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RESEARCH ARTICLE

Predicting Bike Usage and Optimizing Operations at Repair Shops in Bike Sharing Systems

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ABSTRACT Supply chain responsiveness and big data analytics (BDA) have garnered considerable interest in academia and among practitioners. BDA helps researchers understand the current challenges in data management, including the high volume, velocity, and variety of data. This study is concerned with improving the responsiveness of supply chain networks to bike-sharing systems (BSS), which exhibit BDA characteristics. To address the challenges of forecasting bike usage and accordingly optimizing repair shop operations, we analyze multi-factor BSS data (Data from Washington D.C. BSS available to public), wherein attributes, such as weather conditions, registration, humidity, date, and time, are present. We use machine learning algorithms, such as neural networks, decision-tree-based regression, K-nearest neighbor, support vectors, and ensemble random forest, to predict bike usage and repair. This work contests the results and demonstrates the effectiveness of combining machine learning with supply chain network design. Supply chain networks model bike repairs by means of capacity extensions, which entails a nonlinear problem. In this study, we utilize a gradient search to solve a nonlinear supply chain network model. By enabling capacity extension, bike repair shops within the BSS exhibit a promising 50 % reduction in lead repair time. Furthermore, a 25 % overall throughput increase in BSS is achieved. Ultimately, this study demonstrates the importance of operational flexibility in responding to big data challenges.

INDEX TERMS Big data, bike sharing, flexibility, machine leaning, supply chain network design.

I. INTRODUCTION

Cities worldwide are faced with the challenge of combating pollution and greenhouse emissions. According to Barth and Boriboonsomsin [7], approximately one-third of carbon dioxide in the US has been generated by the movement of goods and people. Numerous cities worldwide have built bike routes to mitigate the negative environmental impact caused by vehicle emissions, and are moving toward integrating more state-of-the-art technologies to foster sustainable living [24]. Consequently, the popularity of bike sharing has grown in recent years. Furthermore, smart cities place significant emphasis on modern infrastructure, particularly non-motorized infrastructure, which can reduce road congestion. Bike sharing is generally conducted by means of bike stations (docking stations), where users can rent bikes at a certain cost. The main benefit of Bike Sharing Systems is environmental [64]. In contrast, dockless systems allow users to pick bikes from their nearest location, and drop them upon reaching their destination. In both systems, forecasting the demand for bikes remains a challenge. For example, the oversupply of dockless bikes creates issues in numerous cities [54]. Another challenge in bike-sharing systems is the maintenance and storage of bikes. The constant use, and occasional misuse, of bikes, results in wear-and-tear and failure. In colder climates, corrosion due to the use of salt for de-icing roads exacerbates these problems. Additionally, bikes may be vulnerable to theft and vandalism if left waiting

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for maintenance. All of these challenges call for a model that can maintain and predict bike demand. For bike maintenance, bike-sharing systems (BSS) require a supply chain network of repair shops and part suppliers. According to a McGill University study [52], repair shops are important in generating local jobs and performing maintenance on bikes. Some bike-sharing programs may rely on warranty to outsource maintenance, whereas others incur maintenance costs. User data from different bike sharing systems can provide information regarding upcoming scheduled maintenance and urgent repairs. Therefore, an efficient maintenance system would require a large variety of data (maintenance schedule, usage, weather conditions, etc.).

The widespread use of data in supply chain management (SCM) has resulted in drastic cost savings and improvements in efficiency. Data are crucial for supply chain visibility, lead-time assessment, and the sharing of demand information among supply chain partners [51]. In a BSS, a tremendous amount of data is generated minute-by-minute pertaining to duration of use, location of bikes, date and time of use, bike conditions, user information, weather conditions at time of use, and several other variables. This constitutes a large flux, wide variety, and high velocity of data: the three components of big data [46]. However, access to big data does not necessarily translate to more efficient supply chain operations, especially when supply chain entities are inflexible, and hence unable to respond to the high volume and variety of big data. Slack et al. [49] proposed the concept of supply chain flexibility, defined as the ability to respond promptly to customers' needs.

The supply chain for BSS must encompass (see Fig. 8) three tiers corresponding to bike dock stations, bike repair shops, and part suppliers. The bike dock stations must provide pull demand for the two back tiers of the supply chain. The first challenge in this model is the forecasting of bike demand. This study contests multiple machine learning models, such as K-nearest neighborhood, decision trees, support vector machines (SVM), random forest (RF), and artificial neural networks (ANN). Forecasting bike usage is a challenge owing to the high velocity (minute by minute), variety (different usage durations and user profiles), and volume of data. During seasonal periods of turbulent demand, certain simple techniques may mitigate the challenge of sporadic data, whereas when stability in data is restored, more complex models, such as ANNs and ensemble techniques (RF), might perform better. Therefore, the first challenge of this study is to deliver a time-period-sensitive forecast. The second challenge in the model arises as a result of the short lead-time required for bike repair. Although the model incorporates lead-time crashing by extending capacity via resource augmentation, this results in a nonlinear supply chain. Therefore, this study proposes a gradient search procedure combined with a genetic-based algorithm.

Big data analytics (BDA) refers to the merging of two prominent fields: big data and business analytics. Big data refers to high-volume, high-velocity, and high-variety sets of dynamic data that exceed the processing capabilities of traditional data management approaches. Business analytics (BA) is the study of skills, technologies, and practices used to evaluate business strategies and operations to infer important insights for business planning. Such evaluations range from strategic management to product development and customer service through evidence-based data, statistical and operational analyses, predictive modeling, forecasting, and optimization techniques ([11], [46]).

To synthesize the motivation of the paper, we design a supply chain network consisting of demand nodes (bike docks), repair shops, and suppliers for the procurement of bikes' parts. At the demand side, we utilize multiple machine learning algorithms to predict the demand of bikes needing repair. This translates to demand input in the supply chain network. The repair shops are flexible and can extend their repair capacities (see figure 9) by crashing operational resources. Hence, the repair shops respond to the demanded repairs at the bike docks. Further, the model integrates the transportation costs all through the supply chain. Since the repair of bikes in a BSS is a must for sustaining acceptable service levels, the model supplies decision makers (city planners) with fundamental operational characteristics for optimal service levels and operational costs.

The contribution of the work is highlighted by three important elements. First, the introduction of flexible operations, via the use of capacity extension, brings promising results in overall responsiveness to the repair needs of the BSS. Second, the artificial neural network algorithm tend to bring the lowest prediction error when compared with the rest of the algorithms, at a mean error of less than 1 percent of the actual value. Third, the combination of demand analytics and supply chain modeling produces 25% throughput improvement in the overall model.

The study begins with a literature review (Section II) that examines general BSS-related studies, supply chain network design (SCND) models that investigate BSS or similar systems, and SCND models that integrate flexibility. Section III highlights and explains the paradigms of business analytics and machine-learning techniques to practitioners, and subsequently introduces the SCND model, as well as the procedure for addressing nonlinearity. Section IV presents the mixed-integer nonlinear mathematical model, and details the methodology for the capacity extension and solution procedure. Section V presents the overall results of this study, starting with machine learning. Additionally, it provides examples of the effectiveness of flexible supply chains. The final section presents closing statements and recommendations.

II. LITERATURE REVIEW

Using Google Scholar, Science Direct, ProQuest, and Engineering Village, we searched for Mixed-Integer Programming (MIP) general models that address challenges in the management of BSS. We initially reviewed general BSS, without reference to maintenance, big data, machine learning in predictive demand analytics, supply chain management, or flexible supply chain models.

The service level requirements of bike-docking stations have been frequently explored in the literature. The general allocation of bikes to dock stations is the most common theme in existing studies ([2], [21], [37], [41], [44], [59], [60], [66]). In a typical BSS service-level problem, there is a trade-off between attaining a high customer level (availability of bikes at any time), and the costs of allocating bikes to stations and purchasing a large inventory of bikes. Generally, optimally placing bike-docking stations and repositioning bikes can reduce the routing costs for trucks, which replenish and reposition bikes. In showcasing this theme, Freund et al. [21] examined the number of docks used for each station, bike rebalancing among stations, and expansion planning. The authors applied mathematical programming to achieve an optimal solution by relying on a careful statistical analysis of the data. Collini et al. [13] introduce a predictive methodology and solution for short-term predictions, given available BSS's bikes, smart stations and three months data. They utilize Ensemble and Deep Learning solutions. Ashqar et al. [6] introduce a BSS model that applies machine learning at the level of the network and stations. They use Random Forest and Least-Squares Boosting as univariate regression to model the number of available bike stations. Bustamante et al. [9] employ multiple machine learning algorithms using probabilistic programming through Bayesian inference. Their work study the impact of COVID 19 or ridership. Ngo et al. [40] use Random Forest (RF) and k-fold to predict the hourly demand of bikes in the city of Seoul (Korea) using information related to rental hour, temperature, humidity, visibility, wind speed, dew-point, snowfall, solar radiation, and rainfall. Zhou et al. [69] develop a novel approach of prediction and optimization where optimization and branch-and-price algorithms are used. Their method saves significant costs (operational costs) and reduce the waste of resources.

Overall, studies pertaining to this theme are abundant; however, when we supplemented repair/maintenance with our search criteria, we discovered a noticeable gap in research. Even though one of the important aspects of BSS is maintenance, literature pertaining to that aspect is scarce. This could be because numerous cities outsource maintenance to third-party organizations. However, repair and maintenance are indirect costs that are eventually reflected in BSS cost structures. Furthermore, some cities do manage the repair and maintenance of bikes within their BSS [52].

Big data is intrinsic in BSS because the underlying data structure features all three of its basic features: high volume, high variety, and high velocity. Because BSS are typically installed in large urban centers, data from BSS depositories feature an immense amount of information [76] as the users average in the thousands, if not the millions. Furthermore, numerous attributes, such as user characteristics (registration status, student status, gender, etc.), trip information (GPS tracking, mileage, and maintenance issues), and external characteristics (weather, humidity, holidays, etc.), are highly variable. In addition, high velocity is associated with rapid changes in the data. Most available data structures provide readings on an hourly, or occasionally per-minute, basis. The BSS literature is rich in studies that emphasize big data ([21], [34], [37], [41], [44], [59], [60], [62], [63], [68]). Zhao et al. [68] examined weather variations to develop a comprehensive model for inferring the relationship between weather variability and cycling.

Alternatively, coupling BSS with machine learning has provided a large volume of research. Ashqar et al. [5] studied the availability of bikes at docking stations using random forest (RF) and least-squares boosting. Wang and Kim [55] proposed short-term forecasting for docking stations in Suzhou, China, by means of long short-term memory (LSTM) and gated recurrent units (GRU). They used random forest as a benchmark to test their performance. Singhvi et al. [50] utilized a linear regression model to predict bike demand in New York City. Arque [4] utilized random forest to forecast bike demand. Liu et al. [35] introduced an LSTM model to forecast the number of bikes over multiple time steps. All authors in question reinforced their contributions based on the significance of their practical implications. With the aid of this research, bike-sharing agencies can make better decisions regarding the distribution of bikes to docking stations.

Within the context of SCM, Raviv and Koka [43] conducted a study that analyzes the inventory management of bikes at each station, and proposed an inventory model for the management of these stations, where a numerical solution was presented. Most importantly, they indicated that fluctuations are the biggest challenge in the management of bike-sharing systems. Li et al. [31] reviewed the impact of important factors, such as price, traffic congestion, and supply chain, on bike-sharing selection behavior. They utilized big data to evaluate bike-sharing apps in Beijing over a 4-d period. Unlike that on machine learning applications and service-level bike allocations, research on SCM in the context of BSS is scarce. Adding flexibility to the search criterion yielded negative results. To the best of our knowledge, no existing study considers flexible supply chain networks within the context of BSS.

This study allows for flexibility in how supply chain facilities (suppliers, repair shops, and bike-sharing stations) respond to changes in demand. Although we found no research pertaining to this idea in the context of BSS, several studies have examined the flexibility of general supply chains. According to Gunasekaran et al. [22], production flexibility and responsiveness are important factors in supply chain flexibility. Chatzikontidou et al. [10] proposed a flexible SCND model that uses generalized production/warehousing nodes instead of individual production plants to address uncertainty. Lim et al. [33] designed a supply chain distribution network that accounts for agility, or the ability to quickly respond to unexpected fluctuations in customer demands. Shoja et al. [48] proposed a mixed-integer linear programming (MILP) model, wherein flexibility was modeled using three different delivery modes. The main aim of their study was to enable flexible delivery systems to respond to variability in demand. Esmaeilikia et al. [18] brought an important parallel to our study by considering the expansion of tactical production capacity. Their work numerates capacity expansion as a flexible option for meeting demand. Conversely, our study explicitly extends the production capacity of shops in response to production resource augmentation.

In tying high-frequency data to supply chain network design, we refer to the work of Chong et al. [12], who investigated strategies and sentiments from online user reviews. The authors made a significant contribution to the introduction of big data architecture. Prasad et al. [42] developed a resource dependence model linking big data analytics to superior humanitarian results using a qualitative case study. Zhang et al. [65] introduced a big-data architecture that enables the availability and accessibility of data and information pertaining to a given product. However, none of these three studies can be categorized in the SCND domain, nor do they examine supply chain flexibility. In contrast, Wang et al. [58] proposed a SCND model with big data, including historical data recorded in databases, and updated behavioral data collected from social media (LinkedIn, Facebook, Twitter, and Google+), web clicks, comments, reviews, and complaints. However, their study does not explicitly discuss any algorithmic learning performed on the data.

Concerning the predictive analytics context of SCND, Ma et al. [38] proposed a novel demand modeling technique called demand trend mining (DTM). The authors utilized DTM for predictive life-cycle design, and introduced a nonlinear mathematical programming model. However, this model's objective is product design, rather than supply chain network design. Wang et al. [57] introduced a BDA model to predict the cycle time of semiconductor wafer-fabrication systems. Their work was founded upon data acquisition, preprocessing, analysis, and prediction. However, the objective of their study was not to model or design a supply chain.

We identified a large number of studies pertaining to nonlinear mathematical modeling in supply chain network design ([16], [17], [18], [19], [23], [25], [28], [29], [36], [38], [45], [58]). However, studies that consider big data are limited ([12], [38], [42], [57], [58], [65], [67]). Only two of these studies integrated SCND or accounted for capacity extension (production lead-time flexibility) ([18], [27]). Furthermore, the studies that used predictive analytics are also scarce ([12], [38], [57]). However, general business analytics (including descriptive, prescriptive, and predictive analytics), are well-represented in the literature. Overall, the uniqueness of our study is its focus on the supply chain of the BSS. Accordingly, the study encompasses an SCND model, a nonlinearity objective function, BD, a learning neural network algorithm, predictive analytics, and supply chain flexibility.

III. MACHINE LEARNING IN MULTI-FACTOR DATA

The main scope of this study is cutting-edge machine-learning techniques combined with an optimization model to better manage and coordinate supply chain operations in response to demand fluctuations. It is important to first discuss the nature of the data in question. The first part of this section discusses the scope of this study. The rest is devoted to machine learning algorithms – the algorithms used to navigate and make sense of data.

Algorithms that navigate and interpret data are widely used in everyday life. Some occur beneath our notice, such as algorithms employed by our brains to differentiate between images, whereas others have been designed by humans to solve difficult problems. The main objective of machine learning is to learn these algorithms. Machine learning comprises two phases: training (learning) and solving. Before training, a model generally encompasses many parameters. After training, the model is attached to the task at hand [1], and can be used to predict the future behavior of the attributes of interest. This study uses the K-nearest-neighbor, decision tree, random forest, support vector machine, and artificial neural network-based algorithms to predict patterns within BSS datasets. The use of multiple algorithms is necessary due to the erratic nature of BSS data, where weather patterns and other elements may produce drastic changes. According to Stevenson et al. [51], unstable time series data with abrupt changes, seasonality, and trends may impact overall forecasting performance. To detect recent changes, less complex models, consisting of fewer hidden layers and neurons, may prove more efficient. Therefore, this study employed an ensemble method (random forest) and deep learning (neural networks).

The following section describes each technique in detail.

A. SCOPE OF RESEARCH

Hazen et al. [26] summarized three categories of business analytics: descriptive, prescriptive, and predictive. Wang et al. [57] defined two of these categories as follows: descriptive analytics identifies problems and opportunities within existing processes and functions, whereas predictive analytics features the use of mathematical algorithms and programming to discover explanatory and predictive patterns within data. In this study, we employed descriptive analytical tools to study the data before attempting to identify demand patterns. We used a structured approach to prepare the data, where a visual representation was used to investigate any missing data, data interruptions, illogical outliers, mislabeled data, and other potential errors. The contributions of this study are threefold. First, machine-learning algorithms were used to predict patterns in the data collected from users. To achieve this, we contested different machine learning algorithms: neural networks, decision-tree-based regression, random forests, K-nearest neighbor, and support vectors. Our input data comprised the date of use (hour, day, season, year, holiday or non-holiday, weekend or non-weekend),

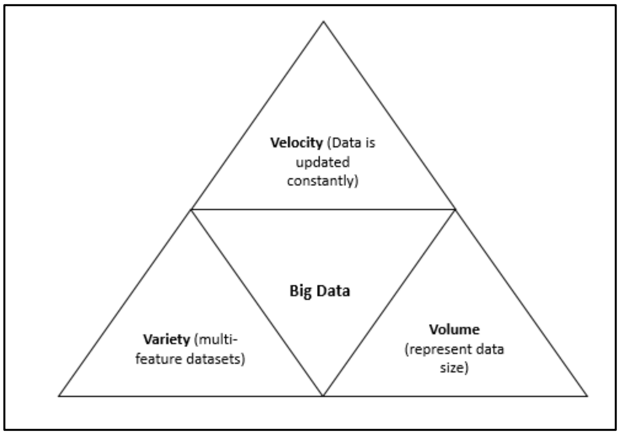

FIGURE 1. Big data paradigm.

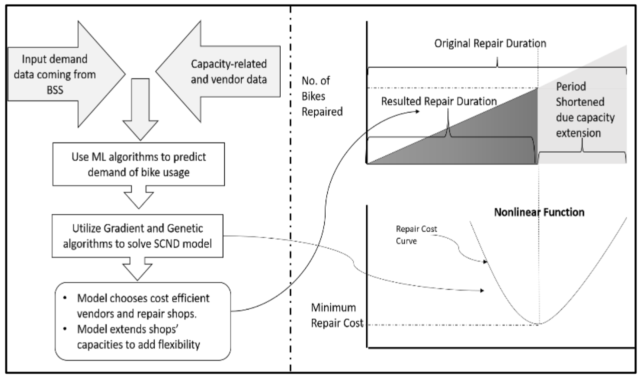

FIGURE 2. Input and output characteristics of the model.

weather pattern (temperature, perceived temperature, wind speed), and user information. Second, the study introduced flexible repair shops to meet the demands of repair. Third, our model enabled repair shops to extend their capacity to better address spikes in demand. The objective of this study was to explicitly demonstrate the impact of state-of-the-art machine learning on demand analytics accuracy in the context of bike-sharing repair and support systems. This work unambiguously demonstrates the impact of nonlinear functions, which enables the extension of the facility's operational capacity. Excellent predictive analytics are rather limited if the corresponding supply chain is not sufficiently flexible to respond in real time to the signals coming from predictive analytics. Therefore, an important contribution of this study is the enabling of capacity extension, which allows the model to responds effectively and efficiently to demand signals. We integrated a nonlinear function that enables capacity extension in a SCND. SCND is a modeling approach with the goal of optimizing the use of operational resources, where operational constraints and attributes, such as cost, location, and functionality, are combined into an objective function that must be maximized. Integrating flexibility into supply chain modeling results in a nonlinear mathematical programming model that is challenging to solve.

This study used data from BSS databases, which are updated at least once per day. Fig. 1 illustrates the big data paradigm with three fundamentals: velocity, variety, and volume. The data in question includes many attributes.

Fig. 2 illustrates the input and output characteristics of the overall model. The SCND model integrates nonlinear capacity functions that enable capacity extensions. The model was solved by combining gradient search with genetic-based search. The features in the dataset serve as key factors in planning capacity, and are important in preparing repair shops within the model for the required production capacity. This in turn improves the planning of human resources, including employees. We have in preliminary studies tested ARIMA, which is an autoregressive integrated moving average model ([71], [72], [73], [74]) but gotten inferior results to those of deep learning.

Furthermore, this data can be shared with vendors to supply the parts needed for repairs. As shown in the figure, repair shops are enabled to extend their capacity, which produces an overall reduction in repair costs. The cost behavior follows the behavior of the crash cost in Liao et al. [32] and Alzaman et al. [3].

B. MACHINE LEARNING ALGORITHMS

1) K-NEAREST NEIGHBOR (KNN)

The K-nearest neighbor (KNN) algorithm is a non-parametric algorithm [14] that has been used for classification and regression problems. The algorithm contests neighboring values of x_i in the proximity of x. Here, K observations are taken for the respective x_i neighbors:

$$\hat{y}(x) = \frac{1}{K} \sum_{x_i \epsilon N_{k,x}} x_i,$$

where $N_{k,x}$ represents the K closest points in the neighborhood of x. Therefore, the predictability of any x_i depends on the K-value (the number of neighbors that should be included). A high K value may overshoot the real value of y, whereas a low K value might also provide a high-error prediction. To obtain optimal results, this study employed a standard Euclidean metric.

2) DECISION TREES

As hierarchical decision orders, decision tree algorithms employ tree-like structures that consist of root nodes, and a set of internal and terminal (leaf) nodes. A binary classification process generally starts at the root node and proceeds toward the leaf nodes, thus splitting a complex decision into smaller and less complex ones [61]. Each branch within the tree represents the true and false possibilities for a given criterion. The decision tree starts from the root node, also known as the parent node. Then, each node can be split into left and right child nodes. The splitting of each successive node into child nodes recurs until a leaf node, which serves as a terminus, is reached. Overall, the data are split in a way that maximizes learning and minimizes MSE in the case of a regression problem.

$$MSE = \frac{1}{N}\sum_{i\epsilon N}(y_i - y_{i,target})^2$$

3) RANDOM FORESTS

Random forests are ensemble techniques [75] that combine multiple models. The two branches of ensemble techniques are bagging (bootstrap aggregation) and boosting.

Bootstrapping, which samples n smaller datasets from an original dataset M [8], is illustrated in Fig. 3. The sampling here is replaced, which implies that there are some repeated elements in each decision tree DT_i. Thus, the random forest utilizes numerous decision trees, where each tree outputs a set of predictions. Subsequently, the predictions are aggregated using the average values from each tree. Consequently, this reduces variability in the overall model.

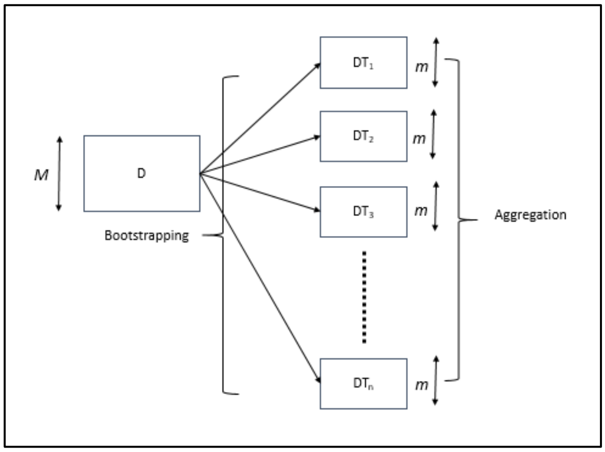

FIGURE 3. Random forest schematic.

4) SUPPORT VECTOR REGRESSION

The main distinct feature of a support vector machine (SVM) is the use of a hyperplane that discriminates between classes of data [75]. Support vector regression (SVR) is an extension of the SVM, where training involves the construction of a symmetrical loss function that penalizes overestimates and underestimates (Fig. 4), thus creating a flexible tube with a minimal radius. The tube is formed symmetrically around the estimation function, and the estimates outside a given threshold are discarded or ignored. Thus, points outside the tube are penalized, whereas points inside the hyperplane are not.

Fig. 4 illustrates the SVR model from a one-dimensional geometric perspective. The SVR algorithm attempts to fetch the narrowest tube around the surface by optimizing the prediction error (difference between predicted and actual values).

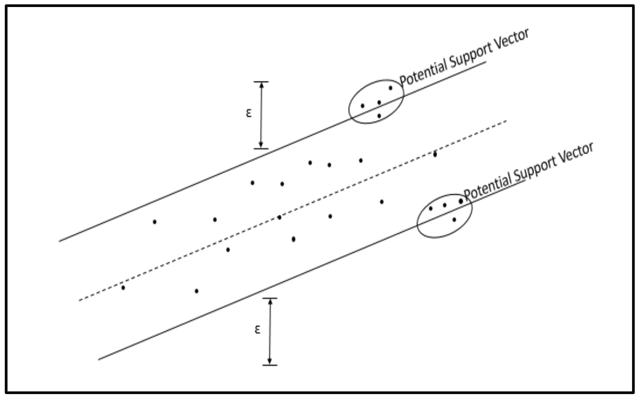

FIGURE 4. Support vector schematic.

5) ARTIFICIAL NEURAL NETWORK

An artificial neural network (ANN), often simply referred to as a neural network, is a simplified abstraction of the complex network of neurons in the human brain. In an ANN, neurons are processing units that perform predefined mathematical operations [47], [75]. According to Chong et al. [12], neural networks are an effective alternative to traditional statistical techniques.

A neural network is composed of one or more neurons, which serve as its basic building units. Each neuron contains one or more inputs, and is associated with a weight applied by the network. Additionally, each neuron produces one or more outputs, which are also weighted when connected to other neurons [53]. Fig. 5 presents an abstract schematic of a neural network where the input nodes, denoted by i, are coupled with weights w.

Therefore, the summation function can be written as:

$$(\sum\nolimits_{j=1}^{n} i_j w_j) + w_0$$

6) DEEP LEARNING

The deep learning algorithm is a supervised learning algorithm in which weights are adjusted with respect to a training set. Each sample of the data is applied to the perceptron, where a linear activation function is used. In our case, the sigmoid function was used; however, the results were suboptimal. This is often the case in regression and time series models, where the input and output of time series parameters requires a continuous range of values, whereas the sigmoid function restricts the output to a binary choice. Several hidden layers are used in the deep learning algorithm (see Fig. 6). A large number of hidden layers tends to increase the network's complexity. In our case, the use of two hidden layers yielded optimal results. Some researchers have reported similar results. Crone and Dhawan [15] cite that some authors have noted the number of hidden nodes to have limited impact on forecasting accuracy. Although they recommended the use of the sigmoid activation function for hidden nodes, our results show that using the sigmoid function, whether in the hidden, input, or output nodes, tends to debilitate the results, thus producing lower accuracy.

We refer to the previous steps as forward propagation as we move forward through the network. Subsequently, the error (difference between expected and actual results) was used to

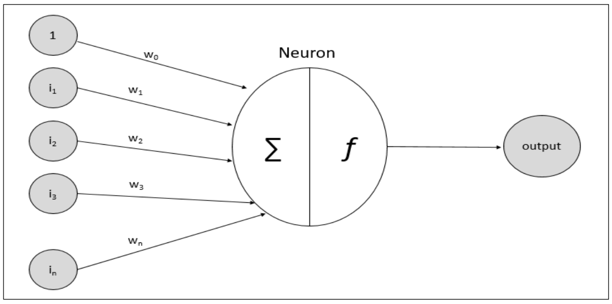

FIGURE 5. Abstract schematic of a neural network: Perceptron.

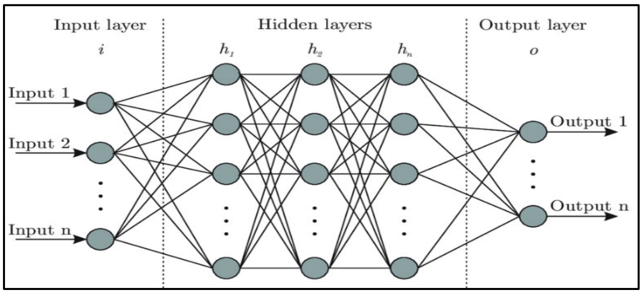

FIGURE 6. Hidden layers in a neural network [20].

adjust the weights.

$$Error = \frac{1}{2}\sum \left(A_i - output_i\right)^2$$

Next, we applied backpropagation [79] to adjust the weights proportionately to the calculated error. The deep learning algorithm follows the schematic shown in Fig. 7.

IV. METHOD

In the method, we shall first give a background on the supply chain characteristics of BSS, repair shops, and suppliers. Then, we shall discuss the model and its challenges.

A. SUPPLY CHAIN NETWORK DESIGN

We proposed a supply chain model (see Fig. 8) that enables flexible bike repair services, where shop capacity can be extended by supplementing production resources. Accordingly, the network includes vendors that supply required parts to the system. The optimal network selects the most cost- and time-effective repair shops to connect to the network. Whereas vendors are selected based only on cost, repair shops are selected based on cost and the ability to extend capacity. The integration of flexible capacity results in nonlinear expressions in the objective function, and nonlinear entities in the constraints. To address these challenges, we combined a gradient search method with a genetic-based heuristic.

Note that repairs occur both at bike stations (on-site) and at repair shops. Typically, smaller and more manageable repairs are performed on-site, whereas more serious repairs are performed at designated repair shops. However, on-site repairs can cause major problems in practice. For example, major repairs may be misclassified as minor. This has an obvious effect on customer experience: having a bike break down in the middle of the trip is displeasing for customers. Furthermore, bikes left waiting for repairs at a station may be mistaken for operational bicycles by the system operator [63]. Therefore, repairs in our model are performed solely at repair shops, regardless of severity. Effectively, service flexibility alleviates the issue of excessively time-consuming repairs. Although our model predicts bike usage, we obtained information concerning repair frequency by evaluating user report data.

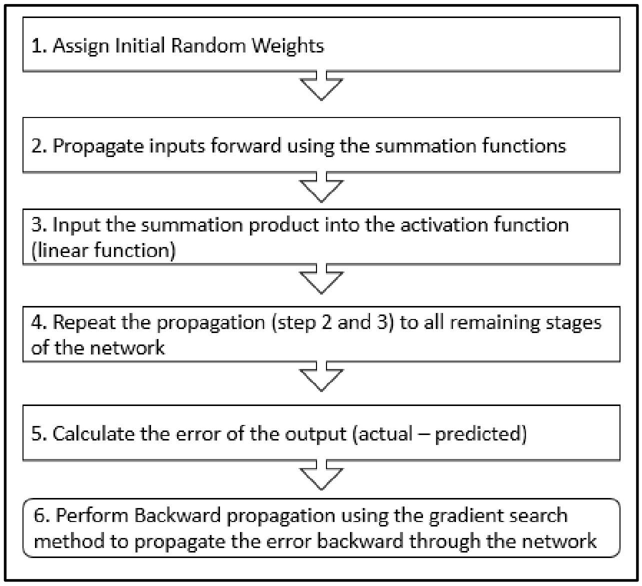

FIGURE 7. Deep learning perceptron algorithm.

This study encompassed a supply chain model that incorporates flexibility in terms of the ability to extend capacity. This model exhibits nonlinearity in the objective function and constraints. The following section introduces the model and subsequently discusses the repair shop flexibility features, where the capacity functions are explained thoroughly. Next, we discuss the challenges arising from solving the model, and provide proof of convexity to facilitate the use of a gradient search. Pinnacle, a machine learning algorithm, was used to predict bike usage.

B. MODEL

This model integrates nonlinear functions that allow for greater flexibility in terms of output augmentation. At each shop facility, capacity can be extended using additional resources ([3], [32]). By allowing for the extension of capacity, the repair lead time is reduced, and, specifically in the context of this study, the bike output per time period is increased.

Sets:

I = Group of Bike Part Suppliers.

J = Group of Repair Shops.

K = Set of Bike Stations.

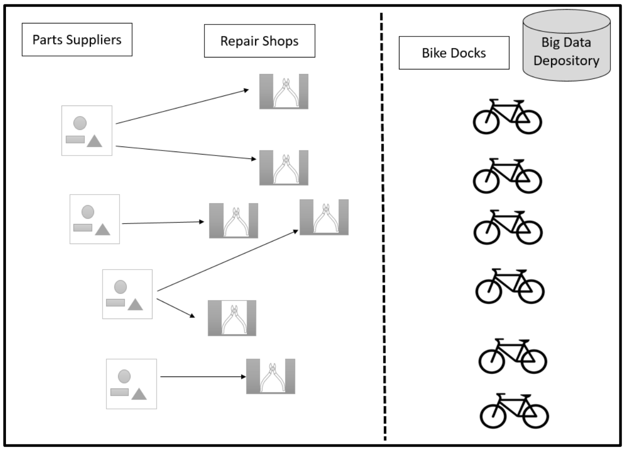

FIGURE 8. Illustration of a supply chain (vendors, repair shops, and bike station docks).

R = Set of part types

T = Set of time periods

Parameters:

$PCr_{i,r,t}$: Procurement cost at vendor i, for one unit of part r, during time period t; $i \in I,\ r \in R,\ t \in T$.

$Rto_{j,t}$: Average bike repair time at shop j if capacity is not extended (no shortening) during period t, where $j \in J$ *and* $t \in T$.

$Tr_{i,j,r,t}$: Cost of transporting part r from vendor i to shop j at time period t, where $i \in I,\ j \in J,\ r \in R$ *and* $t \in T$.

$IC_{j,t}$: Cost of inventory holding at repair shop j, per bike at time period t, where $j \in J$ *and* $t \in T$.

$Tp_{j,k,,t}$: Cost of transporting one bike from shop j to dock station k at time period t, where $j \in J,\ k \in K$, and $t \in T$.

$SCap_{i,r,,t}$ Allowable capacity of part r at supplier i during time period t, where $i \in I,\ r \in R$, *and* $t \in T$.

$F_{j,,t}$: Fixed cost of opening repair shop j for operations during time period t, where $j \in J$ *and* $t \in T$.

$PCap_{j,t}$: Allowable capacity, maximum number of bikes ed that can be repaired at shop j during time period t, where $j \in J$ *and* $t \in T$.

$B_{\mathrm{k,t}}$: Number of bikes needing repairs at station k during period t, where $k \in K$ *and* $t \in T$.

n_r : Number of parts r required for each bike repair, if any, where $r \in R$.

$I_{j,t}$: Initial inventory level of bikes at shop j at time period t, where $j \in J$ *and* $t \in T$.

C_j : Parameter of overhead cost in repairing one bike at j^{th} shop, where $j \in J$.

α_j: Operational cost parameter, which depends on the operational setting for shop j, where $\alpha \geq 0$ for each j, where $j \in J$.

β_j: Exponential factor at shop j for bike repairs, where $\beta \in [0, 1]$ for each j, where $j \in J$.

Decision Variables:

$XP_{i,r,t}$: Number of parts supplied from shop i, for part r, during time period t; i∈I, r∈R, t∈T.

$X_{j,t}$: Number of bikes repaired at shop j during time period t, where $j \in J$ *and* $t \in T$.

$XTp_{j,k,t}$: Number of transported bikes from repair shop j to station k during time period t, where $j \in J,\ k \in K,\ t \in T$.

$XTr_{i,j,r,t}$: Number of parts transported at time t from vendor i to shop j for part r, where, $i \in I,\ j \in J,\ r \in R$, *and* $t \in T$.

$XH_{j,t}$: Number of bikes held at repair shop j during period t, where $j \in J$ *and* $t \in T$.

$S_{j,t}$: Time reduced from the original $Rto_{j,\mathrm{t}}$ for shop j at time period t, where $j \in J$ *and* $t \in T$

$Y_{j,t}$: Assignment variable at repair shop j, set to 1 if the repair shop is operating and 0 otherwise ; *where* $j \in J$ *and* $t \in T$.

$Rt_{j,\mathrm{t}}$: Average bike repair time at repair shop j after reducing repair time by $S_{j,\mathrm{t}}$ in time period t, where $j \in J$ *and* $t \in T$.

$PCF_{j,t}$: Repair cost as a function of S for bikes repaired at shop j during time period t, where $j \in J$ *and* $t \in T$.

Model:

$$
\begin{aligned}
MinZ = & \sum_{i\epsilon I}\sum_{r\epsilon R}\sum_{t\epsilon T} PCr_{i,r,t}XP_{i,r,t} \\
& + \sum_{i\epsilon I}\sum_{j\epsilon J}\sum_{r\epsilon R}\sum_{t\epsilon T} Tr_{i,j,r,t}XTr_{i,j,r,t} \\
& + \sum_{j\epsilon J}\sum_{t\in T} IC_{j,t}XH_{j,t} \\
& + \sum_{j\in J}\sum_{t\in T} X_{j,t}PCF_{j,t} \\
& + \sum_{j\epsilon J}\sum_{k\epsilon K}\sum_{t\epsilon T} Tp_{j,k,t}XTp_{j,k,t} + \sum_{j\epsilon J}\sum_{t\epsilon T} Y_{j,t}F_{j,t}
\end{aligned}
\tag{1}
$$

Equation 1 highlights the minimization of the sum of the following terms: total procurement costs for bike parts at suppliers, shipping costs from suppliers to repair shops, total holding costs at repair shops, total repair costs at repair shops, and costs of transporting fully repaired bikes to docking stations.

$Rt_{j,t}$ is the average repair time, expressed as:

$$Rt_{j,t} = Rto_{j,t} - S_{j,t} \quad \forall j, \forall t \tag{2}$$

Evidently, the repair cost term in (1), the objective function, reduces the repair time and generates a capacity extension. The inworking of the repair cost term is given by Equation 3, which integrates the costs of time reduction with those of normal day-to-day operations.

$$PC_{j,t} = \alpha_j e^{\beta_j S_{j,t}} - C_j S_{j,t} + C_j Rto_{j,t} \quad \forall j, \forall t \tag{3}$$

Subject to

Constraint 4 balances the stored and transported bikes from repair shop j :

r

$$X_{j,t} + XH_{j,t} - XH_{j,t-1} = 0 \quad \forall j, \quad \forall t : \xrightarrow{t=0} XH_{j,t} = I_{j,t} \tag{4}$$

Constraint 5 equates the outbound transportation at supplier to the actual produced.

$$\sum_{j\in J} XTr_{i,j,r,t} = XP_{i,r,t} \quad \forall i, \forall r, \forall t \tag{5}$$

Constraint 6 makes sure parts made at vendor i do not exceed its capacity limit.

$$XP_{i,r,t} \leq SCap_{i,r,t} \quad \forall i, \forall r, \forall t \tag{6}$$

Constraint 7 ensures that the supply of vendors is balanced with the demand for parts at shops.

$$\sum_{i\in I} XTr_{i,j,r,t} = X_{j,t} n_r \quad \forall j, \forall r, \forall t \tag{7}$$

Constraint 8 guarantees that all bike repairs needed at a given station k are met.

$$\sum_{j} XTp_{j,k,t} = B_{k,t} \quad \forall k, \forall t \tag{8}$$

Constraint 9 equates the bikes transported to stations with those repaired at shops.

$$X_{j,t} - \sum_{k\in K} XTp_{j,k,t} = 0 \quad \forall j, \forall t \tag{9}$$

Constraint 10 limits the quantity of bikes repaired at a given shop (i.e. opened repair shop) to the shop's capacity. Here, a reduced production lead time results in excess capacity.

$$X_{j,t} \leq Y_{j,t}(PCap_{j,t} + \frac{S_{j,t}}{Rto_{j,t}}) \quad \forall j, \forall t \tag{10}$$

Constraint 11 enforces non-negative restrictions and binary representations.

$$XTr_{i,j,r,t}, XTp_{j,k,t}, XP_{i,r,t}, XH_{j,t}, X_{j,t}, S_{j,t}, Rt_{j,t}, Y_{j,t} \geq 0 \tag{11}$$

C. FLEXIBILITY IN SCND

Responding to the volume and variation in data requires flexibility in the supply network, which was achieved by incorporating nonlinear cost functions. These functions output repair costs corresponding to the unique operational settings of each shop. The settings allow for capacity extensions by crushing resources (Constraint 4.9), commonly achieved by increasing the direct operational resources (i.e., overtime, better machining, and better tools). This process is illustrated in Fig. 9, which shows that a reduction in the average repair time (R_t) results in an excess capacity.

Some challenges arise when solving this model. First, the inclusion of operational flexibility results in nonlinearity in the objective function and constraints. Furthermore, a robust solution procedure must be designed to effectively solve the model. Two decision variables – $X_{j,p,t}$ and $S_{j,p,t}$ – are multiplied, which further complicates the objective function. In addition, the repair cost $PC_{j,p,t}$ at shops is a nonlinear function of $S_{j.p,t}$. Given these challenges, an effective heuristic must be designed to produce near-optimal solutions.

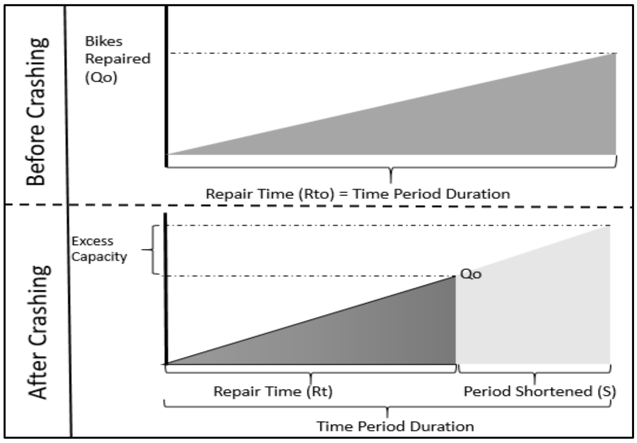

FIGURE 9. Repair time and extended capacity.

D. PROOF OF CONVEXITY PROPOSITION

Proposition: This proposition states that the objective function is convex.

PC denotes the total production cost, and can be expressed as:

$PC_{j,t} = \alpha e^{\beta * S} + C\ (Rto_{j,t}\text{-}S_{j,t})$

For a function $f(x)$ to be convex, its second derivative $\frac{d^2f(x)}{dx^2}$ should be non-negative for every value of x ([39], [70]). Acquiring the second derivative for the sole variable in function S generates the following expression.

$$\alpha\beta^2 e^{\beta S} \geq 0$$

Because α, β, and s are always positive, the overall expression renders positive and is therefore convex.

In addition, the value of PC in the objective function is multiplied by a decision variable X. The two partial derivatives $\frac{d^2f(S)}{dS^2}$ and $\frac{d^2f(X)}{dX^2}$ are both greater than or equal to zero, making the overall expression convex. Given that the sum of convex functions is convex, and because Y is a constant at each iteration of (4.1), the overall objective function is also convex. Further, Y is held constant in the gradient search solution procedure and its value is obtained using a genetic-based search. Both concepts are introduced later.

V. RESULTS

A. DATA CLEANING AND PREPARATION

The obtained data underwent numerous stages of cleaning and preparation, performed using a set of Python libraries geared towards big data (Pandas, Seaborn, matplotlib, SciKit-Learn, and statsmodels). However, R does provide an alternative platform for statistical analysis [77].

Because the original data is raw, the following issues exist.

1. Multiple entries within the same day
2. Errors in dates
3. Inconsistent time durations between dates
4. Dates in non-compatible format
5. N/A or null entries

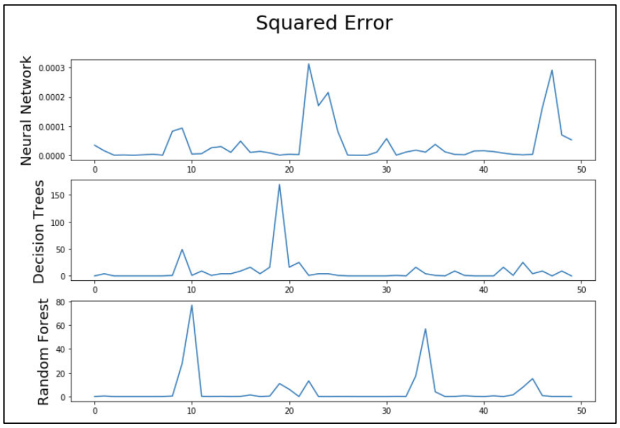

FIGURE 10. Squared error comparison between neural networks, decision trees and random forest.

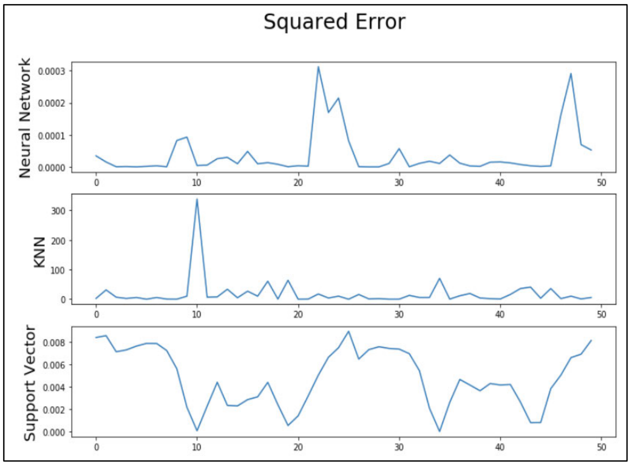

FIGURE 11. Squared error comparison between neural networks, support vector machine, and K-nearest neighbor.

All of these issues relate to preparatory data methodology. Empty entries (denoted by N/A or null) can cause network instability, large errors, and other problems upon being input. Therefore, we identified and eliminated any flawed entries using code from the *panda–Python* library. Subsequently, we organized the data into a readable format using the *Pandas* library. In the process, we sorted the data and identified important insights such as missing dates, uneven time durations, and multiple entries within the same day. Using the other Python libraries, we were able to sum multiple entries within the same day, and place the data in a time series format where the time duration between instances was universally constant. Finally, we used matplotlib to plot the data.

B. PREDICTIVE ANALYTICS (MACHINE LEARNING PERFORMANCE)

We employed the best-performing machine learning algorithm to predict the number of bikes demanded by users. Note that the predictive capabilities of rigid networks are far less effective for supply chain networks. In contrast, flexible networks can respond much more effectively to changing patterns in demand. In the following section, we examine results obtained from the machine-learning algorithms.

To evaluate the effectiveness and performance of each algorithm, we input the bike-sharing data from Washington D.C. (130,644 data logs) into each of them. This dataset includes attributes corresponding to weather, temperature, perceived temperature, humidity level, wind speed, season, registration status (binary), repair frequency, and holiday status (binary). To evaluate each algorithm's performance, we hid 50 data logs, and subsequently used them to test each algorithm by comparing predicted and actual values. Fig. 10 presents a performance comparison between three algorithms: neural network (NN), decision tree (DT), and random forest (RF). We calculated the square error (SE; squared difference between predicted and actual values) for each prediction. These results illustrated the robustness of the NN algorithm as it achieved an accuracy of approximately 100 % for this specific dataset. A further examination revealed that the ensemble-based algorithm (RF) did not significantly improve the results compared with simple decision trees. RF exhibited higher variability, with a standard deviation of approximately 11.7, compared to 10.8 for decision trees. In contrast, NN exhibited a mean error of 0.0001 with a standard deviation of 0.0002.

Fig. 11 compares the NN, K-nearest neighbor (KNN), and support machine vector (SVM) algorithms. Here, both SVM and NN outperformed KNN. Therefore, we can conclude that KNN is not a suitable algorithm for predicting bike usage. In contrast, the SVM algorithm exhibited a very low mean SE of 0.005; next best performance compare to NN.

Overall, the NN algorithm produced the best results, with a mean SE of less than 0.0001. Therefore, we used the NN algorithm to predict bike-sharing behavior for all subsequent computations.

C. SUPPLY CHAIN RESPONSIVENESS TO BSS

To manage the binary variables in the model ($Y_{j,t}$), we use a genetic algorithm (GA) that selects the best-fitting solutions (see Fig. 12). The GA starts with a group of chromosomes known as the population in the form of an Npop×Nbits matrix with a population of Npop chromosomes, which represents the population of genes (number of random solutions devised), with each chromosome having Nbits bits, which represent the number of binary variables associated with the opening and closing of repair shops ($Y_{j,t}$). The Npop×Nbits matrix will be filled with random ones and zeros. Chromosomes are ranked in accordance to their corresponding cost value, from lowest cost to highest cost. At each iteration, a fraction of best chromosomes are selected for mating, while the rest are discarded. A crossover point is randomly selected between the first and last bits of the parents' chromosomes and two offsprings are created. Consequently each offspring inherits portions of the binary codes of both parents. We then perform random mutations on the population matrix at the rate indicated in figure 12. We carry the procedure highlighted in figure 12, four multiple times (four generations).

Procedure of GA

1. Initialization
   1.1 Initiate random   of zeros and ones;
   1.2 Initiate selection rate (selection rate = 0.5)
   1.3 Initiate mutation rate (mutation rate = 0.01)
   1.4 Create population
   1.5 Insure feasibility of N_{pop} chromosomes
      If chromosome is infeasible, then
      Replace by a new feasible chromosome
2. Do
   2.1 Sort Chromosomes from most to least fit
   2.2 Mate top of the population
   2.3 Perform mutations
   2.4 Check and insure feasibility of
   2.6 Insure feasibility of the new N_{pop} chromosomes
      If chromosome is infeasible, then
      Replace by a new feasible chromosome
   2.7 Sort   from fittest to worst
3. Repeat Step 2 till fourth generations.

FIGURE 12. Genetic-based heuristic schematic.

Four generations tend to be optimal for our solution topography, given preliminary runs.

The work employs a gradient search combined with a genetic algorithm to arrive at a solution. The optimal values of $S_{j,t}$ were obtained effectively using the gradient search approach because the model's objective function was convex. Therefore, the objective function f(x) was differentiable at point x, and vector $d \in \Re^n$ is a descent direction for $f(x)$ at point x if

$$-\nabla f(x)\, T^d > 0$$

As per the definition of derivative stated by Kolda [30]:

$$f(x + \alpha d) = f(x) + \alpha \nabla f(x)^T d + o(\alpha)$$

If the variable d, which represents a descent direction with $\alpha > 0$, is sufficiently small, then the equation $x^{k+1} = x^k + \alpha^k d^k$ decreases the objective function value f. This observation forms the basis of the line search approach. At the k^{th} iteration of x – that is, x^k– a descent direction d^k is selected at the iteration, and a search is carried out along this direction for a point at $x^{k+1} = x^k + \alpha^k d^k$ (with $\alpha^k > 0$), with a smaller objective function value f [30]. The goal was to move in the steepest direction, or the fastest path to the global minimum. Accordingly, we applied a gradient search to reach the global minimum. However, because the objective function also includes binary variables, we employed a search algorithm to arrive at the solution of the model.

The following questions are central to this study. Does the extension of repair shop capacity improve the overall BSS supply chain? Furthermore, how do such features relate to or modulate the presence of high-velocity and high-frequency data? To address these research questions, we must contrast two operational scenarios at repair shops: extendable capacity, and fixed capacity.

TABLE 1. Model performance indices.

	Instance	RR (%)	TG (%)	PD (%)	RL (%)
Most favorable Structure	1	50.17	20.50	99.43	97.12
	2	51.30	23.01	99.85	97.85
	3	39.56	14.52	65.74	96.78
	4	52.52	23.87	99.92	97.66
	5	56.22	26.24	79.86	97.16
	6	50.83	21.37	79.74	97.41
	7	53.16	24.14	79.80	97.24
	8	50.68	20.29	99.92	48.94
	9	51.43	23.01	99.03	48.11
	10	53.18	24.07	99.46	46.64
Favorable structure	11	50.62	23.22	99.99	49.27
	12	51.78	20.09	99.38	47.75
	13	52.15	25.51	99.76	47.32
	14	50.95	23.71	99.21	48.77
	15	47.09	20.84	89.22	52.68
	16	43.86	19.10	79.26	55.62
	17	36.25	14.66	57.26	63.10
Least favorable structure	18	21.88	5.99	28.13	77.44
	19	16.11	4.01	19.33	83.23
	20	23.37	6.08	30.68	76.28
	21	23.07	5.55	29.89	76.64
	22	20.37	5.17	25.80	78.97
	23	17.32	4.57	21.03	82.41
	24	22.96	6.58	29.97	76.66
	25	19.54	4.78	24.34	79.65
	26	23.50	5.79	30.69	76.07

If the capacity is fixed, the model becomes simplified, as all $S_{j,t}$ terms become 0. Therefore, no gradient search is required to solve the model. Table 1 shows the percentage differences between the extendable-capacity and fixed-capacity cases.

Table 1 considers the different instances of capacity-enabled repair shops. The first ten shops have a favorable operational structure. The next ten present a less favorable structure. The last ten present the least favorable structure. The percentage difference (PD) between the objective function values of the extendable- and fixed-capacity cases is

$$PD = 100 \times \frac{OV_{null} - OV_{extension}}{OV_{null}}$$

where OV is the objective value for each case. Along with PD, we considered three improvement metrics: TG, PL, and PRD. TG embodies the throughput percent improvement for the capacity extension case as opposed to the null case,

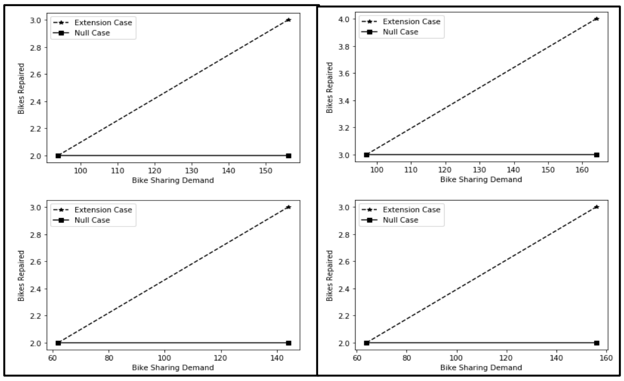

FIGURE 13. Network responsiveness to spikes in demand.

RL encompasses the percentage reduction in lead time, and RR represents the percentage reduction in the average repair duration at shops.

This study presented two important insights in terms of capacity extendibility. First, favorable repair shops enable cost savings, lead-time reduction, and throughput improvement. For instance, we observed a repair lead-time reduction higher than 50%. This had a profound impact on the overall BSS. As observed in the data, spikes in demand owing to weather changes required the supply chain to react quickly. The throughput improvement supported this trend with an increase of approximately 25%, which implied that bikes would be rolled out faster from repair to docking stations.

Referring to the very left column in Table 1, the results are categorized in the range of most favorable to least favorable operational structure, which relates to the values of α and β in equation 3. Herein, favorable characteristics imply that the repair shops have access to additional resources at a favorable cost structure for extending capacity. So extending capacity is more cost-effective and hence advantageous at repair shops with favorable characteristics. Thus, favorable repair shops have equipment, machines, and tools that are readily available to extend their capacity.

Overall, the model exhibited significant improvements when flexibility was adopted. Furthermore, with higher throughput, the need to hold a high number of bikes in the shops was relieved. We observed a higher inventory turnover owing to the high throughput. Note that bike shops tend to largely cluster in urban areas, where property is relatively expensive. Therefore, holding a large number of bikes for repairs is economically impractical for shops.

Second, fluctuations in demand are better met by the flexibility model than the null model. In Fig. 13, we captured points in the data that exhibited a spike in bike-sharing usage. In the extension case, the supply chain could quickly absorb the increment, whereas in the null case, it trailed. We observed this throughout the data. Whenever there was a spike in repair demand, shops were able to respond more quickly.

VI. CONCLUSION AND RECOMMENDATION

Bike-sharing systems are growing in importance, and are being implemented in most cities with high urban densities. These systems may financially exhaust cities owing to the costs of bike maintenance and repositioning. This study illustrated the effectiveness of flexible repair services in managing the maintenance of bikes. High usage of bikes in BSS results in wear-and-tear and possible misuse of bikes. Repair and general maintenance are therefore necessary to control the overall operating cost of a BSS. Our model demonstrated that flexible repair plants can respond quickly to demand spikes. In contrast, in the parallel nonflexible model, this reaction was slower.

The accurate prediction of bike usage is a challenging task. Some latent factors are present in BSS because of consumer behavioral changes. This study investigated these factors and demonstrated the effectiveness of neural networks. Deep learning tends to extract patterns that are latent and unidentifiable using classical algorithms. The coupling of demand data analytics and supply chain modeling produces higher synchronization between maintenance and usage. Repair shops that can quickly extend their capacity can serve as playbooks for best practices. Our results show unique operational characteristics that contrast certain repair shops, which in turn can be imitated and implemented.

For practitioners, demand analytics provides accurate predictions based on given weather conditions. The data used in this study provide multiple relevant features, such as temperature, humidity, wind speed, and season. Given specific temperature, wind speed, and humidity dynamics, our model can predict the bike demand with good accuracy. This is quite important as decision makers have access to reliable weather forecasts. Therefore, demand prediction can be relayed to repair facilities so that operational adjustments can be carried out. Naturally, flexible shops that can quickly extend operational capacity would benefit most from these predictions.

The work incorporates flexible operations, via the use of capacity extension. Our results supply a repair lead-time reduction higher than 50%. While the coupling of demand analytics and supply chain modeling produces a 25% throughput improvement in the overall model. On the demand analytics side, we see a huge advantage of the neural network algorithm, which delivered predictions that are higher than 99% in accuracy.

Given some limitations of this work, there are some important future research opportunities. First, this study focused on docked BSS's, wherein designated stations are built and maintained. Because dockless BSS's are predominant and growing in popularity, future studies could examine maintenance issues with respect to dockless bikes. Furthermore, the demand behavior becomes more cumbersome for dockless systems, and it may be interesting to evaluate the performance of the proposed machine-learning algorithms in such a setting. On the supply chain side, we can look at location-allocation problem [78] in the context of BSS.

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