Int. J. Production Economics 231 (2021) 107868

Contents lists available at ScienceDirect

International Journal of Production Economics

journal homepage: http://www.elsevier.com/locate/ijpe

Big data algorithms and applications in intelligent transportation system: A review and bibliometric analysis

Sepideh Kaffash [a], An Truong Nguyen [a], Joe Zhu [b,*]

[a] Sawyer Business School, Suffolk University, Boston, MA, 02108, United States
[b] Foisie Business School, Worcester Polytechnic Institute, Worcester, MA, 01609, United States

ARTICLE INFO

Keywords:
Intelligent transportation system
Big data algorithms
Survey
Traffic flow prediction

ABSTRACT

The volume and availability of data in the Intelligent Transportation System (ITS) result in the need for data-driven approaches. Big Data algorithms are applied to further enhance the intelligence of the applications in the transportation field. Applying Big Data algorithms has increasingly received attention in both the academic and industrial fields of ITS. Big Data algorithms in ITS have a wide range of applications including but not limited to signal recognition, object detection, traffic flow prediction, travel time planning, travel route planning and safety of vehicle and road. This survey aims to provide a bibliography, a comprehensive review of the application of ITS and a review of most recognized models with Big Data used in the context of ITS. 586 papers are reviewed over the period 1997–2019. This study provides a deep insight into applications of Big Data algorithms in ITS, revealing different areas of those applications and integrates models and applications. The result of the study identifies research gaps and direction for the future.

1. Introduction

In the 1980s the idea of Intelligent Transportation Systems (ITS), originally intelligent vehicle-highway systems, was born by a small group of transportation professionals to recognize the impact of computing and communications techniques in the transportation field (Weiland and Purser, 2000). For the past decade, ITS has played a significant role in the global world and its applications go beyond highway traffic. ITS provides services in navigation, railway, water transport, and air transport systems, resulting in the production of a large amount of data. In October 1997, the “Big Data” concept was introduced by Cox and Ellsworth in an article titled “Application-controlled demand paging for out-of-core visualization” (Cox and Ellsworth, 1997). The term “Big Data” originally means the volume of data that could not be collected, processed and analyzed by traditional database models and tools (Kaisler et al., 2013). The data which include structured data, semi-structured data, and mixed data are collected by advanced data collection techniques (Zhu et al., 2018). Big Data analytics includes the processes of collecting, managing, processing, analyzing and visualizing the continuously evolving data (Marjani et al., 2017).

Big Data production in ITS is evident due to the massive deployment of smart cards, Global Positioning System (GPS), sensors (road site sensor, floating car sensors, wide-area sensors) and connected and autonomous vehicles (CAVs) and other sources. Monitoring equipment such as cameras and roadside sensors are installed in cities to collect data. Connected vehicles exchange information with other devices and the road infrastructure. Individuals use social networks and navigation systems. All these and many other transportation tools generate a huge volume of data. The data generated will continue to grow in size and in complexity, and the increase in automation will further increase data production.

In order to operate, control and manage this huge volume of data, data driven models are needed. Big Data algorithms are developed to improve the ITS operation efficiency, provide information for traffic management decisions, plan better public transportation service, track trucks, airplanes or ships using real-time data, and help users reach their destination in the most suitable route and with the shortest possible time (Zhu et al. (2018). This leads to a revolution in ITS improvement, and its application and the development of more sophisticated models dealing with Big Data.

Recently, a series of literature reviews and surveys that focus on Big Data algorithms in ITS have been published, but most of them tend to discuss a particular function of Big Data, conduct a survey on a special aspect of Big Data in ITS, or concentrate only on bibliometric analysis.

* Corresponding author.
E-mail addresses: skaffash@suffolk.edu (S. Kaffash), anguyen22@su.suffolk.edu (A.T. Nguyen), jzhu@wpi.edu (J. Zhu).

https://doi.org/10.1016/j.ijpe.2020.107868
Received 28 December 2019; Received in revised form 29 April 2020; Accepted 6 July 2020
Available online 19 July 2020

For instance, Amin et al. (2019) explore the role of Big Data in shaping the intelligent transportation system with a focus on road safety. Yang and Pun-Cheng (2018) provide a review of the literature in vehicle detection under varying environments. Vlahogianni (2014) reviews the short-term traffic forecasting. Neilson et al. (2019) review only 28 articles to explore the research and applications of Big Data in the transportation domain for the period of 2012–2017. Zhu et al. (2018) discuss the sources and collection of ITS Big Data and summarize data analytics methods and platforms in ITS.

An et al. (2011) conduct a survey that focuses on the comparison and analysis of international ITS research and key underlying technologies. Qureshi and Abdullah (2013) provide scholars with information on ITS areas. Zhang et al. (2011) review the development of data-driven ITS and the functionality of its key components. However, none of these studies, except Neilson et al. (2019), indicate the number of reviewed papers or the criteria for selecting the reviewed works. There is one ITS bibliometric analysis study in the literature conducted by Cobo et al. (2013) which highlights the conceptual structure of ITS for the period 1992–2011.

A literature review that takes a broad perspective of Big Data algorithms in ITS is yet scarce. This paper examines Big Data algorithms in ITS through an extensive literature review and a bibliometric analysis. To the best of the authors' knowledge, this is the first literature review in the field covering the largest number of papers and conference proceedings (586) and the longest period of study (1997–November 2019).

The goals of this review are to 1) use science mapping analysis to highlight and visualize the development trend of the role and applications of Big Data algorithms in ITS, 2) review extensively the most relevant applications of ITS using Big Data algorithms, 3) explore the most widely used models with Big Data, 4) develop a classification table which connects ITS applications to the most recognized Big Data algorithms, and 5) identify most promising research lines for future work.

Our literature review attempts to address the following research questions:

1 How have the applications of Big Data algorithms in ITS been evolving?
2 What applications of ITS are addressed by Big Data algorithms?
3 Which Big Data algorithms are employed the most for various applications?
4 What is the current state of scientific research?

The remainder of the paper is organized as follows. Section 2 presents the research methodology and statistics. Section 3 provides a bibliometric analysis of 586 papers and conference proceedings. Conceptual, intellectual and social structures, turning points, map analysis of sources, authors, keywords, and dynamics of Big Data algorithms in ITS are visualized, identified and discussed in this section. Section 4 describes the most relevant applications of ITS in which Big Data algorithms are performed, including signal recognition, object detection, traffic flow prediction, and finding optimal route and safety of vehicle and road. Section 5 explores the Big Data algorithms being employed in the top 50 cited papers. A table connecting the recognized Big Data algorithms to ITS applications is presented in this section. Section 6 discusses the findings of the literature review. Section 7 indicates the directions for future studies.

2. Research methodology

To address the research questions, we use the Web of Science (WoS) as the source for material collection. WoS is a research platform from Thomson Reuters containing several databases. It has more than 34,385 records of published and proceeding journals, books, conference papers, and others. To retrieve the relevant articles, a combination of two sets of keywords with the logic term "AND" is being used.

Following Ghofrani et al. (2018) the first set includes Big Data keywords "Big Data", business analytics", "business intelligence", "data mining", "machine learning", and "predictive analytics". The second group contains "Intelligent Transport System(s)", "Intelligent Transportation System(s)", and ITS. The search for combinations of each of the keywords in group one and two were conducted in the following fields: title, abstract, keywords and keywords plus. The initial search results in 1086 works. These papers were filtered by the following rules:

- Articles with pure mathematical modeling of Big Data algorithms are not included.
- The works using simulation data, without a real dataset, are excluded, since most simulation datasets are being used in pure mathematical modeling works.
- Surveys and review works are excluded
- Only works in the English Language are included

The remaining works were reviewed manually, and the final set of dataset consists of 586 documents. Reviewing the 586 papers at the first glance shows the majority of the papers are related to road transportation and there are only six papers in the dataset which cover other types of transportation: Railways (Said et al., 2017; Van Gulijk et al., 2015; Fumeo et al., 2015; Li et al., 2019), subways (Ding et al., 2017) and sea transport (Chen et al., 2019). This indicates that the topic "intelligent transportation system" is not highly significant in railways, sea transport, and air transport research fields and fewer Big Data algorithms are employed in these types of transportations. Ghofrani et al. (2018) review 115 papers with applications of Big Data analytics in railway transportation, however the keyword "intelligent transportation system" was not included in the search methodology. This supports the idea that intelligent feature of transportation is not yet significant in types of transportation other than roads.

3. Bibliometric analysis

Bibliometric is an application of quantitative tools to study science (Pritchard, 1969). Bibliometric analysis has been used in various fields of literature. Over the years, an increasing number of indicators and tools have been developed to quantify the research performance and contribution of authors, journals, institutions, and countries. Another aspect of the bibliometric analysis is monitoring scientific developments and visualizing scientific knowledge from conceptual, intellectual and social structures. In this study, bibliometric analysis is completed using the "Biblioshiny" function in the "bibliometrix" package (Aria et al., 2017).

This section contributes to the literature by providing a deep bibliometric analysis of published works in the applications of Big Data algorithms in ITS. This is the largest dataset of papers (586 papers) in the field that has been reviewed ever in the literature. The dataset contains 329 articles and 257 proceeding papers. Table 1 shows some relevant characteristics of the dataset.

Following Gautam (2017), we use two measures: Publication numbers and Average citation per year, to illustrate the research output of our study. The number of publications is of interest because it is being

Table 1
Relevant characteristics of the dataset.

Description	Results
Documents	586
Sources (Journals, Books, etc.)	336
Keywords Plus (ID)	423
Author's Keywords (DE)	1568
Period	1997–2019
Average Citations per Document	13.18
Authors	1756
Author Appearances	2169
Single-authored Documents	20

used in the literature as an indicator of the level of research output. One relevant measure is the annual growth rate of the number of publications. Fig. 1 illustrates the annual growth rate of research publications for the period of 1997–September 2019. One can observe an exponential growth in published articles starting from 2013, indicating an increase in research publications for Big Data and ITS. By the time this figure is created, there were three months left in 2019 and the authors do not have knowledge of the annual growth rate for the year 2019.

Average citation per year is a measure used to indicate the influence of published papers. Fig. 2 shows the published papers' average times cited per year. One can observe that while the average number of citations is following a smooth increasing trend, there are three remarkable peaks in the average number of citations in years 2003, 2015 and 2016 with average times cited per year being 6.2, 6.5 and 6.5 respectively. The peak in 2003 is the result of two highly cited articles. The first one, "A multivariate state space approach for urban traffic flow modeling and prediction" by Stathopoulos and Karlaftis (2003) discusses urban traffic congestion. The second article is "Traffic sign recognition and analysis for intelligent vehicles" by Escalera et al. (2003), who propose an algorithm for the detection and recognition of traffic signs. In 2014, two papers which attract scholars' attention are published. "Short-term traffic forecasting: Where we are and where we're going" published by Vlahogianni et al. (2014) and "Deep Architecture for Traffic Flow Prediction: Deep Belief Networks With Multitask Learning" by Huang et al. (2014). Both articles discuss traffic flow prediction. The most frequently cited paper in our dataset was published in 2015. "Traffic Flow Prediction with Big Data: A Deep Learning Approach" by Lv et al. (2014) .[1] This article is cited 548 times by the scholars in the field.

The first paper which appears in the literature in our dataset was published in 1997. Dia and Rose (1997) published the paper in the journal of "Transportation Research Part C: Emerging Technology" and developed a multi-layer feedforward (MLF) neural network incident detection model. They test the model on a real-world data set of 100 incidents. The model uses speed, flow and occupancy data measured at dual stations, averaged across all lanes and only from time interval t. The results of Dia and Rose (1997)'s study provide a comprehensive evaluation of the developed model and confirm that neural network models can achieve fast and reliable incident detection on freeways.

3.1. Top relevant sources, authors and highly cited works

In this section, we focus on the most relevant sources, authors and highly cited works. Overall, 586 articles and proceeding papers form our dataset. These works have appeared in 336 different sources. Fig. 3 illustrates the distribution of the top 10 most relevant sources. As it can be observed, the IEEE Transportations on Intelligent Transportation System has the first rank with 49 papers, followed by IET Intelligent Transport Systems with 31 papers. Fig. 4 shows the contribution of each the of top 10 sources over the period 1997–2019. It shows the top ten sources with the highest number of published articles and how they grow in terms of publishing more articles over time. The graph shows that after 2015, there is a surge in the number of published papers specifically in "IEEE Transportations on Intelligent Transportation System", "IET Intelligent Transport Systems", "IET Intelligent Transport Systems", and "Sensors".

Fig. 5 shows the most relevant authors and their annual production over the years. According to Fig. 5, Yang Zhang and Xun Wang are the two authors with the longest period of contribution to the filed. In Fig. 5, the color intensity is proportional to the annual times cited and the bubble size is proportional to the number of yearly productions. For instance, Lv's name has appeared in 7 papers for 2014–2018. For Lv, the size of bubbles indicates two publications for each of the years 2016 and 2017 and one publication for each of the years 2014, 2015 and 2018. However, the intensity of the bubble in 2015 shows this paper has been cited more than others. Lv et al. (2014) are cited 548 times (see footnote 1 page 8).

Fig. 6 shows the most cited papers, over the period 1997–2019. The topic of nine out of the ten most cited papers is traffic flow prediction, and one of the papers discusses traffic sign recognition. The most recent highly cited paper is "'Traffic flow prediction with big data: a deep learning approach" by Lv, Y (2014) with the average times cited being 109 per year.

3.2. Keyword analysis

Fig. 7 shows the Treemap of the top 50 authors' keywords. The map shows the keyword intelligent transportation system and its few variations[2] are the most frequently appearing keywords. In total, this keyword appeared 206 times in the dataset, which is not surprising. Among the second group of keywords (section 2) deep learning, neural network (and neural networks), data mining, machine learning are the most frequent keywords being mentioned by the scholars. Table 2 which represents the top ten keywords used by scholars, also supports that deep learning, neural network(s), data mining, and machine learning are the most frequent keywords appearing in the keyword section.

3.3. Conceptual, intellectual and social structure

In this section, science mapping is used to map three different aspects of scientific knowledge: conceptual structure, intellectual structure, and social structure. Science mapping attempts to discover the hidden patterns of these structures. The conceptual structure shows what science talks about and the main theme and trends. Intellectual structure maps how the work of an author influences a given scientific community. Small and Griffith (1974) for the first time document the principles of co-citation analysis and its applications to map the growth of science. In this work, the historic direct citation network is used to show the intellectual structure base on the first top-cited papers. Finally, the social structure shows how authors, institutions, and countries interact with each other.

For conceptual structure, the thematic evolution of the author's keywords is drawn. Fig. 8 shows an overall picture of the evolution of topics in Big Data and ITS from 1997 to 2019. It demonstrates what science talks about and how the theme and trends have developed. The thematic evolution map is created by applying a clustering algorithm on the keyword network, the different themes of a given domain. Three-time cutting points have been selected based on the volume of the published works: 2011, 2014, 2017.

For the period 1997–2011, "models" and "volume" keywords start as a unique theme and in the next time slice (2012–2014) they merge into "neural networks". Such an occurrence is explained by the more significant role of neural networks as models handling the volume of Big Data in the more recently published works. In the next time slice (2012–2014) neural networks are divided into three branches: "flow prediction", "prediction" and "neural networks". Considering the keywords "neural network" and "neural networks" as one keyword, it's

[1] - The Date of Publication for Journals and Standards on IEEE Xplore represents the very first instance of public dissemination of content. IEEE Xplore had previously made distinctions between physical print date, date of current version, online publication date, etc. This has been simplified with one official date of record.(https://ieeexplore.ieee.org/Xplorehelp/#/ieee-xplore-training/working-with-documents#publication-dates). The paper "Traffic Flow Prediction with Big Data: A Deep Learning Approach" by Lv et al. (2014) has the first instance of public dissemination of content on September 2014, however it has been published in the Volume: 16, Issue: 2, April 2015 of IEEE Transactions on Intelligent Transportation Systems. WoS and biblioshiny take 2015 as the date of publication.

[2] -intelligent transportation systems, intelligent transport systems, intelligent transportation, intelligent transportation systems its.

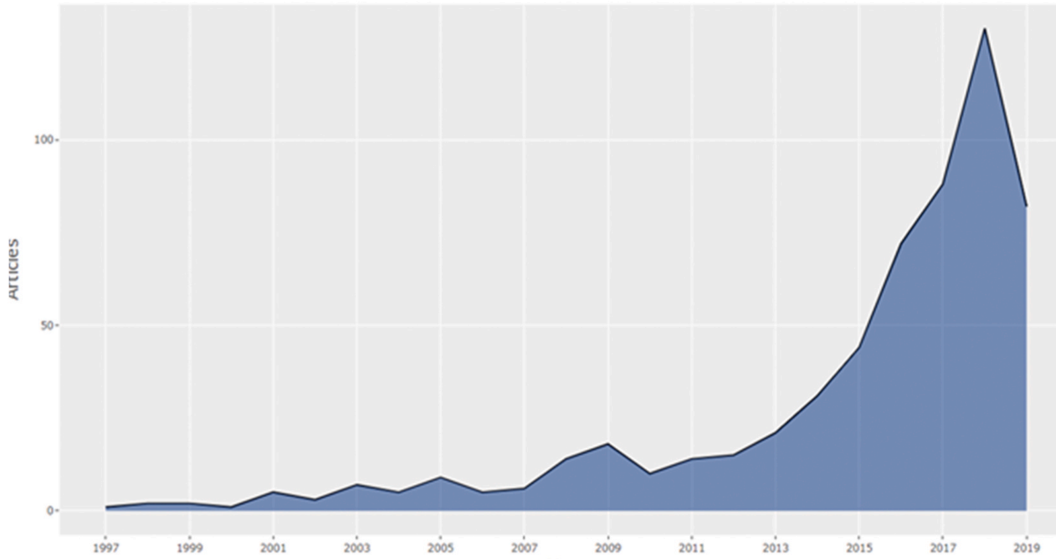

Fig. 1. Annual growth rate.

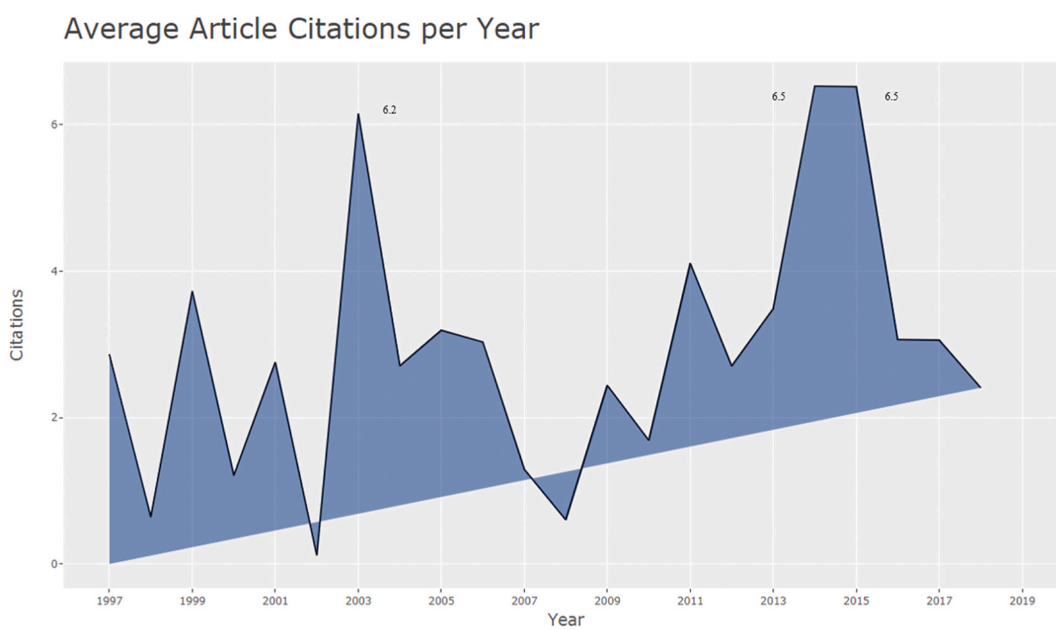

Fig. 2. Average citation per year.

obvious this keyword is a major topic from 2012 onwards. In section 5, the role of neural network algorithms with ITS applications will be explored.

The keyword "prediction" keeps appearing in authors' publications into the next time slice, indicating that a more recent research theme is interested in not only inflow prediction but also other aspects of prediction, such as travel time and speed. For the time slice 2018–2019, the thematic evolution map shows "recognition" and "prediction" as the two major topics in the center of scholars' attention. In section 4, the prediction and recognition and their role in the research will be discussed.

Fig. 9 illustrates the historic direct citation network.[3] This network identifies the first most significant papers on the topic of research and traces the historical development of core authors and papers. The direction of arrows illustrates the chronical change of research trend for the first top ten papers. For instance, it shows that Yisheng Lv who is the first author of the paper "Traffic Flow Prediction With Big Data: A Deep Learning Approach" in 2015, has cited five out of the ten most frequently cited papers in our dataset (Lippi et al., 2013; Dia, 2001; Stathopoulos and Karlaftis, 2003; Vlahogianni et al., 2005; Zheng et al., 2006). By reviewing the title of these ten papers, it can be concluded that all these papers are concentrating on the traffic flow.

To understand how countries, institutions, and authors researching big data modes and their applications to ITS are connected, an assessment of international collaboration based on co-authorship is carried out. Overall, there are 79 pairs of country collaboration.[4] In Fig. 10, the

[3] The historic direct citation network is based on the local citation which means the number of times an article being cited by only the articles inside the dataset (586 articles that we found).

[4] Authors from 79 pairs of various countries collaborate in publishing articles.

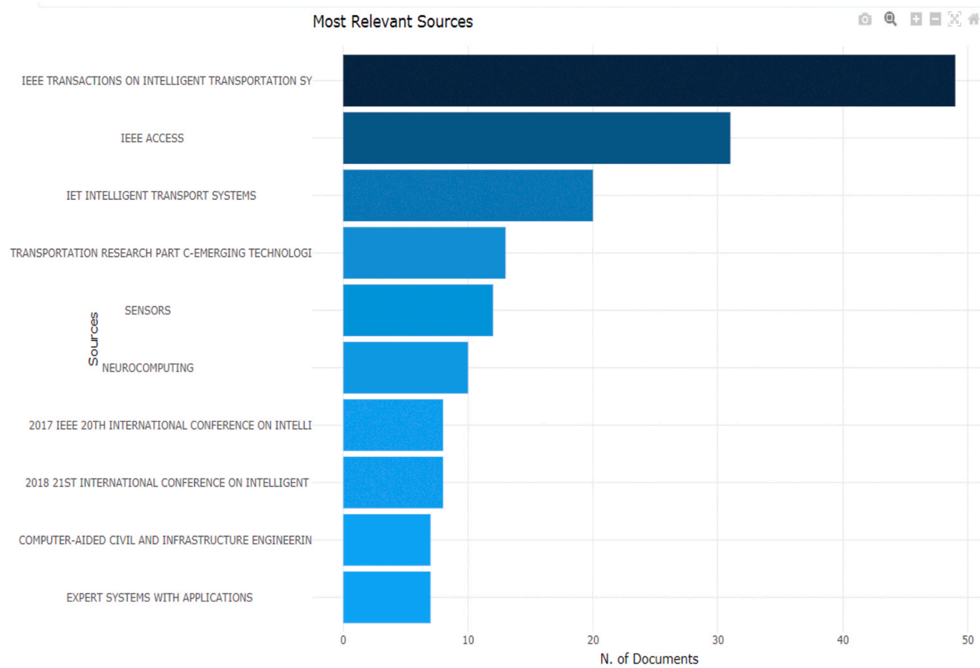

Fig. 3. Most relevant sources.

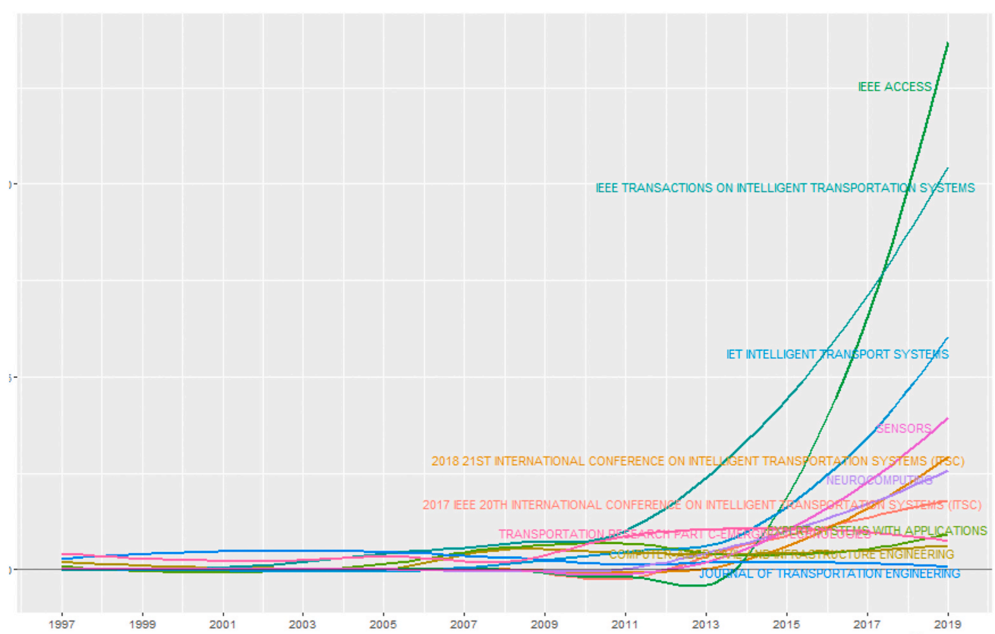

Fig. 4. Contribution of the top ten sources 1997–2019.

thickness of the link between two countries is indicative of the extent of co-authorship (collaboration). The assessment shows that the extent of international research collaboration between China and the USA is relatively higher compared to other countries. 33 papers out of 586 published are the result of this collaboration. Fig. 10 supports this by showing a sticker link between these two countries. From the perspective of each individual country's contribution, China, USA, Taiwan are the leading countries by having 262, 59 and 28 publications out of 586 papers (at least one of the authors is located in the country). The next interesting finding shows that China, the USA, and Greece have the highest total citations of papers. The papers published by Chinese institution scholars have been cited in 2553 times in the literature. This number is 1383 and 921 for the USA and Greece, respectively.

4. Top relevant application of big data algorithm in ITS

This section reviews the most significant applications of big data algorithms in ITS: prediction, recognition, detection, safety, and optimization. Literature is rich when it comes to prediction applications. It covers various attributes such as speed prediction, travel time prediction, and traffic flow prediction. The words "forecasting" and "prediction" appear in the titles of 229 works out of 586 articles and proceeding conference papers in this review study. Another dominant ITS application that attracts scholars' attention is "detection" and "recognition".

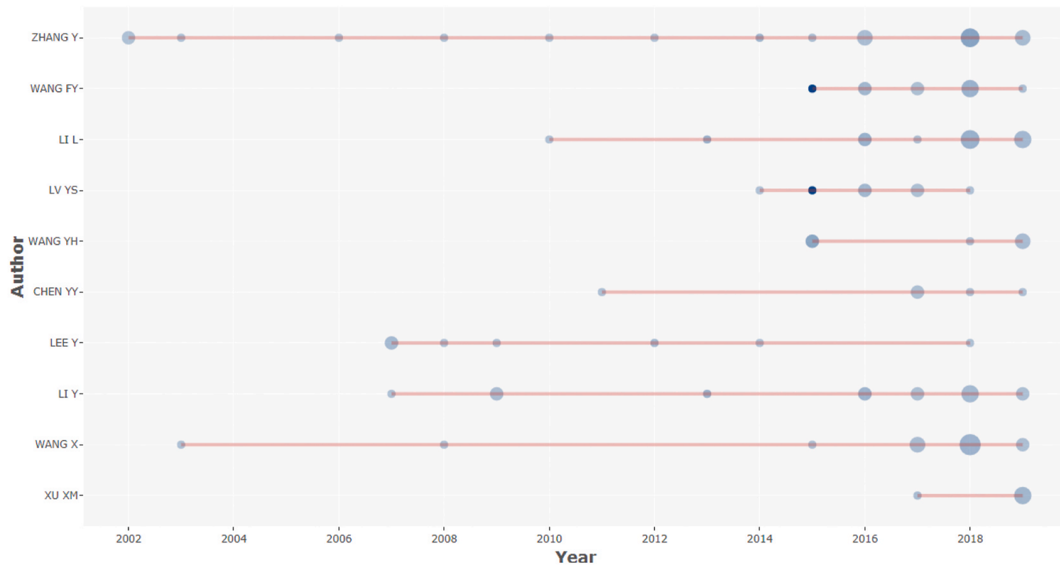

Fig. 5. Most relevant authors and production over the years.

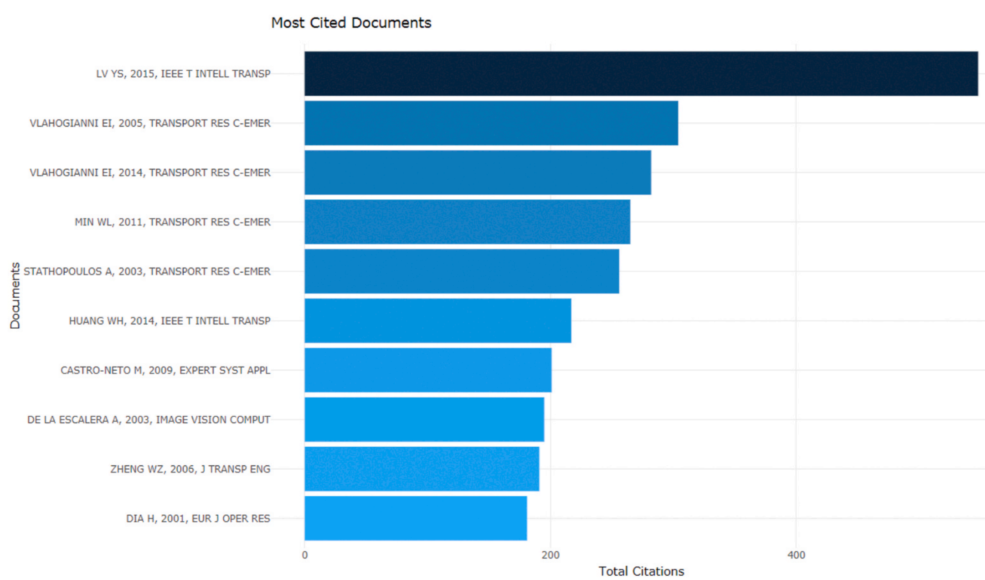

Fig. 6. Most cited papers.

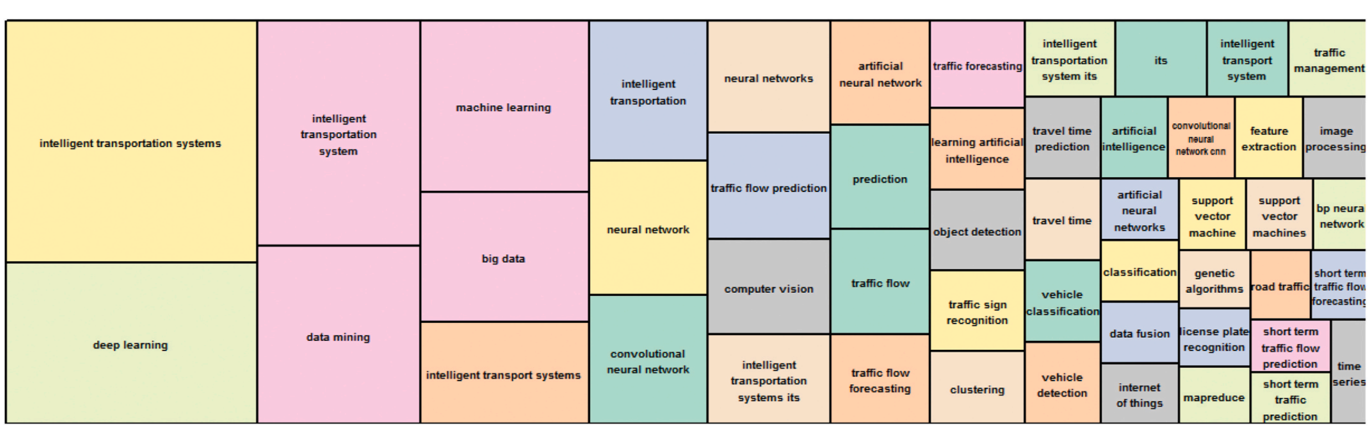

Fig. 7. Threemap of top 50 authors' keywords.

Table 2
Most frequent keywords.

intelligent transportation system[2]	206
deep learning	59
neural network(s)	43
data mining	42
machine learning	42
big data	32
convolutional neural network	22
traffic flow prediction	19
computer vision	17
artificial neural network	15

These two applications have been used in combination in some studies. This study attempts to separate them based on the specific word that appear in each article. However, when it comes to an object such as a traffic sign, drawing a clear line becomes challenging. In the following section we review the most frequently cited papers in the literature for each application.

4.1. Prediction

Getting an accurate prediction of the future states and conditions of traffic is an attractive topic for many researchers in the field of ITS. Having the ability to predict traffic attributes such as speed, travel time and traffic flow, plays an important role in various components of ITS such as Advanced Traveler Information Systems (ATIS), or Advanced Traffic Management Systems (ATMS) (Vanajakshi and Rilett, 2004).

With most of the research being conducted in the subject of ITS related to forecasting and predicting, scholars use advanced computational models for Big Data such as deep learning, neural networks and clustering algorithms to address the existing problems or to improve the current condition of predicting traffic attributes. 85% of the studies in our survey which are published between 2010 and 2019, explore prediction and forecasting traffic topics including but not limited to traffic congestion, traffic flow, travel time and incident prediction for transportation services.

Since Prigogine and Andrews (1960)'s research, there have been many other studies in the literature dealing with traffic flow prediction. There are some review works in the literature which specifically focus on the prediction of traffic flow. Adeli (2001) reviews papers applying neural network techniques in traffic engineering and highway engineering areas. Van Lint and Van Hinsbergen (2012) explore the short-term traffic and travel time prediction models. More recently, Vlahogianni et al. (2005) review the existing short-term traffic forecasting papers in ten challenging directions. In this sub-section, we review some of the highly cited papers.

Zhu and Yang (1998) introduce the Advanced Traveler Information System (ATIS) to predict traffic flow behaviors in Changchun, China using Big Data algorithms. Ever since, ATIS and the other components of ITS had been comprehensively studied, validated and successfully applied. Dia (2001) develops an object-oriented neural network model to predict short-term traffic conditions on a section of the Pacific Highway between Brisbane and the Gold Coast in Queensland, Australia using a Time Lag Recurrent Network (TLRN). The model is successfully able to predict traffic up to 5 min ahead of time with percentage errors as low as 6 percent. Another study by Stathopoulos and Karlaftis (2003) tackles the problem of traffic congestion by conducting short-term traffic predictions in Metropolitan areas using multivariate time-series state-space models. Their data are collected by an urban area loop detector on the upstream traffic to predict the conditions of downstream locations. Zheng et al. (2006) introduce a hybrid model, combining linearly basis function neural network into the Bayesian neural network model to predict traffic rate in Singapore's Ayer Rajah Expressway with a 15 min time interval.

Before 2009, the studies assumed that traffic was operating under optimum conditions. However, Castro-Neto et al. (2009) have made a turning point in ITS studies when adding elements of atypical traffic conditions (vehicular crashes, constructions, weather conditions, or holidays) into a prediction model which increases prediction model accuracy. Like other fields, the application of Big Data algorithms has been popularized in ITS during the recent decade. Huang et al. (2014) incorporate multitask learning (MTL) into a deep learning model to learn the effective features for unsupervised traffic flow prediction. This model of deep learning had allowed the prediction process to be automated while still ensuring a high level of accuracy.

Lippi et al. (2013) use Autoregressive Integrated Moving Average (SARIMA) along with a Kalman filter to perform the analysis for predictions which is an improvement from the supervised learning perspective. Lv et al. (2014) develop a deep learning model using stacked autoencoders (SAEs) to learn generic traffic flow features through different layers. This is the first study to have applied the deep architecture of SAEs to represent traffic flow features for predictions.

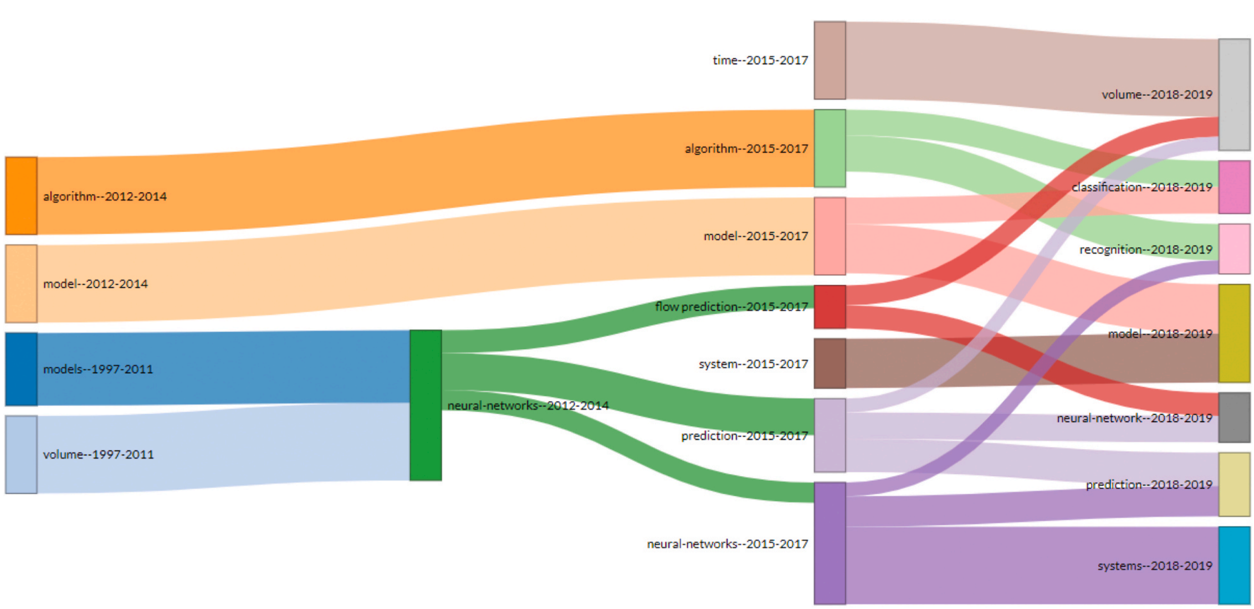

Fig. 8. Thematic evolution of authors' keywords.

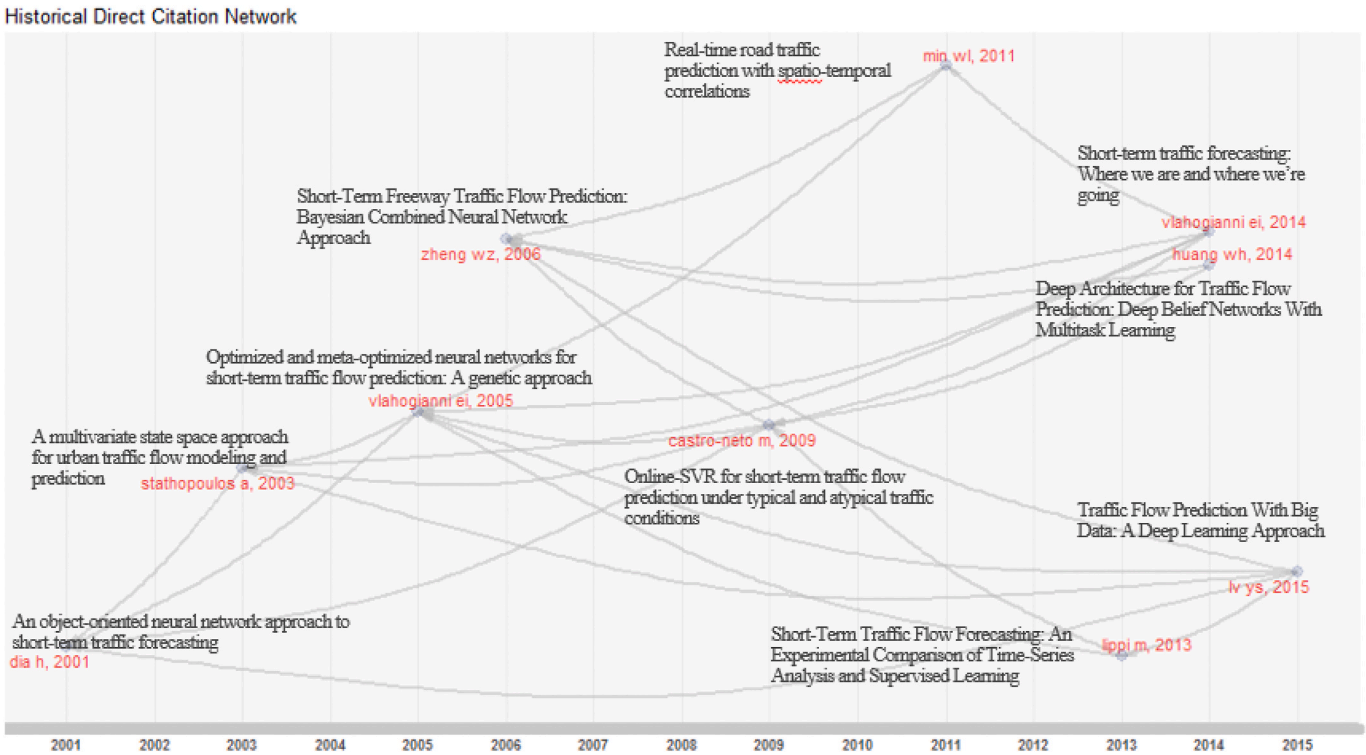

Fig. 9. Historic direct citation network for the top ten authors.

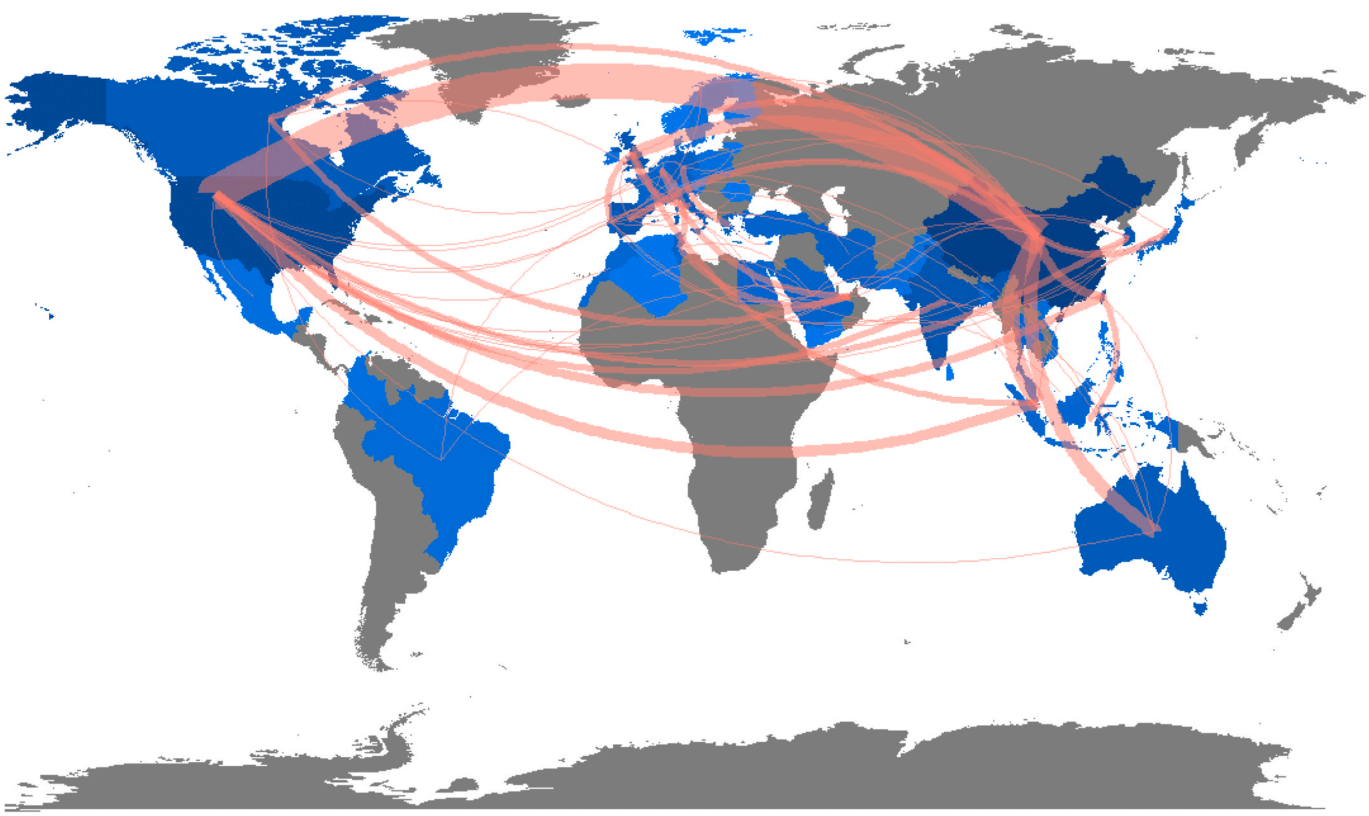

Fig. 10. Country collaboration.

Regarding traffic speed prediction, Hamad et al. (2009) introduce a hybrid one that combines the use of the empirical mode decomposition (EMD) and a multilayer feedforward neural network with backpropagation to forecast multiple-period freeway station speeds, from which travel times can be directly estimated. Kehagias et al. (2015) propose a model based on road profiles generated from the application of data clustering techniques in real traffic data to forecast the values of appropriate traffic status indicators such as average travel time or speed, for one or more time steps in the future until the next half hour. Vanajakshi and Rilett (2004) and Yao et al. (2017) use SVM for the short-term prediction of traffic speed. Qiu et al. (2011), Wang et al. (2016) and Song et al. (2017) use deep learning algorithms to predict traffic speed.

4.2. Recognition

Recognition and detection are two very similar techniques for identifying objects, however, they are varied in the execution. In Big Data algorithms object detection is the subset of object recognition, in which the system not only identifies the object but also has to locate it. Object detection has a wide range of applications in the field of ITS, most mentioned applications include incidents, traffic signs, and driver behaviors (Yuan et al., 2016).

In the context of ITS, recognition topic is the activity of identifying various objects including, but not limited to, license plates, traffic signs, drivers' behaviors, vehicles (makes and models). The growing size of the data and the computational complexity of Big Data algorithms have allowed recognition approaches in recent years to be more accurate (Sun et al., 2014). This section reviews some of the highly cited articles in the literature which discuss recognition topics in ITS.

License plate recognition has a wide range of applications, from traffic enforcement to tracking stolen vehicles down. In early studies, the proposed techniques suffer from many constraints including off-line functionality, uncontrollable lighting conditions, and the presence of other objects (De la Escalera et al., 2003). Zhang et al. (2013) propose a multi-filter based license plate recognition (LPR) framework for plates localization and character recognition to resolve the problems. The accuracy of the framework was tested by using 800 images taken from various scenes under different conditions. The error rate of the proposed framework was seven percent. With many great scientific breakthroughs in terms of mobile technologies, people can access to mobile devices with a powerful central processing unit (CPU). Do et al. (2016) develop an Android application to capture and process the images of license plates using mobile devices' integrated camera system. The program uses a neural network model to convert the images of license plates to computer-encoded text for further applications such as stolen car detection, parking system management, and automatic transport charging system. This eliminates the need for using expensive high definition cameras systems for recognition purposes.

Traffic sign recognition (TSR) in ITS is also getting a lot of attention from scholars and researchers in the past recent years. Despite facing some difficulties, there is still a wide range of applications that systems with this recognition capability can get benefits such as highway maintenance, sign inventory, driver support system, intelligent autonomous vehicles (De la Escalera et al., 2003). Sun et al. (2014) propose an algorithm based on artificial neural network and extreme learning machine (ELM) to produce more effective results in terms of traffic signs recognition. The model was tested using German traffic signs recognition benchmark (GTSRB) datasets to prove its feasibility and efficiency. Using the same datasets, Jin et al. (2014) develop a convolutional neural network (CNN) model trained by hinge loss stochastic gradient descent (HLSGD) method. The model is proven to deliver faster and more stable convergence and a recognition rate of 99.95 percent.

Behaviors and vehicle type recognition have not been extensively studied by scholars comparing to other recognition topics. However, some noticeable scholarly sources raise the importance of driving behaviors and vehicle type recognition (Wang, 2009; Zhang et al., 2015). Most of those sources used different variations of neural network models to perform their recognition tasks.

4.3. Detection

Due to the high costs of congestion caused by incidents such as accidents, vehicles' malfunction, or construction works, there has been a worldwide interest in the last decades for developing an efficient and effective automated incident detection methods. This subject of study in ITS started as early as 1997 when Dia and Rose (1997) discuss a multi-layer feedforward (MLF) neural network incident detection model. The model is trained with a real-world dataset of 100 incidents in which variables such as speed, flow and occupancy data measured at dual stations to detect unwanted events. A study by Jin et al. (2001) proposes a new technique using a constructive probabilistic neural network (CPNN) to detect freeway incidents. The model is tested on Ayer Rajah Expressway (AYE) in Singapore to achieve a detection performance of 92 percent. Another recent study by Ozbayoglu et al. (2016) forces primarily on freeway accidents, one of the major problems in transportation systems. They propose a preliminary real-time autonomous accident-detection system based on computational intelligence techniques using Istanbul's 2015 traffic data.

Traffic signs detection is a significant component of ITS with great application potentials. The research on sign detection can be classified into two segmentations: one through color thresholding, region detection, and shape analysis and the other through the border detection in a black and white image and their analysis (De la Escalera et al., 2003). Sheng et al. (2008) develop a new algorithm to process 220 real images taken in Nanjing, China using the probabilistic neural networks (PNN) model. Yuan et al. (2016) model can achieve a near-real-time result with single image processing using the deep learning method. Another paper by Abedin et al. (2017) presents a new approach where detecting tasks is conducted with a fuzzy rules-based color segmentation method.

Driving behavior detection is a crucial component in surveillance applications since aggressive and abnormal driving behaviors may cause serious accidents and traffic congestion (Qi et al., 2017). To encourage good driving behaviors and enhance traffic safety, Big Data algorithms related to driving behaviors are being extensively studied and tested to apply to real-world problems. Chen et al. (2018) propose a seat belt detection algorithm for a more complex road background based on multi-scale feature extraction trained by a convolution neural network (CNN). This method is useful to process images collected by road surveillance cameras. Ghaleb et al. (2017) develop an effective misbehavior detection model based on Artificial Neural Network (ANN) techniques. The model uses real-world traffic datasets to construct and produce the most accurate detecting results. Vehicle steering behavior is also studied by Qi et al. (2017) which a solution for vehicle steering detection using a smartphone is proposed. The study takes complex driving conditions such as speed and curvature of the bend into consideration, all of which were mostly ignored by previous research. The model can analyze the patterns of five common driving behaviors (left turn, right turn, left lane, right lane, and U-turn) to detect steering behaviors at 4 different speed levels with accuracy as high as 90 percent.

As an autonomous driving system, the patrolling system is gaining more popularity road detection, pedestrian detection, sound detection, are becoming more to the center of scholars' attention (Xu et al., 2010; Shi et al., 2016; Singh et al., 2017).

4.4. Safety

One other important applications of Big Data algorithms in ITS is Safety. Big Data algorithms not only are used to improve vehicle safety but also widely are applied to increase road and highway safety. Understanding the causes of high-risk scenarios such as drivers' behaviors, roadway designs, traffic flow, or weather conditions and including them in the ITS safety modeling can help the increase of safety of roads. Several studies in the literature explore the safety of roads and vehicles. Amin et al. (2019) review the role of Big Data in improving ITS from a safety perspective.

Road safety relies on collision prediction models to estimate the expected safety levels of specific road entities such as intersection and sections under specific conditions (Pan et al., 2017). One of the complex parts of the road network is an intersection that involves various participants, such as vehicles and pedestrians (Alajali et al., 2018). Providing an accurate traffic flow prediction is crucial to enhance traffic efficiency and increase safety. Alajali et al. (2018) develop an effective and scalable decision tree for the regression model to analyze large amounts of data published by VicRoads for the state of Victoria, Australia.

One of the features of road safety is the presence of vehicles with size other than normal in the roads. Traffic conditions of truck flow influence the safety of the road. Jin et al. (2019) introduce a multiple logistic regression method to classify the truck-related effect into safe, risky, and dangerous road risk levels. Hsieh et al. (2014) develop a machine learning technique to improve driving safety for scooters, one of the most important means of transportation in Taiwan.

Autonomous driving is a new emergent area of ITS. In an attempt to increase safety on autonomous vehicles, Parmar et al. (2019) propose a deep-learning-based approach to range finding. The model can reduce the errors of range estimation down to an acceptable number for highway scenarios. Autonomous vehicles also consider drivers' behaviors when providing the needed assistance to ensure safety. López and Pinilla (2012) present an intelligent driver behavior model based on the neural network along with the GPS data logging system (position, velocity, acceleration, and steering angle) which improves the safety of roads and vehicles. The model is implemented and validated in a real-world environment to classify drivers into two different categories, aggressive and moderate with high accuracy. Yuan et al. (2016) suggest a different approach, focusing primarily on single image detection and recognition tasks, in which they used a mono-camera mounted on a moving vehicle to perform recognition actions under non-stationary conditions.

4.5. Optimization

Optimizing operations is becoming more important in making better decisions in terms of operational efficiency, strategic resource planning, and improving performance and process quality to provide customers with better quality services in the most cost-effective manner (Borgi et al., 2017). In ITS context, optimization is applied in terms of finding the optimal route for vehicles, optimal speed, optimal energy consumption and optimal waiting time.

Rilett and Park (2001) introduce a fuzzy logic-based multiple objective route choice model to find optimal real-time routing system and experiment it in the cities of Houston and Austin, Texas. The model can consider multiple attributes of the current traffic to suggest alternative routes in case of possible congestion. Lo and Chang (2012) design a real-time fuzzy bus holding system (FBHS) to optimize the waiting time of mass vehicles along with their passengers. The models use real-time traffic information acquired by the intelligent transport system through GPS. The system reduces significantly passengers' waiting time and improves the performance of public transportation services. Wu (2018) compares the three forecasting methods of a linear regression forecasting model, grey prediction model and time series prediction model to explore bus system optimization. Wong and Woon (2008) present a novel method for optimizing traffic timing plans via the use of clustering algorithms to automatically generate Time-Of-Day (TOD) intervals. La Iglesia et al., (2017) propose an intelligent engine management system for e-bikes. The system uses the information collected from sensors to optimize battery energy and time.

5. Relevant big data algorithms in ITS

Many Algorithms of ITS have successfully been applied in traffic flow prediction, traffic time prediction, traffic sign recognition, incident detection, optimization and safety of vehicles and roads. These approaches can primarily be classified into parametric and non-parametric techniques (Yao et al., 2017). Among the wide variety of statistical parametric and non-parametric techniques, several algorithms have been applied in ITS.

Parametric techniques include but are not limited to regression models (Rice and Van Zwet, 2004), auto-regressive integrated moving average (ARIMA) family models (Ahmed and Cook, 1979; Lee and Fambro, 1999; Guo et al., 2013; Kumar and Vanajakshi, 2015; Fu et al., 2016), Kalman filter models (Yuan et al., 2016; Zhou et al., 2018). Non-parametric approaches such as artificial neural networks (Dia and Rose, 1997; Park et al., 1999; Jeong and Rilett, 2005; Khodayari et al., 2012), k-nearest algorithms (Chang et al., 2012; Xia et al., 2016; Yu et al., 2016) support vector machines (Hong et al., 2011; Jeong et al., 2013; Sun et al., 2015), genetic algorithms (Vlahogianni et al., 2005; Zhang et al., 2014; Lopez-Garcia et al., 2015) and deep learning (Yanwu et atl., 2010; Lv et al., 2014; Koesdwiady et al., 2016). In recent years, the combined usage of these algorithms in order to address ITS problems become more prevalent (Boto-Giralda et al., 2010; Sun et al., 2012; Lippi et al., 2013; Zhao et al., 2017).

To give an insight into the most widely used Big Data algorithms in ITS, a brief review of proposed techniques and employed models in the top-cited papers are presented in this section. The most frequently cited papers mostly attempt to introduce new models to address traffic flow prediction, traffic time prediction, traffic sign recognition, and incident detection problems. Table 3 represents these highly cited papers in terms of applications, algorithms and the Big Data algorithms employed. It can be observed that artificial neural networks and deep learning algorithms are the first two algorithms that are widely employed by scholars. Not surprisingly, traffic flow prediction is the application area in ITS that attracts researchers' attention the most. In the following section, we review the papers for each algorithm.

5.1. Artificial neural networks algorithm

Artificial neural networks (ANN) can perform the non-linear mapping between inputs and outputs through the consideration of hidden layers. This characteristic of (ANN) makes it suitable for addressing transportation problems (Sumalee and Ho, 2018) such as traffic flow prediction, traffic sign detection, travel time prediction, and incident detection.

Dia and Rose (1997) discuss a multi-layer feedforward (MLF) neural network incident detection model that was developed and evaluated using field data. A comparative evaluation demonstrates the substantial improvement in incident detection performance obtained by the neural network model. The results confirm that neural network models can provide fast and reliable incident detection on freeways. Park et al. (1999) employ a spectral basis artificial neural network (SNN) that utilizes a sinusoidal transformation technique to increase the linear separability of the input features. It was found that the SNN outperformed a conventional artificial neural network and gave similar results to that of modular neural networks. Jin et al. (2001) proposed a technique for freeway incident detection using a constructive probabilistic neural network (CPNN). A more impressive size reduction by a factor of 50 was achieved after the model was adapted for the new site. Dharia and Adeli (2003) present a neural network model for forecasting the freeway link travel time using the counter propagation neural (CPN) network.

Jeong al. (2005) develop a model to predict bus arrival time using Automatic vehicle location (AVL) data and apply the model for real-time applications. It was found that ANN models outperformed both the historical data-based model and the regression model in terms of prediction accuracy. Zheng et al. (2006) introduce a neural network model that combines the prediction from single neural network predictors. Wei and Lee (2007) create an adaptive procedure for sequential forecasting of incident duration, and the procedure includes two adaptive Artificial Neural Network-based models.

Boto-Giralda et al. (2010) propose an approach for short-term predictions of time series data at isolated cross-sections. A self-organizing

Table 3
Top cited papers.

Author	Big Data Algorithms	Application	Model
Zheng et al. (2006)	Artificial Neural Network	Traffic flow prediction	Bayesian Combined Neural Network (BCNN)
Boto-Giralda et al., 2010	Artificial Neural Network	Traffic flow prediction	Fuzzy ARTMAP Neural Network (FAMNN)
Sun et al., 2012	Artificial Neural Network	Traffic flow prediction	NN and Gaussian Process Regression (GPR)
Escalera et al., 2003	Artificial Neural Network	Traffic sign recognition	Adaptive Resonance Theory Neural Network (ARTNN and GA)
Jin et al., 2014	Artificial Neural Network	Traffic sign recognition	Convolutional Neural Network and Stochastic Gradient Descent (CNN and SGD)
Park et al. (1999)	Artificial Neural Network	Travel time prediction	Spectral Basis Artificial Neural Network (SNN)
Dharia and Adeli (2003)	Artificial Neural Network	Travel time prediction	Counter Propagation Neural (CPN)
Jeong and Rilett (2005)	Artificial Neural Network	Bus arrival time prediction	Neural Network
Khodayari et al. (2012)	Artificial Neural Network	Car–following behavior prediction	Neural Network
Dia and Rose (1997)	Artificial Neural Network	Incident detection	Neural Network
Wei and Lee (2007)	Artificial Neural Network	Incident detection	Neural Network and Data Fusion
Yanwu et al., 2010	Artificial Neural Network	Pedestrian detection	RBFN
Jin et al. (2001)	Probabilistic	Incident detection	Convolutional Probabilistic Neural Network (CPNN)
Lv et al., 2014	Deep Learning	Traffic flow prediction	Stacked Autoencoders (SAES)
Koesdwiady et al., 2016	Deep Learning	Traffic flow prediction	Deep Belief Network (DBF) and Decision-Level Data Fusion
Huang et al. (2014)	Deep Learning	Traffic flow prediction	Deep Belief Network and Multitask learning (DBN and MTL)
Tian and Pan (2015)	Deep Learning	Traffic flow prediction	Long Short-Term Memory Recurrent Neural Network (LSTM RNN)
Fu et al. (2016)	Deep Learning	Traffic flow prediction	Long Short-Term Memory Recurrent Neural Network, Gated Recurrent Units and neural network (LSTM RNN,GRU-NN)
Zhao et al. (2017)	Deep Learning	Traffic flow prediction	Long Short-Term Memory Recurrent Neural Network (LSTM-NN)
Dia (2001)	Deep Learning	Traffic flow prediction	Time-Lag Recurrent Network (TLRN)
Ma et al. (2015)	Deep Learning	Traffic congestion prediction	Restricted Boltzmann Machine and Recurrent Neural Network (RBM and RNN)
Vlahogianni et al. (2005)	Genetic	Traffic flow prediction	Genetic and Neural Network (NN and GA)
Lopez-Garcia et al. (2015)	Genetic	Traffic congestion prediction	Hierarchical Fuzzy Rule-Based System, Genetic Algorithm with Cross Entropy (Parallel HFRBS and GACE)
Zhang et al. (2014)	Genetic	Traffic congestion prediction	Hierarchical Fuzzy Rule-Based System (HFRBS)
Yu et al. (2016)	Instance-based	Traffic flow prediction	K-Nearest Neighbor (KNN)
Chang et al. (2012)	Instance-based	Traffic flow prediction	K-Nearest Neighbor Non-Parametric Regression (KNN-NPR)
Xia et al. (2016)	Instance-based	Traffic flow prediction	Spatial–Temporal Weighted K-Nearest Neighbor (STW-KNN)
Castro-Neto et al. (2009)	Instance-based	Traffic flow prediction	Online Learning Support Vector Regression (OL-SVR)
Jeong et al. (2013)	Instance-based	Traffic flow prediction	Online Learning Weighted Support-Vector Regression (OLWSVR)
Lippi et al. (2013)	Instance-based	Traffic flow prediction	Radial Basis Function (RBF) Seasonal Kernel and the Second Linear Seasonal Kernel
Hong et al., 2011	Instance-based	Traffic flow prediction	Support Vector Regression Genetic Algorithm-Simulated Annealing (SVRGA-SA)
Yao et al. (2017)	Instance-based	Traffic speed prediction	Support Vector Regression
Sun et al. (2015)	Instance-based	Passenger flow prediction	Least Square Support Vector Machine and Wavelet (Wavelet-SVM)
Zhang et al. (2014)	Time Series	Traffic flow prediction	Autoregressive Integrated Moving-Average (ARIMA)
Min and Wynter (2011)	Time Series	Traffic flow prediction	Multivariate Spatial-Temporal Autoregressive (MSTAR)
Stathopoulos and Karlaftis (2003)	Time Series	Traffic flow prediction	Multivariate Time-Series State Space
Kumar and Vanajakshi (2015)	Time Series	Traffic flow prediction	Seasonal Autoregressive Integrated Moving-Average (SARIMA)
Yang et al. (2009)	Time Series	Travel time prediction	Generalized autoregressive conditional heteroscedasticity (GARCH)
Goh et al. (2012)	Probabilistic	Traffic flow prediction	Hidden Markov Model (HMM)
Zhou et al. (2018)	Kalman Filter	Traffic flow prediction	Interacting Multiple Model with the Multi-Kalman Filter (IMM and MKF)
Yuan et al. (2016)	Kalman Filter	Traffic sign recognition	Kalman Filter
Dobre and Xhafa (2014)	Context-Aware Platform	Traffic congestion prediction	Actual Contextaware Application (CAPIM)
LL et al., 2012	Data Fusion	Travel time prediction	Information Fusion Model
Shi et al. (2016)	Ensemble	Road crack detection	Random Forest
Abdulhai et al. (2003)	Reinforcement Learning	Traffic sign recognition	Q-Learning
Rice and Van Zwet, 2004	Linear Regression	Travel time prediction	Linear Regression (LR)
Lee et al. (2011)	Bottleneck Mining	Traffic congestion prediction	Spatiotemporal traffic bottleneck mining (STBM)

fuzzy neural network is optimized in its configuration parameters for the learning and recognition of these patterns. Yanwu et al. (2010) propose an extended detection speed metric, named feature-per-object (FPO) to measure the detection speed independently from execution. Sun et al. (2012) propose four prediction models from combining two models with single-task learning (STL) and multitask learning (MTL), improving the experimental efficiency and accuracy. Khodayari et al. (2012) propose a modified neural network approach to simulate and predict the car-following behavior based on the instantaneous reaction delay of the driver-vehicle unit as the human effects.

5.2. Deep learning algorithm

Among the series of data-driven Big Data, deep learning models are considered one of the most promising models to tackle various features of ITS. Highly cited papers in ITS which apply deep learning techniques mostly covers problems with traffic flow prediction, sign detection, and traffic congestion evolution.

Dia (2001) discusses an object-oriented neural network model that was developed for predicting short-term traffic conditions. The results obtained indicate that the Time-Lag Recurrent Network (TLRN) is capable of predicting speed up to 5 min into the future with a high degree of accuracy (90–94%). Jin et al. (2001) propose a new technique for freeway incident detection using a Constructive Probabilistic Neural Network (CPNN). Lv et al. (2014) propose a novel deep learning model that has lately received the attention of other scholars. The model considers the spatial and temporal correlations inherently and is combined with a Stacked Autoencoder (SAE) model to learn generic traffic flow features. The result of the experiment of this model compared to other deep learning models shows that the proposed model is superior in traffic flow prediction. Huang et al. (2014) develop a deep architecture consisting of two parts: a Deep Belief Network (DBN) at the bottom and a multitask regression layer at the top which is used for supervised prediction.

The result of the experiment demonstrates that the incorporation of a multitasking regression layer in deep architecture is promising in traffic flow prediction. Koesdwiady et al. (2016) incorporate DBN and decision-level data fusion scheme to firstly find a correlation between weather parameters and traffic flow and secondly enhance traffic prediction accuracy using weather conditions. In predicting the short-term traffic flow most early models require the length of the input historical data to be predefined and static. However, Tian and Pan (2015) address this shortage by suggesting Long Short-Term Memory Recurrent Neural Network (LSTM RNN) model which can determine the optimal time lags dynamically. Ma et al. (2015) use deep RNN-RBM architecture into a large-scale transportation network with 515 links and the generated speed information from 4000 taxis to predict traffic congestion evolution based on GPS.

Fu al., (2016) used Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) neural network methods to predict short-term traffic flow. The experiments demonstrate that the Recurrent Neural Network (RNN) based deep learning methods such as LSTM and GRU perform better than autoregressive integrated moving average (ARIMA) model. Zhao al., (2017) propose a traffic forecast model based on the LSTM network which considers a temporal-spatial correlation in traffic system via a two-dimensional network. A comparison with other representative forecast models validates that the proposed LSTM network can achieve better performance.

5.3. Instance-based algorithm

Instance-based algorithms typically compare new data to the existing database using a similarity measure to find the best match and make a prediction. The most popular instance-based algorithms are k-nearest neighbor (kNN), Learning Vector Quantization (LVQ), Self-Organizing Map (SOM), Locally Weighted Learning (LWL), Support Vector Machines (SVM). Among different instance-based techniques, kNN and SVM are the dominant ones in the ITS field. Some of the highly cited papers employing these two techniques are discussed in this section.

Mostly kNN in the ITS literature is applied for traffic flow prediction. Chang et al. (2012) propose a dynamic multi-interval traffic volume prediction model, based on the kNN non-parametric regression (kNN-NPR). Yu et al. (2016) introduce a short-term traffic condition prediction model based on the kNN algorithm with spatial-temporal parameters. The results show the proposed prediction model provides a good performance compared with the support vector machine (SVM) model, ANN model, real-time-data model, and history-data model. Xia et al. (2016) develop Spatial–Temporal Weighted kNN model, named STW-kNN, to enhance the accuracy and efficiency of short-term traffic flow forecasting.

Due to complex nonlinear, non-stationary traffic data SVM is a suitable modeling and prediction tool for a variety of applications. A version of SVM for regression is called support vector regression (SVR). The techniques are being used mostly for prediction in ITS literature. Castro-Neto et al. (2009) propose the Online-SVR model to predict short-term freeway traffic flow under both typical and atypical conditions. Since the prediction of traffic flow under untypical conditions is more challenging than prediction under typical conditions, the proposed Online-SVR is more suitable and useful in real-world operations. The result of online-SVR is more promising compare to the Gaussian maximum likelihood (GML), Holt exponential smoothing, and ANN models. Hong (2018) introduce SVR traffic flow forecasting model which employs the hybrid genetic algorithm-simulated annealing algorithm (GA-SA). The model is experimented using traffic flow data from northern Taiwan. Experiments show the model produces more accurate results compared to existing models.

Lippi et al. (2013) present two new support vector regression models, the first Radial Basis Function (RBF) Seasonal Kernel and the second Linear Seasonal Kernel. The proposed models are capable of exploiting the seasonality of traffic data, resulting in an interesting compromise between predictive accuracy and computational costs. Jeong et al. (2013) present a novel prediction model, called online learning weighted support-vector regression (OLWSVR), for short-term traffic flow predictions. Sun et al. (2015) develop a novel hybrid model Wavelet-SVM which combines the complementary advantages of Wavelet and SVM models and also overcomes the shortcomings of the existing models. The model is experimented in on the historical passenger flow data in the Beijing subway system and shows more accurate forecasting compared to the existing ones. Yao et al. (2017) propose SVM models for short-term traffic speed prediction. The first model is a single-step prediction model considering spatial and temporal parameters. The second model is a short-term traffic speed prediction model which includes the multi-time-step traffic prediction of several road links.

5.4. Times series algorithms

Since the early 1980s, extensive part transportation literature is concentrated on traffic flow forecasting. The literature is rich when it comes to time-domain approaches from Autoregressive Moving Average (ARIMA) to dynamic generalized linear models. ARIMA model is one of the most widely used regression techniques. Its applications in freeway traffic forecasting can be traced back to 1979 (Ahmed and Cook, 1979).

As a result of the introduction of uncertainty and variability in traffic data, the traditional modes with the assumption of constant variance are not suitable anymore. Thus, the researchers develop statistical volatility models that overcome these shortages. Stathopoulos and Karlaftis (2003) present a flexible and explicitly multivariate time-series state-space model using core urban area loop detector data near downtown Athens to predict traffic flow. Yang et al. (2009) introduce a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to study the volatility of travel time and forecasting it more accurately.

Min and Wynter (2011) adopt a Multivariate Spatial-Temporal Autoregressive (MSTAR) model to predict real-time road traffic. Zhang et al. (2014) propose a model to provide deeper insights into underlining traffic patterns and to improve the prediction accuracy and reliability by decomposing data into three techniques components an intra-day or periodic trend by introducing the spectral analysis technique, a deterministic part modeled by the ARIMA model, and the volatility estimated by the Glosten-Jagannathan-Runkle (GJR)-GARCH model. Kumar and Vanajakshi (2015) develop a model for short-term traffic flow prediction using Seasonal ARIMA (SARIMA). This model overcomes disadvantages in Box-Jenkins ARIMA models which demands a sound database for model building.

5.5. Genetic algorithm

Goldberg (1989) explains that the earliest optimization approaches such as the calculus-based, the enumerative and the stochastic methods have several disadvantages. For instance, they are local-based search models and suffer from the implications of the "dimensionality curse" while Genetic algorithms (GAs) are stochastic approaches that search over a population of points, not a single point. Vlahogianni et al. (2005) provide an advanced GA multilayered structural optimization model to help firstly the proper representation of traffic flow data with temporal and spatial characteristics and secondly the selection of the appropriate neural network structure. Zhang et al. (2014) and Lopez-Garcia et al. (2015) develop a Hierarchical Fuzzy Rule-Based System (HFRBS) model optimized by GAs and the Cross-Entropy (CE) to develop an accurate and robust traffic congestion prediction.

5.6. Other models

Among top highly cited papers, few papers use models other than above mentioned. Following, we discuss these models briefly. Yuan et al. (2016) introduce a unified incremental computational framework for traffic sign detection, tracking, and recognition tasks. The framework combines the tracking results using the motion model obtained by Kalman filter with the appearance detection to get a more accurate localization of traffic signs. Zhou et al. (2018) explore how to achieve dependable content distribution in the device-to-device (D2D)-based cooperative vehicular networks. In doing so, firstly vehicle trajectory is predicted by combining the Interacting Multiple Model (IMM) estimations with the Multi-Kalman Filter (MKF) approach based on GPS and GIS Big Data. Secondly, the determination of content distribution groups with different lifetimes is formulated as a coalition formation game.

Lee al. (2011) proposed a three-phase Spatiotemporal Traffic Bottleneck Mining (STBM) model, including several spatiotemporal traffic patterns to discover urban network spatiotemporal traffic bottlenecks. Goh et al. (2012) propose an online map-matching algorithm based on the Hidden Markov Model (HMM) that is robust to noise and sparseness to accurately map the GPS trajectories to the road network in real-time. LL et al. (2012) develop an adaptive information fusion model to predict the short-term link travel time distribution.

Dobre and Xhafa (2014) introduce a platform designed to automate the process of collecting and aggregating context information on a large scale named actual context-aware application (CAPIM). Shi et al. (2016) present a model based on a random structured forest to detect road crack. Abdulhai et al. (2003) present a Q-learning, a simple yet powerful reinforcement learning algorithm with an application to traffic signal control. Rice and Zwet (2004) Employed a linear regression model for predicting travel times on freeways.

6. Conclusions

Continuous development of ITS, its various aspects, and the increase in volume, variety, velocity and veracity of ITS data result in more researches that aim to overcome the shortcomings of the exiting Big Data algorithms to explore new dimensions of the field. Most existing review papers in the literature investigate deeply into the mathematical modeling or focus only on one specific application of Big Data algorithms in ITS. However, this paper not only reviews the most relevant applications of ITS in which Big Data algorithms play a crucial role, but also provides an insight into the link between these applications and the employed models. Therefore, one of the outcomes of this paper is its clear classifications in terms of applications and algorithms for scholars in the other fields who are interested in learning about the application of Big Data algorithms in ITS.

Literature shows that as the number of Big Data algorithms increases and the computational tools become more capable of handling sophisticated models with the larger size of data, there is an increasing trend in combining different algorithms to address disadvantages of earliest models and solve more complicated problems in ITS filed, with more accurate result in a shorter period of time. From the reviewed articles, conspicuously, the artificial neural network and deep learning algorithms are the most dominant ones. Our findings show that the boundaries between Big Data algorithms are becoming less visible. By observing the novel merging of parametric and non-parametric statistical models and the development of new combined models, it can be concluded that the traditional borders are fading.

From the bibliographic perspective, the results indicate that IEEE Transaction on Intelligent Transportation System is the most relevant journal in the field. Yang Zhang and Xun Wang are the authors with the longest period of contribution to the filed. "Traffic flow prediction with Big Data: a deep learning approach" by Lv, Y (2014) is the most frequently cited article in our collection. In terms of Big Data algorithm keywords, "deep learning" and "neural network(s)" are the most repeated keywords. Another finding of this review is that although Big Data algorithms are applicable to the various types of ITS such as railway, water transport, air transport, roads, and others, we only find a few articles in our dataset with applications not related to roads.

Regarding various ITS applications, the most widely observed application in literature is the prediction concept. 229 works out of 586 articles and proceeding conference papers we reviewed contain the word "predict" or "forecast" in the title. This numerical evidence indicates the significant role of the prediction topic in the ITS. Among different features of prediction in the transportation system, "traffic flow prediction" is the hottest topic for researchers. Other dominant ITS applications that attracts scholars' attention is "detection" and "recognition". Although in this paper, we attempt to separate them based on the specific word that appeared in each individual article, when it comes to an object such as a traffic sign drawing, a clear line becomes challenging.

7. Roadmap for future research

The premise of ITS hinges on the desire to improve transportation using technology and more recently Big Data algorithm. Despite the consistent development of new models for improving various aspects of ITS, there are still many issues to be considered in terms of research and development. There are a few gaps in literature around the topic of our study that follow our findings and would benefit from further research, which we discuss in this section.

In this review, we find very few studies using Big Data algorithm that cover other types of transportation than road. Future work could include studying the reasons behind this.

Our findings show that deep learning is the most dominant Big Data algorithm in ITS. However, little adoption is found in operations research and business analytics (Kraus et al., 2020). Future studies could focus on determining how to adopt deep learning models in ITS from an operations research perspective. Another compelling direction for future research is applying performance measurement models such as Data Envelopment Analysis (DEA) in ITS in the existence of Big Data. The novel DEA models (Khezrimotlagh et al., 2019) propose a framework with the capability of evaluating large-scale data.

In the end, the fact remains that further research into ITS is needed now more than ever. As the level of traffic congestion continues to increase, more vehicles are connected, more information is exchanged in real-time, the resulting air pollution becomes more of an environmental and health threat, and the demand for faster, more efficient transportation becomes more apparent.

Acknowledgement

The authors thank two anonymous reviewers for their helpful suggestions and comments.

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