision-making processes into a more intelligent and data-oriented approach.

To define the business problem that is addressed in this paper effectively, first, the dynamics of global strategic sourcing and procurement operations is explained. In addition, a brief description of the electronics manufacturing and the telecommunications business is also provided.

1.1. Strategic Sourcing and Global Procurement

Successful global organizations focus their effort and talent on their core business and use outsourcing for non–core business activities. At Verizon, the focus is on the network and technology—for instance, 4G and 5G networks, fiber optic broadband services, and media content creation and delivery. Any business operation that is not within Verizon's core business expertise will be outsourced to qualified vendors and suppliers. This practice is known as *indirect procurement*. On the other hand, to run the network and communication towers, Verizon uses a variety of fiber optic cables, electronic boards, switches, and routers that are sourced from well-known electronic manufacturers and suppliers. This approach is known as *direct procurement*, and suppliers in this category are often treated as strategic business partners with business models such as gain sharing and transparent pricing. In general, sourcing products and services that are used within the products and services a company sells directly is direct procurement and everything else is indirect procurement.

At Verizon, global strategic sourcing teams and category sourcing managers are responsible for supplier selection, evaluation, negotiations, and contracting for the abovementioned procurement strategies. Negotiating contracts is time consuming, as it involves a strong detailed financial analysis; planning and coordination; and legal, compliance, and global clearance reviews. As a result, contract negotiation lead times can vary from a few days to a few years depending on the complexity of the contract terms and the monetary value of the contract. In addition, sourcing operations often impact the company's profit and loss (P&L) statement and financial earnings, which require financial planning and analysis (FP&A).

To evaluate strategic sourcing operations, key performance indicators (KPIs) are defined by Verizon's FP&A teams. These indicators are often used to benchmark a sourcing organization's effectiveness in comparison with other internal and external organizations industry wide. Table 1 lists and defines the important KPIs that are used by the Verizon strategic sourcing and FP&A organizations for reporting and financial analysis. At Verizon, a sourcing operation starts with a sourcing request form (SRF), submitted by a business unit. A supplier master agreement (MA), an agreement (AGR), or a contract amendment is the output of successful sourcing operations. A category sourcing expert (CSE) manages multiple SRFs at a time for one or multiple sourcing categories. CSEs often conduct a request for information (RFI), a request for proposal (RFP), a request for quote (RFQ), or a request for bid (RFB) to identify proper suppliers. Conducting an RFX, where X could be any one of the previously mentioned requests, could take anywhere from a few weeks to a few months to complete. Depending on the RFX's result, CSEs might decide to sign a contract with an existing supplier or onboard a new supplier to the supplier network.

Table 1. Important KPIs for Strategic Sourcing

Metric type	KPI	Definitions
Operational	SRF lead time	Time between an SRF and contract execution
	SRF hold time	Waiting time for an SRF approval by internal business unit executives
	Number of RFX conducted	Total number RFXs conducted by CSEs
	Number of Mas	Total supplier master agreements negotiated
	Number of AGRs	Total agreements or amendments negotiated
Financial	ROI per CSE	Sourcing return on investment (ROI) per CSE
	Managed spend	Company spend managed by sourcing teams
	PPU	Year-over-year price per unit of sourced categories
	Commodity maturity	Level of procurement efficiency for a sourced commodity
	Savings %	Percentage of spend savings compared with baseline (prior year spend)

1.2. Original Equipment Manufacturer and Value-Added Reseller

Within electronics manufacturing, manufacturers can also choose to manufacture everything related to their products in-house or source from other manufacturers. The term original equipment manufacturer (OEM) is often referred to as the original manufacturer of an electronic product, part, component, or software. Large electronics manufacturers often use smaller manufacturers' microprocessors and other components in their products. To keep track of their bill of material (BOM), these manufacturers either overwrite the OEM number, a unique identifier to a product, of these smaller components with their own OEM number or use a manufacturer part number (MPN) instead. Telecommunication companies such as Verizon often use these OEM numbers or MPNs in their procurement, whereas financial systems use unique identifiers of the sourced items for reporting and planning purposes. Verizon network planning teams usually refer to these identifiers to plan for network spend and project management activities, and accounting teams use them for taxing and bookkeeping. There are other use cases for this information, for example, in contract management, product price variance analysis, and negotiations with the suppliers.

Total spend with a supplier is a good reference point to start contract negotiations. However, deciding on the total spend with a supplier requires visibility to all the OEM numbers within a sourced product and the ability to trace the supplier spend at the OEM level. Enterprise resource planning (ERP) systems often fail to address the need for this information because most of them are built for general purposes and not customized to telecommunication business needs. For instance, when Verizon initiates a purchase order (PO) to a vendor, the required OEM or MPN information is often sent to the vendor via emails or as an attachment to the PO, generating large unstructured data within ERP data warehouses. The sourcing teams would need to refer to these files or PO attachments through manual search for any internal financial analysis, project planning, and vendor auditing.

The sourcing channel may also cause missing or inconsistent OEM information in ERP systems as well. Large companies often choose to engage numerous suppliers to source the same category for various reasons—best price, portfolio diversity, short-term requirements, and risk management are some of these reasons. Some of these suppliers are resellers of OEM products. Therefore, the same product or service can be sourced from either the OEM or a value-added reseller (VAR). VARs often carry inventory holding risks for their customers (e.g., Verizon) but demand large profit margins when negotiating with OEMs and their customers in return. Inventory holding risks are often the cause of product price variances between VARs and OEMs. If an item is procured through a VAR, depending on the VAR's ERP system data governance, the OEM information might not be captured by the VARs. Thus, the VAR might not be able to pass them on to Verizon, which could complicate the OEM's total spend calculation.

The procurement challenges Verizon faces today are industry wide and not unique to the Verizon business model. To name a few, business process outsourcing (BPO) (Feeny et al. 2005), wholesaling, automobile manufacturing, pharmaceutical distribution, and even startup (Yoon et al. 2018a) businesses are always exposed to inconsistent data governance, decentralized decision making, lack of visibility on end-to-end pricing decisions, and supplier negotiations. Although the business problem addressed in this paper focuses on rationalizing tail spend suppliers, the Verizon Supplier Rationalization Tool (VSRT) developed to solve this problem can be applied to suppliers of any spend size or industry, providing valuable information to their procurement teams and speeding up contract execution.

The structure of this paper is as follows: A survey of existing supplier rationalization works using data analytics is provided in Section 2. The business goals and explanation of the business environment are provided in Section 3. Topics related to the machine learning algorithms and optimization methods used in VSRT to solve this problem are covered in Section 4. A review of the VSRT implementation results is provided in Section 5. Final remarks about this end-to-end VSRT solution are provided in Section 6.

2. Literature Review

Supplier evaluation has been mainly addressed in the literature using conceptual, empirical, or quantitative models. Talluri and Narasimhan (2004) reviewed most of the available conceptual and empirical models and briefly covered some of the available quantitative techniques. With the recent advancements in machine learning and big data technologies, decision makers are more interested in *prescriptive* techniques; therefore, conceptual and most of the available empirical models in the literature have become impractical. Table 2 provides a high-level comparison of the tools, techniques, and algorithms between the existing literature and the VSRT. To have a consistent comparison, four major capabilities are used for comparison: data processing engine, supplier evaluation engine, supplier ranking algorithm, and reporting/visualization engines.

The majority of the existing quantitative models in supplier evaluation are using data envelopment analysis (DEA) (Charnes et al. 1978). DEA is a well-known

Table 2. Capability Comparison Between VSRT and Existing Literature

Publication	Data processing engine	Supplier evaluation engine	Supplier ranking algorithm	Reporting and visualization engines
Kleinsorge et al. (1992)	X	DEA without KPIs	X	X
Narasimhan et al. (2001)	X	DEA	X	X
Talluri and Narasimhan (2003)	X	DEA	X	X
Talluri et al. (2013)	X	DEA	Performance diversity index	X
Wu and Olson (2010)	X	DEA and Monte Carlo	Hierarchy base	X
Yoon et al. (2018b)	X	Probabilistic models (Erlang)	X	X
Narasimhan et al. (2006)	X	MIP (Minimax)	X	X
Rao et al. (2017)	X	MIP and fuzzy theory	X	X
Sarkara and Mohapatrab (2006)	X	Fuzzy theory	Weighted average	X
Bayrak et al. (2007)	X	Fuzzy theory	Fuzzy preference index	X
Verizon Supplier Rationalization Tool (VSRT)	NLP and RNN	Clustering and inverse DEA with KPIs	TOPSIS and Shannon entropy	Interactive visualization

optimization technique used for benchmarking manufacturing and service business units with their peer units, known as decision-making units (DMUs). Kleinsorge et al. (1992) used DEA to monitor the performance of a single supplier over time. Narasimhan et al. (2001) expanded the use of DEA models for supplier evaluation and included operational and strategic KPIs within their model; however, their model was focused only on manufacturing industries, did not cross-evaluate supplier based on different categories, and was not useful for evaluating service-providing suppliers. The first DEA model that cross-evaluated suppliers was introduced by Talluri and Narasimhan (2003). Similar to Narasimhan et al. (2001), this model was only using operational KPIs as well.

Identifying candidate suppliers for rationalization can be formulated into a mixed integer program (MIP) (Taha 1975). An MIP has an objective function that could minimize or maximize the impacts of supplier rationalization on the business subject to various business constraints. Talluri and Lee (2010) formulated an MIP to choose the optimal terms for contracts such as contract duration and product order quantities in the presence of market price uncertainty, supplier discounts, investment costs, and supplier capacity constraints.

Recent academic works in supplier evaluation cover areas such as evaluating suppliers at the sourcing category level (Sarkara and Mohapatrab 2006), sourcing services (Ellram and Tate 2015), and public procurement (Loader 2015). Supplier risk management concept (Yoon et al. (2018b) was also added to supplier evaluation techniques using probabilistic functions derived from an Erlang or normal distribution function. For instance, Wu and Olson (2010) included value-at-risk calculations, and Rao et al. (2017) incorporated an auction theory mechanism within their models to shortlist suppliers before evaluation. Other quantitative techniques such as multiobjective goal programming (MOGP) (Narasimhan et al. 2006), where suppliers were evaluated based on multiple business objectives, or Bayrak et al. (2007), where the likelihood of suppliers meeting their target KPIs were modeled using fuzzy numbers, have also been introduced in the recent supplier evaluation models.

Processing large volumes of unstructured supplier data has been a major shortcoming of the existing literature. All of the existing supplier evaluation techniques would require significant manual data processing and computation time to provide insights on suppliers. In today's business world where speed and agility to provide insights to decision makers are critical for successful negotiations, spending time and resources on processing supplier data will make the existing models in the literature impractical. VSRT includes a data preprocessing engine, which leverages natural language processing (NLP) (Manning and Schütze 1999) and recursive neural networks (RNNs) (Schmidhuber 2015) to build high-quality data models. These data models are used within other stages of the solution to reduce computation time and user interaction time with the solution and provide quality results. The data processing capability will also help with scenario analysis, tool reliability, and user experience.

Most of the existing supplier evaluation techniques either are missing critical factors such as strategic KPIs or provide nondeterministic results that are often difficult to explain to business users, are not objective, do not assign different weights to influential sourcing parameters, lack comparison with alternative suppliers, and do not address supplier performance at the sourcing category level. Deploying a solution with these shortcomings is risky for any businesses regardless of their size or industry. In addition, none of the existing literature focuses on the tail spend suppliers. Unlike the existing literature, the VSRT clusters suppliers based on their business attributes and cross-evaluates them within their own cluster. This allows the VSRT's supplier evaluation engine to perform complex computations on a large volume of supplier data, scaling up the solution on the entire supplier base and providing deterministic results that are simple to explain to the business users.

Similar to VSRT, Talluri et al. (2013) provided a DEA model to evaluate suppliers with their peers; however, following their DEA model, they used a supplier performance diversity index (PDI) to rank the rationalization candidates. This new approach was tested on published data sets. The results were compared with an existing ranking method, the maverick index (Doyle and Green 1994), which uses the mean of suppliers' efficiency score to rank suppliers. They concluded that evaluating suppliers using both MIP and PDI in tandem helps identify suppliers that not only excel with respect to their peers but also offer a unique set of capabilities that other suppliers lack. Bayrak et al. (2007) also used a fuzzy preference index (FPI) (Bilsel et al. 2006) to rank suppliers based on a set of fuzzy numbers. The VSRT ensures that suppliers that provide similar sourcing categories are compared with their peers by clustering them according to their business attributes and then applies a supplier ranking algorithm to identify the rationalization candidates. The technique for order preference by similarity to ideal solution (TOPSIS) (Hwang et al. 1993), which is a data-driven ranking algorithm, is combined with the Shannon entropy (Shannon 1948) to rank suppliers and identify the rationalization candidates subject to multiple business criteria. The VSRT approach is superior to the existing literature because it is unbiased and data oriented and can be customized according to the CSE needs.

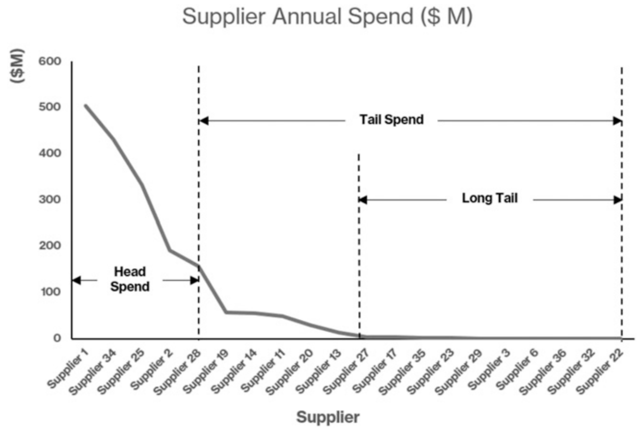
The interactive reporting and visualization provided by the VSRT have not been within the scope of any of the existing literature. However, for a successful solution deployment, interactive reports and visualization are key to communicate complex information and recommendations. VSRT equips sourcing teams with several detailed reports at both category and SKU levels, providing spend visibility for all the OEMs within the supplier network.

3. Business Goals, Environment, and Assumptions

3.1. Tail Spend Definition

Figure 1 is a Pareto chart showing Verizon aggregated supplier spend, in which larger spend suppliers, known as head spend suppliers, appear to the left on the chart and others, known as tail spend suppliers, appear to the right. The definition of tail spend can be quite

Figure 1. Tail Spend Suppliers



abstract because in practice, the head of the tail spend (suppliers 28, 19, 14, and 11) is hard to differentiate from the head spend suppliers. For large organizations like Verizon, a supplier with annual spend of $5 million might be considered a tail spend supplier, whereas for smaller companies, the cap might be a lot lower. The long tail suppliers (suppliers 27 and so on) are a lot harder to rationalize and consolidate than the head of the tail suppliers, because these suppliers could be niche, offering products or services that are important for Verizon's business or have geographical representation and strategic advantages.

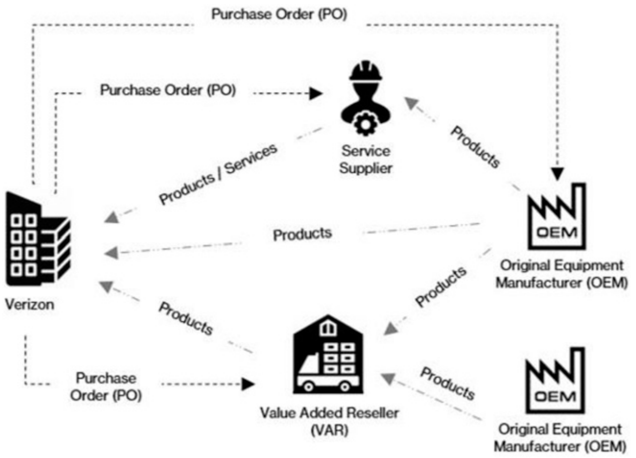
3.2. Business Environment

Consider a business environment where there are multiple suppliers (or OEMs) per sourcing category and different sourcing channels (e.g., a business can source their products and services either directly from the OEMs or from VARs). In addition, a supplier can use other OEMs' products or services to create a new product, build kits, or provide service and product bundles to a business. Figure 2 illustrates this business environment. The decision on which sourcing channel or supplier to choose and source from is a function of several factors: PPU of the products and services, discounts, bundled/tiered pricing, order volume consolidation, delivery date and location of ordered items, previous agreements with the vendors or OEMs, and even tariffs and corporate taxes are among these factors. For simplicity, these factors can be assigned to two major classifications: pricing and quality metrics (KPIs).

3.3. Business Goals

The primary goal of the VSRT is to provide insights to the sourcing teams to rationalize Verizon's tail spend suppliers. More specifically, this solution aims to provide data-driven tools and capabilities to

Figure 2. Verizon Sourcing Business Environment



1. reduce the number of tail spend suppliers and supplier management overhead costs;
2. identify a subset of suppliers that provide products and services that minimize the overall Verizon spend while maximizing the quality metrics; and
3. recommend alternative suppliers, from the head spend supplier set, to take over the tail spend supplier's order volume and consolidate order quantities.

3.4. Assumptions and Definitions

Achieving the abovementioned goals requires some business assumptions:

- At least two active suppliers per category are already in the Verizon supplier network.
- No new supplier is added to the network for any of the categories under study.
- Suppliers are able to add categories that they are not currently covering in their offerings, which is subject to supplier negotiations.

This decision-making problem can be translated into mathematics. Definition A.1 in Appendix A defines this problem as follows: There should be a subset of suppliers, s, where their KPIs and PPUs are competitive with others in almost all sourcing categories. To avoid this supplier subset being empty, Verizon always prioritizes quality over pricing. To create this subset of suppliers and achieve the abovementioned goals, transaction level spend data and other data sources need to be analyzed. Because the data size for transaction level data can be quite large, traditional data analysis techniques will not be able to solve this decision-making problem fast enough and provide business insights for decision makers. Therefore, different types of analytics and algorithms were combined in an innovative sequence to tackle this problem. The next section will cover the details of this unique approach.

4. Solution Methodology

The VSRT methodology consists of four main stages: data models, machine learning models, optimization models, and interactive visualizations. Figure 3 shows these stages where different models were applied and the departments impacted by each within VSRT. The solution's analytics journey starts with structuring transaction level invoice line and PO data, blending them with external structured data sets and build data models. Using the data models, the machine learning engine clusters suppliers based on their business attributes. The optimization engine uses an inverse DEA model to evaluate suppliers within each cluster with their peers and creates a supplier efficiency score matrix. A TOPSIS algorithm, which uses Shannon entropy and the suppliers' efficiency score matrix, ranks the suppliers and identifies the rationalization candidates. Results are reported to the decision makers using interactive visualization. The outputs of each stage are inputs of the next stage. Figure 4 explains the details of these stages and the functionality of each stage. Because data models are critical components of any analytical solution, first, the data models are explained.

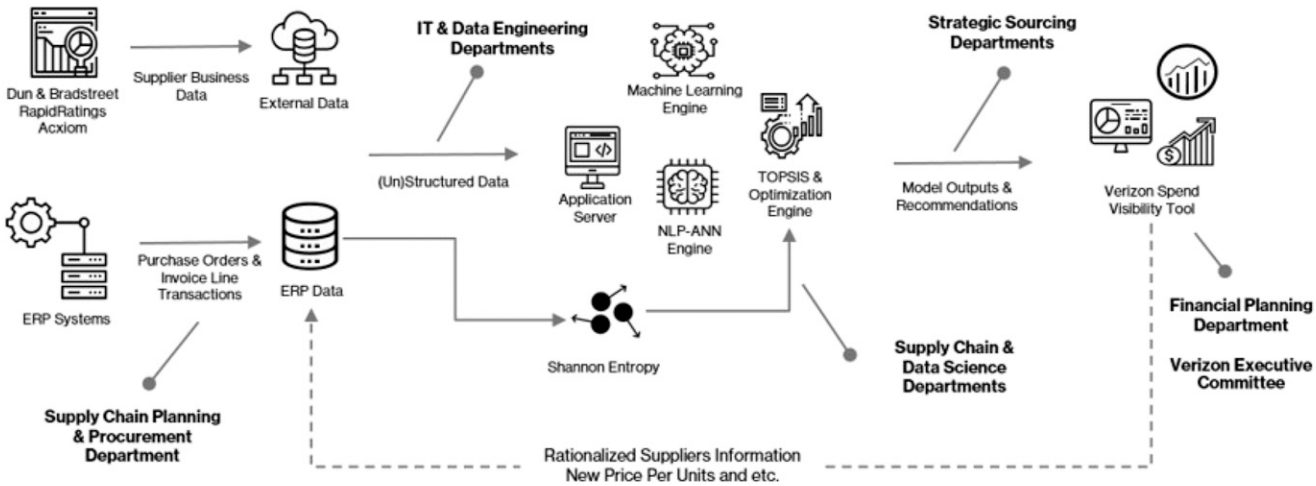
4.1. Data Models

A blend of Verizon internal and external (third party) data sources was used to build supplier business profiles. For the internal data sources, transaction level PO and invoice line data generated by Verizon's ERP systems were used. ERP data warehouses were often filled with enormous quantities of unstructured data, where key data elements such as OEM numbers/names, MPN, spend classifications, and taxonomies are either missing or mislabeled. That being said, NLP was used to tokenize transaction level PO and invoice line data to extract key information and fill in missing data.

A set of RNNs was built followed by the NLP text mining results to predict spend categories or relabel the existing data, OEM names, or MPNs if needed. The developed RNN models have multiple hidden layers and were trained and retrained iteratively on high-quality data sets provided by OEMs until their accuracy reached 98% (i.e., 98% of the time, the RNN was able to predict the exact missing information as the OEM provided information). Figure 5 illustrates the sequence of NLP and RNN models and details about their configurations used to predict or relabel missing information within the Verizon ERP data sets.

External data sources also were added to the structured supplier spend data to build the suppliers' business attribute matrix (BAM). Financial and market intelligence data sets from external sources including

Figure 3. VSRT Models, Data Flow, and Covered Business Departments



Dun & Bradstreet, RapidRatings, and Acxiom, along with other data sets such as suppliers' geo-footprint, diversity, compliance, risk, and capabilities, were added to enrich the structured spend data and strengthen the overall analysis. Table 3 shows important examples of the data sources and type of variables used to build the supplier BAM. The complete list of these variables is exhaustive and proprietary to Verizon. Hadoop Super Cluster and Hive platforms were used as a system of records (SOR) to host and process all data models. The outputs of this stage are structured high-quality supplier business data, which can be consumed by machine learning models in the next stage. In addition, high-level business reporting and spend analysis can be built with the outputs of this stage.

4.2. Machine Learning Models

Assume there are S tail spend suppliers with M business attributes per supplier where Verizon sources C distinct sourcing categories. The suppliers' BAM will have S rows and $C \times M$ columns. If creating a combination of these attributes, that is, $\binom{C\times M}{k}$, where k is the number of distinct attributes, the dimensions of this matrix grows exponentially. For instance, consider a supplier that has capabilities to provide tower installation services (a highly demanded sourcing category by Verizon) in New Jersey, United States, and in Dublin, Ireland, and maintains a diverse portfolio of supplementary products (e.g., cables, wires). This supplier could have three business attributes for the tower installation category (i.e., three different columns with binary values, $C = 1$ and $M = 3$). If all of these business attributes were combined ($k = 3$), this supplier would have a fourth attribute (i.e., another column) that indicates that the supplier could provide installation services in the United States and Ireland and has a diverse portfolio of supplementary products, that is, $\binom{1\times 3}{3} + 3 = 4$.

The algorithm complexity for searching the solution space of this matrix is of the order of $O(n^3)$.

Figure 4. VSRT Analytics Journey

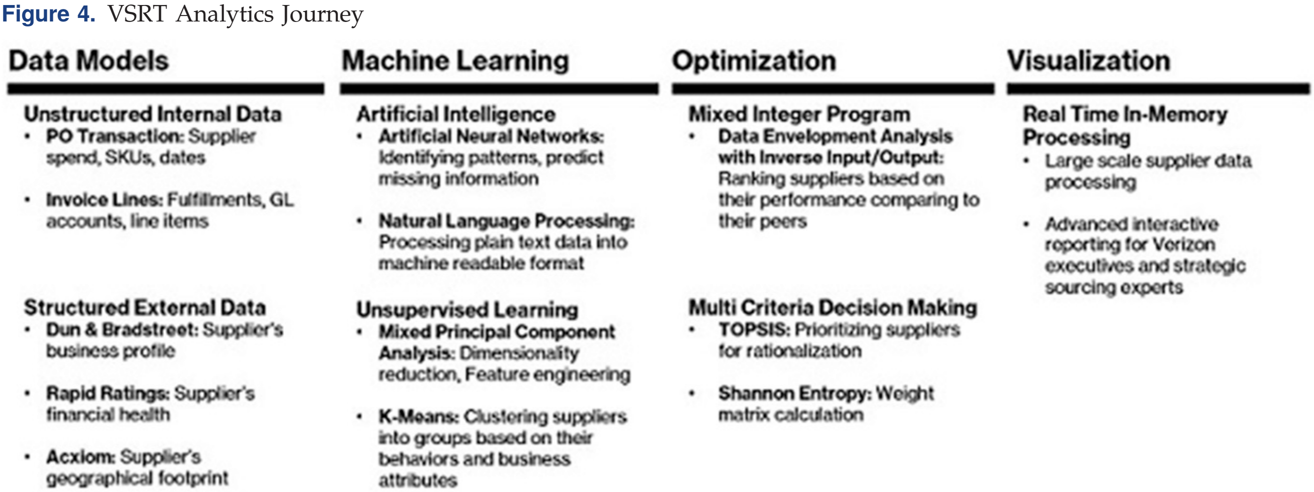
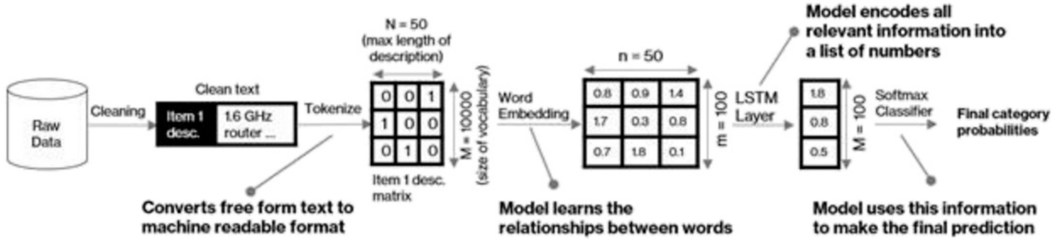


Figure 5. Natural Language Processing and Recurring Neural Network Used to Predict Missing Data



This matrix is highly sparse and has large dimensions, exceeding the computation capability and equipment memory requirements of any traditional machine learning algorithms that could generate business insights from this data set. In addition, Table 3, which shows the data components of this matrix, consists of mixed data types (i.e., integer, binary, and categorical), adding more computational complexity for this matrix. Because generating insights from high-dimensional and sparse data with blended data types is very difficult and inefficient, any analysis on this matrix calls for some level of aggregation or simplification to a level that the characteristics of the data remain the same (Geiger and Kubin 2012) while reducing computation time without a loss in output quality.

There are algorithms available in the literature that can perform on high-dimensional sparse data in linear time. For example, factorization machines (Rendle 2010) is a good algorithm to apply to this matrix, but it is not easy to implement. Famous decision tree pruning algorithms (e.g., alpha-beta pruning) can reduce the search space within this matrix as well (Furnkranz 1999). Using the sourcing team's subject matter expertise to short-list the supplier list can be another creative strategy to reduce the dimensions of this matrix; however, there could be inconsistency among opinions on the importance of any of these business attributes or suppliers.

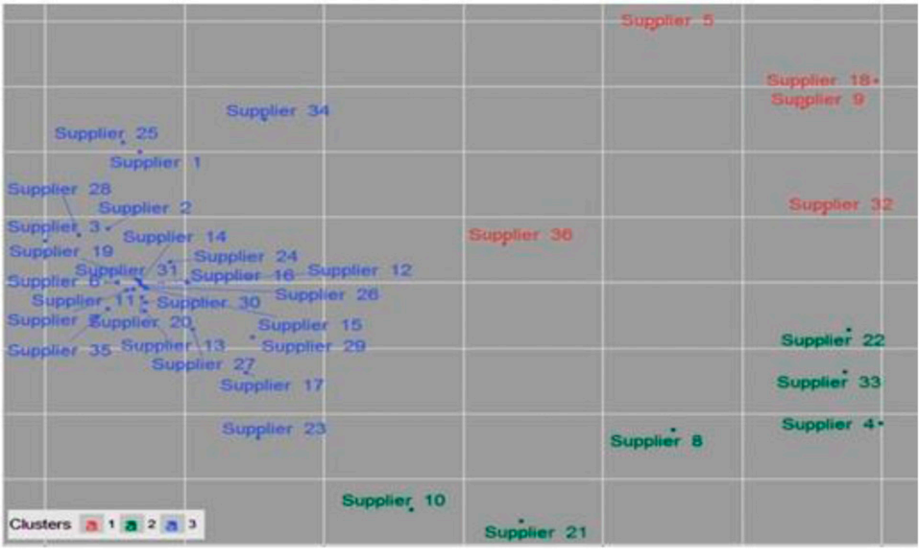
For simplicity, a mix of unsupervised machine learning algorithms were used to reduce data dimensions, build supplier profiles, and cluster suppliers according to their business attributes. Becaues the suppliers' BAM is highly sparse and has a mixed data type, mixed principal component analysis (MPCA) (Rencher 2002a) is used to reduce the dimensions of this matrix and to identify important business attributes independent of sourcing category managers and business unit opinions. Top contributing components were then fed into a K-Means (Rencher 2002b) clustering algorithm to build clusters of suppliers according to their business attributes and behaviors. Clustering suppliers helps supplier comparison and benchmarking because it is not fair to compare suppliers that do not provide similar categories. For example, suppliers that supply Verizon with switches and routers should not be compared with suppliers that provide fiber optics and cables.

Figure 6 shows an example of the supplier clustering for suppliers listed in Figure 1, which has three distinct clusters. The shape of a cluster is due to the business attributes of its member suppliers. Therefore, rationalizing suppliers within their own clusters will be easier than rationalizing suppliers between clusters because members of the same cluster can absorb others' volume with the least amount of impact to Verizon's sourcing operations and help supplier consolidation. Identifying rationalization candidates still is not a trivial task at this stage as each one of these suppliers provides Verizon with multiple categories of products and services. That being said, more detailed analyses are needed for Verizon sourcing teams to identify the right rationalization candidates (e.g., comparing suppliers with their peers based on their KPIs and PPUs of sourced categories and items). The outputs

Table 3. Main Data Sources Used in VSRT

Source	Category	Example(s)	Data type
Internal	Spend	YoY spend, sourcing category	Integer, categorical
	Items	OEM number, MPN, item description	Categorical
	Diversity	Portfolio or workforce diversity	Binary
	Accounting	Sourceable or nonsourceable spend	Binary, integer
External	Acxiom	Geographic, socioeconomic, demographic	Integer, categorical, binary
	RapidRatings	Financial health, risk	Integer, categorical
	Dun & Bradstreet	Financial ratings, market intelligence	Integer, categorical

Figure 6. (Color online) Clustering Suppliers by Their Business Attributes



of this stage are clusters of suppliers that can be compared with each other or with other clusters.

4.3. Optimization Models

DEA works well for evaluating suppliers across multiple categories with their peers. DEA establishes relationships between inputs and outputs of the suppliers and evaluates all of the other suppliers with the efficient frontier supplier, a supplier that provides the best PPU and KPI (or any other metrics) in that category compared with its peers. Higher inputs to a supplier calls for higher outputs and performance.

The inputs to suppliers can be annualized PO values sent to a supplier, and outputs can be PPU of items purchased and procurement KPIs. Table 4 reviews some of the procurement KPIs that are considered by Verizon contract management teams when evaluating suppliers and used in the developed DEA model. The developed DEA model in this paper establishes inverse relationships its inputs and outputs as the higher the spend with a supplier is, the lower the KPIs and PPUs should be. DEA models can take different inputs and outputs. Readers can refer to Cook et al. (2014) to investigate the appropriate model orientations for their use case.

For this stage, the goal is to calculate an efficiency score, within each cluster, for each supplier and category combination, in turning financial resources and POs to the lowest levels of PPUs of items and KPIs for Verizon. The two-dimensional scoring matrix shown in Figure 7 is the resulting output of the DEA model for suppliers in the same cluster. Appendix B provides a detailed explanation of the mathematical optimization model, used to calculate the Figure 7 scoring matrix.

Let D^g be the mathematical model for a cluster of suppliers, g, where it compares the suppliers' inputs with their outputs subject to a group of business constraints. The mathematical problem, D^g, needs to be solved to optimality iteratively, that is, once per supplier, s, and category c. The resulting scoring matrix of Figure 7 can be used to identify suppliers with low efficiency for turning inputs to outputs within any categories. Once the dimensions of this matrix increase (i.e., more suppliers and categories are added), category sourcing managers will have difficulties following the insights and directions of this matrix. Thus, even with the information provided by the efficiency matrix, identifying rationalization candidates is still difficult as the results of this matrix could be could interpreted differently by different

Table 4. Important Supplier KPIs Used by Verizon's Strategic Sourcing Teams

KPI	Definition
Delivery lead time accuracy	Lead time variance of product or service deliveries to Verizon specified location (noncarrier)
Fill rate accuracy	Percentage of POs not fulfilled by a supplier regardless of lead time
Number of defects	Total number of SKUs with defects when inspected by Verizon engineers
Return rate	Total number of SKUs returned because of technical mismatch with PO
Price accuracy	Total financial value of invoice vs. contract price variance
Quantity accuracy	Variance between PO quantity and delivered quantity

category managers. In reality, no category manager wants to rationalize their managed suppliers or sourcing categories since this could jeopardize their careers. Therefore, discussions about rationalizing suppliers between sourcing teams and business units are often unproductive and biased.

To avoid running into this situation and to facilitate a data-driven conversation between sourcing teams and business units when identifying rationalize candidates, an objective unbiased approach is required. The output of this stage is the suppliers' efficiency score matrix. The next section will cover details of the unbiased approach used within VSRT's optimization engines to solve this problem.

4.4. Biases in Supplier Ranking

The subjectivity of identifying and evaluating candidate suppliers for rationalizing is often addressed with a balanced scorecard (Kaplan and Norton 1992), in which suppliers are scored by subject matter experts across various criteria and metrics. The results of these individual evaluations will then get aggregated and reported to decision makers as a ranking score. Such an approach is highly biased and subject to the tenure and expertise of evaluating individuals. Also, this approach does not differentiate between suppliers that provide high-risk and expensive categories, which are business sensitive, compared with other categories. For instance, suppliers with active cellsite equipment (ACE) category in their portfolio have more exposure to supply disruption than the ones with minor material (i.e., nuts and bolts) categories. Thus, Verizon's risk tolerance for the ACE category suppliers is a lot smaller than the minor materials category suppliers. A traditional scorecard might allocate the same importance weight to suppliers with ACE category as to minor materials suppliers and recommend unrealistic supplier ranking. This issue calls for a reliable, holistic, and objective evaluation approach for final supplier rationalization recommendations.

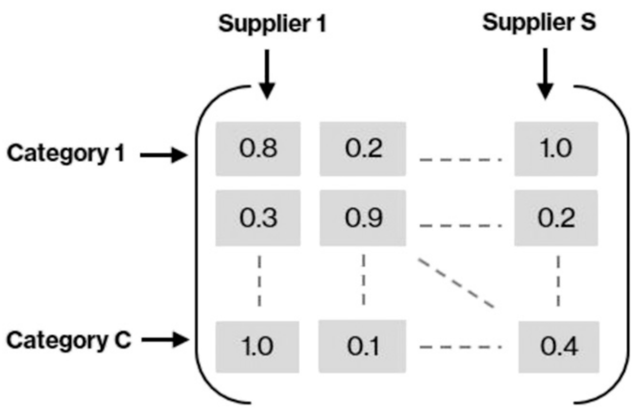


Figure 7. Example of Suppliers' Efficiency Score Matrix

To provide an objective approach when identifying candidates for supplier rationalization, another set of algorithms have been used, taking into account Verizon sourcing managers' business acumen and transaction level supplier spend data. A novel method based on the TOPSIS (Hwang et al. 1993) is used to solve the problem of ranking rationalization candidates based on their score of efficiency in each category and a set of additional business constrains (i.e., benefit and cost criteria).

The idea behind TOPSIS is as follows: the best alternative supplier to a rationalization candidate would be a supplier that maximizes the benefit criteria and minimizes the cost criteria. The goal of this stage is to rank suppliers according to their (1) score of efficiency, (2) benefits, and (3) cost criteria. Suppliers with lower ranks are candidates to rationalize. However, as it was mentioned earlier, Verizon strategic sourcing teams might value each category differently. Suppliers with higher spends in specific categories might have a higher risk to rationalize regardless of their performance efficiency. Therefore, different weights could be assigned in evaluating each category.

To use the TOPSIS algorithm, a supplier decision matrix (DM) needs to be created. Appendix C provides a detailed explanation of the DM, D, composite and its dimensions. In addition, the suppliers' efficiency score matrix could be used to fill in the entries of the decision matrix (i.e., D) and subject matter expertise of the Verizon sourcing teams could be leveraged to populate the weight matrix (i.e., W). Similar to the balanced scorecard, this approach will be highly subjective because every sourcing team values their categories and suppliers more than other teams' categories and suppliers. To avoid this highly biased approach, rather than using Verizon's subject matter inputs to populate the weight matrix, transaction level spend data and Shannon entropy were used to normalize the weighting matrix, W. Following the steps of the TOPSIS algorithm and using the weight matrix, the supplier efficiency score matrix, and the business criteria, the overall efficiency score of the suppliers across all the sourcing categories can be calculated. Readers can refer to Hwang et al. (1993) for the details of the TOPSIS algorithm implementation steps. The output of this stage is final supplier ranking for rationalization. The next section provides discussions on the results of implementing this end-to-end solution.

5. Solution Results

The VSRT is implemented on a Hadoop Supplier Cluster and a Hive environment (Apache Hive 2018) where most of the Verizon spend transaction data are stored. All machine learning models including NLP,

Table 5. Long Tail Suppliers Ranking for Rationalization

Supplier	Ranking	Overall efficiency score	Annualized spend ($M)
Supplier 20	1	0.63	2.70
Supplier 13	2	0.61	2.60
Supplier 36	3	0.59	0.40
Supplier 35	4	0.55	2.40
Supplier 32	5	0.51	0.10
Supplier 29	6	0.47	1.00
Supplier 6	7	0.44	0.50
Supplier 17	8	0.36	0.36
Supplier 22	9	0.15	0.15

RNNs, and unsupervised learning models were implemented in Python 3.6 (Python 2018). The DEA model is solved using the IBM CPLEX 12.6 optimization engine (IBM 2017). Advanced interactive visualizations and executive dashboards were built using Qlik (Qlik Sense 2018). Transaction level data from FY2016 through the end of FY2018 were used to build input data models.

To demonstrate the results of this solution, suppliers in cluster number 2 of Figure 6 are selected. Table 5 includes the result of applying the presented methodology to all of the suppliers within cluster 2. Suppliers 6, 17, and 22 are good rationalization candidates because their overall efficiency score across all the categories they provide is the lowest among their peers.

Verizon sourcing teams could then take the Table 5 results and start negotiating with the alternative suppliers, conducting RFPs and sourcing operations to move the business volume while the business units' planning teams update ERP systems and the budgeting. Now that the rationalization candidates are finalized, the next step is selecting alternative suppliers that can absorb the rationalized suppliers' business volume while providing better pricing (i.e., PPU) and service quality (i.e., KPIs).

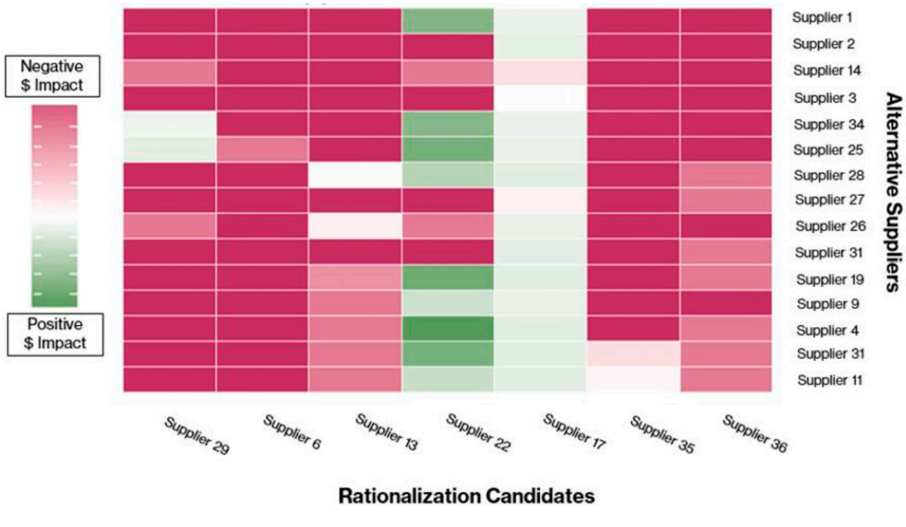
Knowing the historical order volume, Q, and new price per unit, $nppu$, for an SKU, u, new supplier spend (i.e., $nppu_u \times Q_u$) can be calculated after rationalization. The alternative suppliers' matrix and this new supplier spend can be used to identify alternative suppliers for the rationalized suppliers. Figure 8 shows the SAM for the suppliers in Table 5, where positive financial impacts of moving volume from a rationalized candidate supplier to an alternative supplier are illustrated in green (color online) or light gray (in print) and the negative overall impact is shown in red (color online) or dark gray (in print). These financial impacts are calculated across all of the categories and items provided by the suppliers.

The alternative suppliers' matrix is a powerful tool to provide insights on selecting alternative suppliers for the sourcing teams; hence, it does not provide detailed information at the SKU level. Table 6 illustrates the impact of supplier rationalization at the SKU level to some of the sourced SKUs. The price per unit variance (PPUV) of most of these items reduced on average from 23% to 4.25% after supplier rationalization, except for parts 15 and 16, where Verizon is getting a higher PPU because of volume consolidation and shift to alternative suppliers and missing the existing contractual price brackets with its current rationalized supplier. However, this variance was affordable because the overall portfolio of sourced SKUs was net positive after rationalization. The price variance is calculated comparing to the baseline unit price of the items.

6. Conclusion

The implementation of this end-to-end solution was successful and eliminated tens of millions of dollars from Verizon bottom line expenses while improving labor productivity and contract execution cycle times. This solution added value to the Verizon global supply chain organization from the start, providing clear

Figure 8. (Color online) Alternative Suppliers' Matrix



directions, gaining trust among business partners, and achieving strong executive support. Although analytics was key for the success of this project, flawless execution by Verizon category sourcing managers and the trusted partnership built with suppliers also significantly influenced the business results.

The design of this solution was creative—different types of analytics were used in a unique sequence: (1) natural language processing and artificial neural networks were used to structure and transform Verizon's large-scale unstructured spend data into high-quality inputs for machine learning algorithms; (2) a blend of internal and external data sources was used to enrich the supplier segmentation and clustering; (3) operations research techniques were used in unique and innovative ways to generate insights and drive meaningful conversations when comparing suppliers at the category level; (4) multicriteria decision making (MCDM) methodologies such as TOPSIS and Shannon entropy were used to tackle bias with objective data-driven approaches, taking emotions out of supplier conversations and executive decisions; and (5) advanced visualization was used to communicate the complex algorithms and their results to our business partners so that they were able to understand and accept our recommendations.

This solution provided a fast and efficient toolset to perform supplier rationalization for Verizon strategic sourcing teams and tremendously helped supplier negotiations, the RFP process, linear price performance, and similar part analysis. Supplier negotiations and execution of this solution's recommendations are strategic and long term. Thus, more financial benefits are expected to be realized over time as the solution is rolled out when most large contracts are renegotiated and volumes are further consolidated.

Table 6. SKU Price per Unit Variance Before and After Supplier Rationalization

Manufacturer part number	PPUV before rationalization	PPUV after rationalization
Part 1	32%	0%
Part 2	32%	31%
Part 3	31%	0%
Part 4	24%	0%
Part 5	23%	0%
Part 6	14%	0%
Part 7	14%	0%
Part 8	14%	11%
Part 9	14%	0%
Part 10	13%	3%
Part 11	10%	0%
Part 12	9%	0%
Part 13	8%	6%
Part 14	8%	0%
Part 15	8%	15%
Part 16	7%	19%
Part 17	6%	0%
Part 18	5%	0%
Part 19	5%	0%
Part 20	3%	0%
Average	23%	4.25%

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Appendix A. Problem Formulation

To formulate this business problem in simple mathematical terms, the following mathematical sets and indices need to be defined:

$s \in S$: Suppliers (VARs, OEMs, etc.)
$c \in C$: Product or service category
$u \in U$: SKU or item
$k \in K$: KPI
ppu_u: Price per unit of item u
PPU_c: Price per unit of a category c
Q_u: Quantity of item u sourced from a supplier

With the help of the above notations and indices, the following definition can define this problem in mathematical notations:

Definition A.1. Define s as $s = \{s \subseteq S \mid s_k = \max_s s_k, s_{PPU_c} = \min_s s_{PPU_c} \forall c, k\}$, where $PPU_c = \frac{\sum_u Q_u ppu_u}{\sum_u Q_u} \forall c$, $|s'| \leq |S|$ and $s \neq \emptyset$.

Appendix B. Optimization Model Formulation

A linear programming (LP) optimization model has been formulated to score suppliers in each category within each cluster. Let problem D^g be the DEA optimization model used for evaluating suppliers within each cluster g. Problem D^g is the dual of the primal DEA model. This dual model is easier for the business users to follow. Readers can refer to available literature (Charnes et al. 1978) to investigate the primal formulation. The following notations are used to describe the optimization model D^g formulation:

B.1. Indices and Parameters

g: A group or a cluster of suppliers
ϵ: Very small positive number
i: Vector of inputs to suppliers (number of POs, PO values, supplier spend, etc.)

o: Vector of outputs from suppliers (fulfilled POs, provided PPU, etc.)

s^0: Supplier under consideration (current DMU)

x^c_{is}: Amount of input (POs or PO values) used by supplier s in category c

y^c_{os}: Amount of output (KPIs and PPU) generated by supplier s in category c

B.2. Decision Variables

θ^c_s: Score of efficiency of supplier s in category c

λ^c_s: Weight coefficient of supplier s in category c

$Slack^c_i$: Auxiliary variable for input i shortage in category c

$Surplus^c_o$: Auxiliary variable for output o surplus in category c

$$D^g: \quad \min \theta^c_{s^0} - \epsilon\left[\sum_{i \in inputs} Slack^c_i + \sum_{o \in outputs} Surplus^c_o\right] \tag{B.1}$$

$$\text{s.t.} \quad \sum_{s \in S} \lambda^c_s x^c_{is} + Slack^c_i = \theta^c_{s^0} x^c_{is^0} \quad \forall c, i, s^0 \in S; \tag{B.2}$$

$$\sum_{s \in S} \lambda^c_s y^c_{os} - Surplus^c_o \geq \theta^c_{s^0} y^c_{os^0} \quad \forall c, o, s^0 \in S; \tag{B.3}$$

$$\lambda^c_s, \quad Surplus^c_o, \quad Slack^c_i \geq 0 \quad \forall s, c, o, i, s \in S; \tag{B.4}$$

$$1 \geq \theta^c_{s^0} \geq 0 \quad \forall s^0, c, s^0 \in S. \tag{B.5}$$

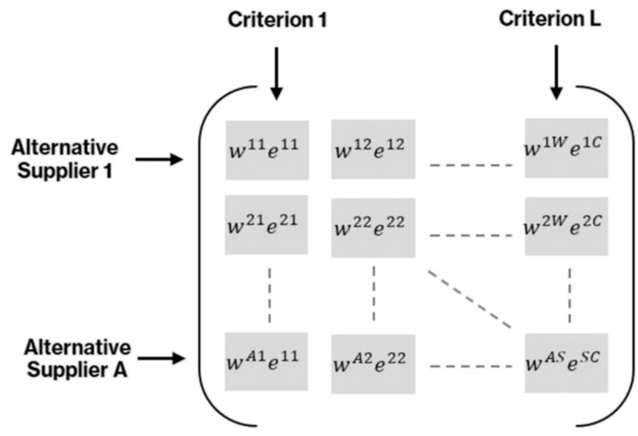
The problem D^g needs to be solved for each cluster of suppliers separately as it is problematic to compare suppliers that do not provide Verizon with similar categories. Objective Function (B.1) minimizes the sum of *Slack* inputs (i.e., PO values) to suppliers and *Surplus* outputs (i.e., PPUs and KPIs) from suppliers across each sourcing category. In the best-case scenario, current DMU s^0 has no excess in using inputs but has as much excess outputs as possible.

To constrain supplier excess and shortage of inputs and outputs, a set of constraints needs to be included to the model D^g. When comparing supplier s^0 with its peer suppliers s within a category c, Constraints (B.2) ensure that there will be no surplus of inputs to the supplier s^0, whereas Constraints (B.3) ensure that there is no shortage of outputs from the supplier in comparison with its peers. Constraints (B.4) and (B.5) are feasibility constraints indicating that λ^c_s, $Surplus^c_o$, and $Slack^c_i$ are continuous and non-negative, and $\theta^c_{s^0}$ is between 0 and 1.

Appendix C. TOPSIS Decision Matrix

Let A be a set of alternative suppliers to the rationalization candidates that can absorb the volume of rationalized suppliers. This is the supplier set toward the head spend of Figure 1. Let L also be a set of criteria the sourcing teams are interested in (e.g., lead time for delivering products in a category must be less than 45 days). A decision matrix, D, can be built similar to Figure 7 where rows are alternative suppliers and columns are criteria. Let matrix W be the weighting matrix for each criterion where rows and columns are alternative suppliers and sourcing categories and $\sum_{c \in C} \sum_{s \in S} w^{cs} = 1 \forall l \in L$ The supplier efficiency score matrix, e, which has the same dimensions as the weighting matrix W, can be blended to create the decision matrix D. Figure C.1 illustrates this matrix where each row is an alternative supplier, a, and the each column is a criterion, l.

Figure C.1. Decision Matrix Composite Structure



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Verification Letter

John M. Vazquez, Senior Vice President, Global Supply Chain & Global Real Estate, Verizon, One Verizon Way, Basking Ridge, New Jersey 07920, writes:

"It is truly my pleasure to submit the results of the work our Business Analytics team has done, for publication in the *INFORMS Journal on Applied Analytics*. The Tail Spend Supplier Rationalization project was a team effort between our Spend Analytics and Global Strategic Sourcing teams, utilizing all areas of analytics. This project started adding value to Verizon from the start, providing clear direction for our sourcing experts, which helped us gain our business partners' trust. While analytics was key for this project's success, the flawless execution of our category sourcing managers and the trusted partnership we built with our suppliers really delivered the business results.

"To provide some background about this work, in 2017 Verizon announced its plans to reduce its operating costs by $10 B within three years, initiating one of the worlds largest public business transformation initiatives. This required revisiting of major business processes and practices across all Verizon business units. Verizon's Global Strategic Sourcing organization was one of the pioneers in this transformation. Through this project we leveraged an innovative blend of Artificial Intelligence, Machine Learning and Optimization to reinvent our strategic sourcing approach on how we think of supplier selection, supplier evaluation, and supplier negotiations.

"The analytical solution our Business Analytics teams created was able to run through millions of rows of transactional spend data which incredible speed and provide business insights needed for successful suppliers negotiations. This work would have taken weeks for our sourcing teams to manually get through, extend negotiations and decrease our leverage.

"Some of the immediate benefits included: multimillion dollars of cost savings in contract negotiations, price per unit variance reduction, centralized category management strategy, a patent with United States Trademark and Patent Office and winning the third place award in the prestigious Innovative Applications of Analytics Award in April 2019. In addition, we expect the long-term benefits to materialize after we apply this process to our remaining sourcing categories.

"When I look at the path we have gone through to execute this project, I not only see the Verizon credo in play but also I see the INFORMS community values in action. Here at Verizon, we believe by enabling transparent communication with our suppliers we can achieve our corporate mission: Deliver the promise of the digital world.

"Please feel free to contact me directly if you have any questions and I thank you and the editorial board, especially Juan Jamarillo and Erick Wikum, in advance for giving us this opportunity and considering this work for publication."

Hossein Abdollahnejadbarough currently leads a global team of machine learning engineers, data scientists, and software engineers at Verizon, focusing on building and deploying algorithms, solutions, and intelligent assets that personalize Verizon customer experiences. Hossein led the competition team that won third place in the INFORMS 2019 Innovative Applications in Analytics Award for Verizon. Before Verizon, he was a senior data scientist at the Boston Consulting Group (BCG) GAMMA, advising BCG clients in retail, consumer packaging goods (CPG), industrial goods, and biopharma. He was also a data scientist at Cardinal Health, where he won the Best Overall Analytics Work award in 2015. He holds an MS degree in industrial and systems engineering from Northern Illinois University (NIU). He is a graduate of Harvard Business School CORe program and an INFORMS member since 2012. In 2013, he won the outstanding academic achievement graduate student award and the outstanding graduate student award at NIU.

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Yanai S. Golany heads the data science organization that supports Facebook's Global Data Centers. Before joining Facebook, he built and led a data science organization in Verizon supporting supply chain, operations, procurement, sourcing, and real estate across all business units. Previously he held several leadership roles in Verizon's global supply chain organization, in the defense industry, and as a Special Forces officer in the military. He received his graduate degrees from Massachusetts Institute of Technology (MIT) Sloan School of Management (MBA) and MIT School of Engineering (MS) as part of the Leader for Global Operations program. Before attending MIT, he received a BS degree in industrial engineering and management from the Technion-The Israel Institute of Technology.

Anne G. Robinson is chief strategy officer and is responsible for accelerating Kinaxis strategy development to add further value to customers. She and her team collaborate closely with customers, external stakeholders, and the rest of the senior executive team to drive the strategic roadmap and thought leadership and identify emerging technologies and new industry opportunities. A proven leader in analytics and digital transformation, with expertise in operations, supply chain, and strategy, she has extensive experience in managing supply chains for complex, global organizations. As executive director, global supply chain strategy, analytics and systems at Verizon, she was responsible for the strategic vision of the company's global end-to-end supply chain, driving excellence through world-class data analytics, process innovation, and employee empowerment. Before Verizon, she spent several years at Cisco, where she was responsible for managing advanced analytics, business intelligence, and performance management teams. She is a past president of INFORMS and a seasoned industry speaker and has served on several advisory boards. Originally from St. John's, Newfoundland and Labrador, Anne has a BScH from Acadia University, an MASc from the University of Waterloo, and an MS and PhD in industrial engineering from Stanford University.

Vedat Akgun has more than 20 years of supply chain, transportation and logistics, revenue management, price optimization, and retail analytics experience. At Verizon, he leads a team of advanced analytics and data science experts to provide innovative predictive and prescriptive analytics techniques and expertise in machine learning and artificial intelligence for all business units of the global supply chain and global real estate. He holds a PhD in operations research from the University at Buffalo. He is a former finalist for the Franz Edelman competition. At Menlo Worldwide, he designed and implemented an aircraft hub-and-spoke network optimization system, which was awarded as one of the outstanding examples of management science and operations research practice in the world by INFORMS as a Franz Edelman finalist in 2003. Leveraging that experience, he was one of the leaders of the team at Verizon to develop a descriptive, predictive, and prescriptive analytics methodology for tail spend supplier rationalization that won third place in the INFORMS' Innovative Application of Analytics Award in 2019.