Review on "Vehicle Mobility Prediction for Intelligent Application by Using RNN"

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Abstract:

The recent advances in vehicle industry and vehicle to-everything communications are creating a huge potential market of intelligent vehicle applications, and exploiting vehicle mobility is of great importance in this field. Hence, this paper proposes a novel vehicle mobility prediction algorithm to support intelligent vehicle applications. First, a theoretical analysis is given to quantitatively reveal the predictability of vehicle mobility. Based on the knowledge earned from theoretical analysis, a deep recurrent neural network (RNN)-based algorithm called Deep VM is proposed to predict vehicle mobility in a future period of several or tens of minutes. Comprehensive evaluations have been carried out based on the real taxi mobility data in Tokyo, Japan. The results have not only proved the correctness of our theoretical analysis, but also validated that DeepVM can significantly improve the quality of vehicle mobility prediction compared with other state-of-art algorithms.

Keyword

Vehicle mobility, vehicle-to-everything (V2X), recurrent neural network, deep learning.

INTRODUCTION

With the recent advance of automobile technologies, the motor vehicle has evolved from a simple mechanical device to a smart platform incorporating various communication, computation and sensing functions. It is expected that future vehicles can provide not only pleasant and safe driving experiences, but also various kinds of services such as multi- media infotainment and social interactions. One of the most promising technologies to meet such expectations is vehicular networks that enable vehicles to efficiently exchange information through vehicle-to-vehicle, vehicle-to-infrastructure, and vehicle-to-pedestrian communications. The Third Generation Partnership Project (3GPP) group collectively defines these technologies as vehicle-to-everything (V2X) communications [1]. Gartner estimates that the annual production of network- connected vehicles will reach 61 million by 2020 [2] and this leads to a great potential market of many intelligent vehicle applications like self-driving assistance, vehicle-based sensing data collection, traffic safety, geo-advertising, in-vehicle Inter- net access, and pothole detection [3–7].

The mobility of vehicles makes the topology of V2X networks highly dynamic, and this is one of the main challenges faced by V2X communications. Thus, exploiting vehi- cle mobility is of great importance in implementing intelligent vehicle applications. As an example, a number of smart city applications only require sensing data periodically and are delay-tolerant to data transmission, e.g., smart grid applications like advanced metering are tolerant to a data delay from tens of minutes to several hours [8], and an application that monitors the running statuses of street lights is tolerant to a delay of several hours or even longer [3]. Since it is quite expensive to deploy so many femtocells of cellular networks to transmit these sensing data generated by a large amount of geo-distributed IoT devices, many researchers suggest utilizing short-rangeV2Xcommunicationtooffloadthesedelaytolerant data from cellular networks [3, 8–10]. Two representative short-rangeV2XcommunicationstandardsareIEEE802.11p and LTE-V2X Mode 4 [12] that cover a communication range from several hundred meters to very few kilometers. Figure 1 illustrates an example of applying vehicle mobility prediction to support this application. Assume that taxis $A and B$ are moving around a city and they opportunistically collect sensing data via short-range communication when they encounter the sensors deployed in city (i.e., when vehicles enter the communication range of sensors). Both taxis want to deliver these sensing data to a road side unit (RSU) in the left of figure by short-range communication, and this RSU utilizes wired broadband networks to transmit sensing data back to adata center for further processing. When two taxis encounter each other, taxi *A* can intelligently forward its stored data to taxi *B* by short-range communication if taxi *B* is predicted to be moving towards the RSU. Consequently, when taxi *B*encounters the RSU later, the data from taxi *A* are successfully delivered even if taxi *A* never encounters that RSU directly. This kind of multi-hop data forwarding strategy powered by mobility prediction can significantly improve the quality of vehicle-based sensing data collection [9, 10]. Other intelligent vehicle applications that may benefit from mobility prediction include geo-advertising that utilizes vehicle mobility to broad- cast advertisement in a specific city region [7] and mobile edge computing that utilizes vehicle mobility to stimulate the computationalresourcesharinginV2Xnetworks [13]. However, since most vehicles move at their own wills, it would be difficult to obtain a perfect knowledge about their future mobility. To avoid this great uncertainty, existing works either make use of some metrics such as the encounter and inter-encounter time distributions to implement coarse- grained vehicle mobility predictions [10, 13, 14], or simplify the problem to a Markov model that is not sufficient to make accurate prediction [9]. .

Consequently, this paper proposes a deep recurrent neural network (RNN)-based algorithm called DeepVM to predict vehicle mobility accurately, and its main contributions are:

(1) A solid theoretical analysis is presented to reveal the predictability of vehicle mobility quantitatively;

(2) Based on the knowledge earned from theoretical analysis, a deep RNN-based algorithm called DeepVM is proposed to predict vehicle mobility. To the best of our knowledge, DeepVM is the first trial of deep learning technology in this field worldwide;

(3) Extensive evaluation results based on real taxi move- mentshave not only validated the correctness of our theoretical analysis, but also shown that DeepVM significantly improves the quality of vehicle mobility prediction compared with the state-of-art algorithms.

A preliminary study of this work was presented in a conference paper [15]. Compared with its conference version, this paper supplements an entropy-based theoretical analysis to quantitatively evaluate the predictability of vehicle mobility and its correlation with vehicular trajectory knowledge. This analys is not only reveals the benefits of using deplearning for vehicle mobility prediction, but also explains the motivation of the proposed DeepVM algorithm. Furthermore, this paper sup- plements extensive evaluations to validate DeepVM from dif- ferent aspects. Instead of simply comparing the performances of DeepVM and other state-of-art algorithms, the evaluation results presented in this paper emphasize on clarifying the theoretical factors that contribute to the superior performance of DeepVM. Over 75% analysis and evaluation results of this paper are first presented. Finally, the introduction and related work parts of this paper are also improved to better illustrate the application scenarios and novel points of DeepVM.

RELATEDWORK

There are many existing works aim at predicting vehicle mobility in the background of selecting a stable wireless link for routing data in vehicle ad-hoc networks [16–18]. Agarwal et al. proposed a Dead Reckoning mechanism that uses the linear sum of a vehicle's instant position and velocity to predict its near future positions [16]. Balico et al. adopted a shallow feed forward neuralnetwork with one hiddenlayer to predict vehicle mobility [17]. Their neural network accepts the instant position and velocity of a vehicle as input, and outputs its predicted next position with a time interval from 0.5 to 2 seconds. Evaluation results based on real vehicular trajectories have illustrated that this algorithm reduces mobility prediction error when compared with the Dead Reckoning and Kalman filter-based algorithms. Aljeri et al. described a prediction algorithm based on a Particle filter [18]. They modeled the mobility prediction problem as an iterative Particle filtering process on three parameters, i.e., the position, velocity, and acceleration of a vehicle. Their results have validated that the Particle filter-based algorithm outperforms those based on Kalman and extended Kalman filters. However, since these works only aim at predicting vehicle mobility to improve the quality of ad-hoc data routing, they assume a vehicle's kinetic parameters like velocity and acceleration are relatively constant during the concerned data transmission period of a few seconds. Obviously, this assumption does not hold in the scenario with a longer prediction period like several or tens of minutes. Zhu et al. have proved that the uncertainty of future vehicle mobility can be reduced by giving the knowledge of previous vehicular trajectory, and used a 2-order Markov model-based algorithm to predict vehicle mobility accordingly [9]. However, there are two limitations in their work: (1) The theoretical analysis only concerns predicting a vehicle's position in the next one time slot; and (2) Based on their incomplete theoretical analysis, a 2-order Markov model is claimed to be sufficient for predicting vehicle mobility. Our work in this paper not only extends the theoretical analysis in

[9] to predict vehicle mobility in multiple future time slots, but also proposes a novel deep learning algorithm that outperforms Markov model-based algorithms significantly.

Several existing works also introduce the intelligent vehicle applications that may benefit from an accurate prediction of vehicle mobility. Bonola et al. evaluated the performance of using 120 taxis to collect and disseminate sensing data in Rome, Italy [3]. They have shown that even a small fleet of 120 taxis can disseminate sensing data to 80% areas of Rome in one day. However, their work does not exploit the possibility of predicting vehicle mobility to accelerate this process. Lin et al. introduced a sensing data collection framework by using the short-range V2X communication in smart city [10]. Their algorithm extracts the regular routes of vehicles from their daily mobility trajectories, and derives the encounter opportunities between different pairs of vehicles and RSUs accordingly. As a result, they let a vehicle with less opportunities to encounter RSUs forward its sensing data to other vehicles that have more opportunities to encounter RSUs. This kind of multi-hop data forwarding strategy can not only improve the success ratio of data collection, but also reduce the delay of data collection significantly. Compared with our work that focuses on predicting vehicle mobility, Lin et al. hypothesized that vehicle mobility is almost regular and their algorithm does not try to use any vehicle mobility prediction approach to estimate the encounter opportunities between vehicles and RSUs. Liu et al. proposed a mobile edge computing architecture that can be applied to V2X networks [13]. In this architecture, a vehicle partitions itscomputational task into several subtasks and delegates them to the service providers like RSUs and other vehicles that are opportunistically encountered during movement. Service providers start to execute the received subtasks by using their own computational resources. When the execution of a subtask is finished, the requesting vehicle downloads task results from the corresponding service provider when they encounter again. This architecture adopts some coarse-grained mobility statistics such as the encounter interval and duration between vehicles and service providers to accelerate task completion while ignoring the potential of trajectory-based mobilityprediction

Finally, an increasing number of researchers are applying deep learning technology to explore the crowd and traffic flows in city [19–22]. Song et al. proposed a deep RNN architecture to jointly learn human mobility and transportation transition model from a heterogeneous data source of human movements and city transportation networks [19]. Their algorithm receives sequential input data of five time steps, and successfully explores the correlation between human mobility and their transportation modes to give accurate prediction. Compared with their work, our proposal presented in this paper aims at predicting vehicle mobility from raw GPS data only, and adopts a different RNN architecture that receives a much longer sequence of input data to against the high uncertainty of vehicle mobility. Zhang et al. designed a novel architecture called DeepST to predict the crowd flow in city [20]. They modeled the in-flow and out-flow of the crowd in different city regions and used a sequence of convolutional neural networks to learn the spatial-temporal pattern soft these flows. A software tool was also developed for users to view the historical, real- time and forecasting crowd flows in city. Lv et al. studied predicting the macro-level traffic flow in city with a deep stacked autoencoder, and trained the network layer by layer greedily [21]. They have proved that the deep learning-based model is more accurate compared with other baseline models. Li et al. proposed a deep belief network to mine the hidden features of the traffic data in Macao, and combined the deep belief network with a support vector regression classifier to predict traffic congestion accordingly [22]. Different from the previous three works [20–22] that mainly focus on optimizing urban transportation system by using city-wide traffic statistics to predict the macro-level flows of vehicles and crowd, our work in this paper aims at applying deep learning technology to predict the micro-level mobility of a vehicle by using its mobility trajectory directly.

It can be concluded from the above discussion that none of the existing works considers the possibility of using deep learning technology to predict vehicle emobility.Thus,ourwork presented in this paper validates the potential and superiority of this strategy by providing both theoretical and empirical evidences. Compared with the existing works on predicting the macro-level statistics of vehicular traffic flow, our proposal is more helpful to the intelligent vehicle applications that are driven by the separate mobility of each vehicle and aim at utilizing the opportunistic communication window between nearby vehicles and other internet of things to provide novel services.

Fig. 2: The snapshot of taxi mobility in one day.

Propose Work

Basic Idea

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Block Diagram

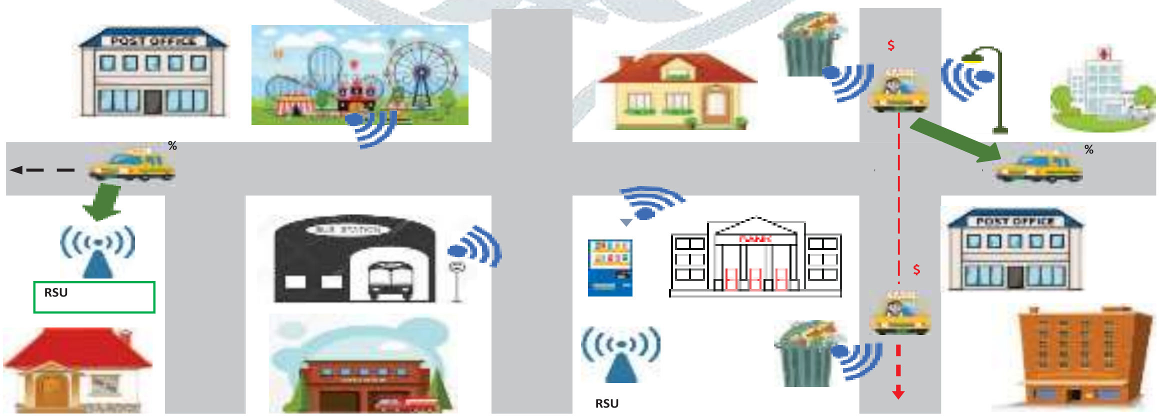

Figure1: Applying vehicle mobility prediction to assist the delay- to leran sensing data collection in smart city.

Above Figure illustrates an example of applying vehicle mobility prediction to support this application. Assume that taxis A and B are moving around a city and they opportunistically collect sensing data via short-range communication when they encounter the sensors deployed in city (i.e., when vehicles enter the communication range of sensors). Both taxis want to deliver these sensing data to a road side unit (RSU) in the left of figure by short-range communication, and this RSU utilizes wired broadband networks to transmit sensing data back to a data center for further processing. When two taxis encounter each other, taxi A can intelligently forward its stored data to taxi B by short-range communication if taxi B is predicted to be moving towards the RSU. Consequently, when taxi B encounters the RSU later, the data from taxi A are successfully delivered even if taxi A never encounters that RSU directly. This kind of multi-hop data forwarding strategy powered by mobility prediction can significantly improve the quality of vehicle-based sensing data collection. Other intelligent vehicle applications that may benefit from mobility prediction include geo-advertising that utilizes vehicle mobility to broadcast advertisement in a specific city region and mobile edge computing that utilizes vehicle mobility to stimulate the computational resource sharing in V2X networks. However, since most vehicles move at their own wills, it would be difficult to obtain a perfect knowledge about their future mobility. To avoid this great uncertainty, existing works either make use of some metrics such as the encounter and inter-encounter time distributions to implement coarse-grained vehicle mobility predictions, or simplify the problem to a Markov model that is not sufficient to make accurate prediction.

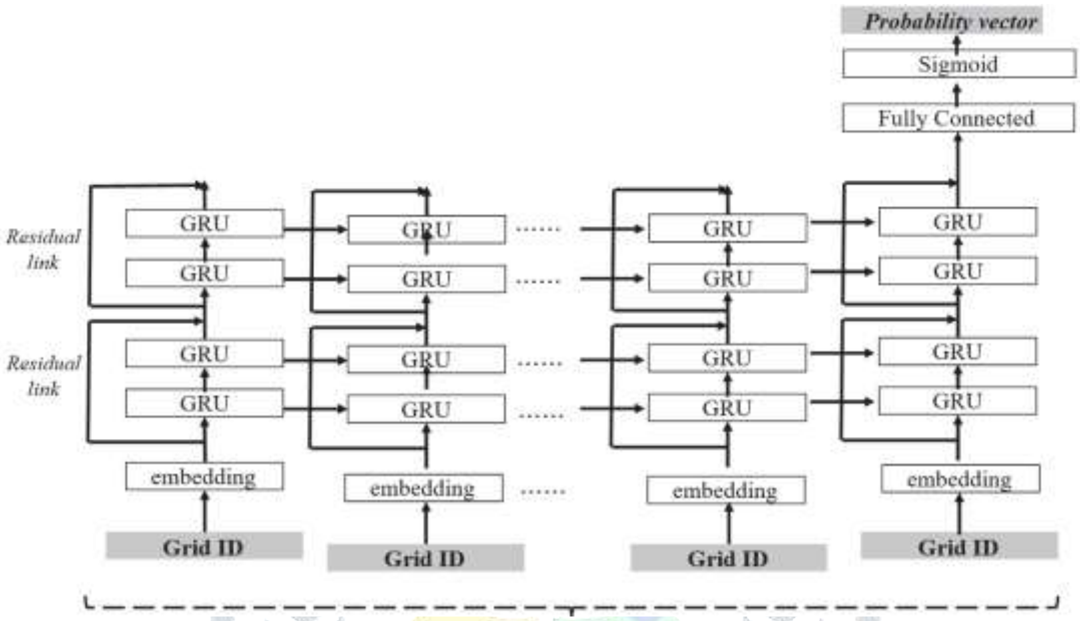

Figure 2: The neural network architecture of DeepVM algorithm unfolded in time

This section describes the mechanism of our proposed DeepVM algorithm in detail. Briefly speaking, DeepVM adopts a deep RNN architecture and processes a 16-order vehicular trajectory to predict vehicle mobility. The choice of a 16-order trajectory is somewhat arbitrary, and it is determined to balance the trade-off between algorithm performance and our computational resources. As illustrated by the previous theoretical analysis, a longer trajectory may further improve the performance of DeepVM. Figure 4 shows the neural network architecture of DeepVM unfolded in time. DeepVM first encodes every grid identity to an ndimensional one-hot vector where n is the number of grids in city space, e.g., a grid identity of 2 is encoded to (0, 0, 1, 0 · · · 0). Every input data item of DeepVM contains a sequence of 16 grid identities that represent where a vehicle located in the past 16 time slots. The advantage of this one-hot vector representation is that it takes each grid identity equally regardless of the geographical location of grid. However, it also leads to a very sparse data item that delays the convergence of deep learning, e.g., there may exist thousands of ’0’s but only a ’1’ in a vector. Thus, DeepVM uses an embedding layer to transform a sparse grid identity vector into a smaller and-denser feature vector. As will be shown in Section VI, this embedding step helps to accelerate the convergence of DeepVM without much performance degradation, and it is a well-accepted feature extraction method in deep learning. The embedded vector of vehicular trajectory is fed into the RNN cells of DeepVM. Hoch Reiter et al. have proved that vanilla RNN cells cannot extract the long temporal dependency of input data due to the gradient vanishing and exploding problems, and Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) cells have been widely used to address these drawbacks. DeepVM adopts GRU cells based on the two observations in our preliminary experiments: (1) The performance discrepancies between two kinds of cells are usually less than 1%; and (2) GRU cells converge faster in training since they employ less parameters than LSTM cells. DeepVM integrates two GRU blocks, and each block is composed by two layers of GRU cells. When trained by the embedded vectors of vehicular trajectory, these GRU blocks are able to learn and store the spatial-temporal correlations among the embedded vectors and use them to make predictions. A residual link is added to connect the input and output layers of each GRU block, and it helps to alleviate the issue of gradient vanishing in GRU blocks.

Conclusion

This paper proposes a deep learning-based vehicle mobility prediction algorithm called DeepVM to support intelligent vehicle applications. A theoretical analysis is first given to show that a long vehicular trajectory helps to reduce the uncertainty of future vehicle mobility. Based on the knowledge earned from theoretical analysis, DeepVM uses a deep recur- rent neural network to predict vehicle mobility. Comprehensive evaluations have proved that DeepVM can largely improve the quality of vehicle mobility prediction, and this superiority mainly comes from its ability to process a much longer vehicular trajectory than other state-of-art algorithms.

REFERENCES

[1] "Study on lte-based v2x services (release 14)." Tech. Specifi- cation Group Serv. Syst. Aspects (TSG SA), 3GPP TR 36.885, 2015.

[2] Gartner, "Forecast: Connected car production, worldwide," 2016.

[3] M.Bonola,L.Bracciale,P.Loreti,R.Amici,A.Rabuffi,and

G. Bianchi, "Opportunistic communication in smart city: Ex- perimental insight with small-scale taxi fleets as data carriers," *Ad Hoc Networks*, vol. 43, pp. 43–55, 2016.

[4] J. E. Siegel, D. C. Erb, and S. E. Sarma, "A survey of the con- nected vehicle landscapearchitectures, enabling technologies, applications, and development areas," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 8, pp. 2391–2406,2018.

[5] A. Fox, B. V. Kumar, J. Chen, and F. Bai, "Multi-lane pot- hole detection from crowdsourced undersampled vehicle sensor data," *IEEE Transactions on Mobile Computing*, vol. 16, no. 12, pp. 3417–3430,2017.

[6] B. Lonc and P. Cincilla, "Cooperative its security framework: Standards and implementations progress in europe," in *World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2016 IEEE 17th International Symposium on A*. IEEE, 2016, pp.1–6.

[7] J. He, L. Cai, P. Cheng, and J. Pan, "Delay minimization for data dissemination in large-scale vanets with buses and taxis," *IEEE Transactions on Mobile Computing*, vol. 15, no. 8, pp. 1939–1950,2016.

[8] N. Cheng, N. Lu, N. Zhang, T. Yang, X. S. Shen, and J. W. Mark,"Vehicle-assisteddevice-to-devicedatadeliveryforsmart grid," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 4, pp. 2325–2340,2016.

[9] Y. Zhu, Y. Wu, and B. Li, "Trajectory improves data delivery in urban vehicular networks," *IEEE Transactions on Parallel and DistributedSystems*,vol.25,no.4,pp.1089–1100,2014.

Z. Lin, Y. Lai, X. Gao, G. Li, T. Wang, and G. Huang, "Data gatheringinurbanvehicularnetworkbasedondailymovementpatterns," in *Computer Science & Education (ICCSE), 2016 11th International Conference on*. IEEE, 2016, pp. 641–646.

[10] S. Ucar, S. C. Ergen, and O. Ozkasap, "Multihop-cluster- based ieee 802.11 p and lte hybrid architecture for vanet safety message dissemination," *IEEE Transactions on Vehicular Technology*,vol.65,no.4,pp.2621–2636,2016.

[11] R. Molina-Masegosa and J. Gozalvez, "Lte-v for sidelink 5g v2x vehicular communications: A new 5g technology for short-range vehicle-to-everything communications," *IEEE Vehicular TechnologyMagazine*,vol.12,no.4,pp.30–39,2017.

[12] W. Liu, R. Shinkuma, and T. Takahashi, "Opportunisticresource sharing in mobile cloud computing: The single-copy case," in *The 16th Asia-Pacific Network Operations and Management Symposium*. IEEE, 2014, pp.1–6.

[13] K. Lee, Y. Yi, J. Jeong, H. Won, I. Rhee, and S. Chong, "Max- contribution: On optimal resource allocation in delay tolerant networks," in *INFOCOM, 2010 Proceedings IEEE*. IEEE, 2010, pp.1–9.

[14] W. Liu and Y. Shoji, "Applying deep recurrent neural networkto predict vehicle mobility," in *2018 IEEE Vehicular Networking Conference (VNC)*. IEEE, 2018, pp.1–6.

[15] A. Agarwal and S. R. Das, "Dead reckoning in mobile ad hoc networks," in *Wireless Communications and Networking, 2003. WCNC2003.2003IEEE*,vol.3.IEEE,2003,pp.1838–1843.

[16] L.N.Balico,H.A.Oliveira,E.L.Souza,R.W.Pazzi,and
E. F. Nakamura, "On the performance of localization prediction methods for vehicular ad hoc networks," in *Computers and Communication (ISCC), 2015 IEEE Symposium on*. IEEE, 2015, pp.359–364.

[17] N. Aljeri and A. Boukerche, "Performance evaluation of move- ment prediction techniques for vehicular networks," in *Com- munications (ICC), 2017 IEEE International Conference on.* IEEE, 2017, pp.1–6.

[18] X. Song, H. Kanasugi, and R. Shibasaki, "Deeptransport: Pre- diction and simulation of human mobility and transportation mode at a citywide level." in *IJCAI*, vol. 16, 2016, pp. 2618– 2624.

[19] J. Zhang, Y.Zheng, D. Qi, R. Li, and X. Yi, "Dnn-based prediction model for spatio-temporal data," in *Proceedings of the 24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. ACM, 2016, p.92.

[20] Y.Lv, Y.Duan, W. Kang, Z. Li,andF.-Y.Wang,"Traffic flow prediction with big data: a deep learning approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 2, pp. 865–873,2015.

[21] D. Li, L. Deng, Z. Cai, B. Franks, and X. Yao, "Intelligent transportation system in macao based on deep self coding learning,"*IEEETransactionsonIndustrialInformatics*,2018.

[22] W. Liu, K. Nakauchi, and Y. Shoji, "A neighbor-based proba- bilistic broadcast protocol for data dissemination in mobile iot networks," *IEEE Access*,2018.

[23] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, "Distributed representations of words and phrases and their compositionality,"in*Advancesinneuralinformationprocessing systems*, 2013, pp.3111–3119.

[24] S.HochreiterandJ.Schmidhuber,"Longshort-termmemory,"
Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[25] K.Cho,B.VanMerriënboer,C.Gulcehre,D.Bahdanau,
F. Bougares, H. Schwenk, and Y. Bengio, "Learning phrase rep- resentations using rnn encoder-decoder for statistical machine translation," *arXiv preprint arXiv:1406.1078*, 2014.

[26] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp.770–778.

[27] M.Abadi,P.Barham,J.Chen,Z.Chen,A.Davis,J.Dean,
M.Devin,S.Ghemawat,G.Irving,M.Isard*etal.*,"Tensorflow: a system for large-scale machine learning." in *OSDI*, vol. 16, 2016, pp.265–283.