Abstract. This systematic mapping study investigates the use of Long short-term memory networks to predict time series data about air quality, trying to understand the reasons, characteristics and methods available in the scientific literature, identify gaps in the researched area and potential approaches that can be exploited on later studies.

Keywords: Long Short-term Memory (LSTM), Time Series, Air Quality, PM$_{2.5}$ prediction, Systematic Mapping

1. Introduction

Air pollution has become increasingly worrying for the population in recent times. As a result, data on air quality has been gradually increasing and the science underlying health-related impacts is also evolving rapidly [WHO 2016]. There are several air pollutants, the most common of which are Carbon Monoxide (CO), Ozone (O$_3$), Nitrogen Dioxide (NO$_2$), Sulfur Dioxide (SO$_2$) and Particulate Material (PM$_{10}$ and PM$_{2.5}$), which are pollutants monitored to make the so-called Air Quality Index (AQI) which qualitatively says the state of the environment. The monitoring of these pollutants is usually done on a macro-scale by meteorological stations scattered at strategic points in cities.

These pollutant data are said to be a time series, which is a set of observations ordered in time. This makes it possible to use analytical methods to tell whether the air quality is good for the population or not. Among these methods there is descriptive analysis, which only describes current and past events. Predictive analysis, which uses past data to try to predict future actions. There is also prescriptive analysis, which uses predictive and/or descriptive analysis to make or recommend decisions based on the results obtained by the analyzes.

There are some ways to make data prediction, including the use of artificial neural networks (ANN) that are commonly used to recognize patterns [Crone and Kourentzes 2010]. As the data have a strong relationship with time, one of the most recommended networks is a recurrent neural network (RNN) [Boné et al. 2003] which uses previous information to serve as an understanding of the current data in the neural network. With the wide application of time series models based on the RNN, greater precision of prediction and the long short-term memory recurrent network (LSTM-RNN) [Azzouni and Pujolle 2017] has been proposed. LSTM-RNN not only retains the timing characteristics of the RNN structure, but also has the memory function for time series.
The systematic mapping presented in this paper investigates the following questions: (i) the vehicle and dates of publication of the studies; (ii) the contexts of problems that have been addressed in LSTM networks related to Time Series; (iii) the LSTM models that are being used to treat problems in Time Series; (iv) effectiveness of LSTM models in predictions; (v) which are the hyperparameter configurations of the networks; (vi) which air quality characteristics are being used the most; (vii) what other neural network methods are being used in conjunction with the LSTM. This mapping was structured in 7 research questions, where 155 studies were selected and analyzed, 57 of which were approved by reading the abstract and keywords, and from these, 12 had the data extracted, according to the systematic mapping method used.

This article is organized as follows. Section 2 presents a theoretical foundation about the research. Section 3 the research protocol used. Section 4 the main results. Section 5 a discussion of the results. Section 6 concludes the work.

2. Background
In this section, to aid in the decision-making of research questions, which is the object of systematic mapping, and define the scope of our investigation, we discuss some of the key concepts in the research areas studied (LSTM).

2.1. LSTM
The original LSTM idea was initially proposed by [Hochreiter and Schmidhuber 1997] and since then different models have been proposed to improve the performance of LSTM [Cho et al. 2014], [Li et al. 2019], [Karevan and Suykens 2020], [Hu et al. 2020]. The LSTM uses a locking mechanism to control the information that must be maintained over time, the duration that must be maintained and the time that can be read through the memory cell.

The LSTM recurrent neural network consists of a module with memory cells that can learn data characteristics in the time domain. It has been widely used in many fields due to its improved processing performance for time series data. The memory module in the LSTM recurrent neural network contains three multiplication units: an input gate, a forgetting gate and an output gate. These gates control the input, update and output of information, respectively, so that the network has a certain memory function. On the other hand, the network has more learning parameters due to these gates.

3. Research Protocol
This systematic mapping study was performed following the guidelines proposed by the systematic literature reviews that involve three main phases [Keele et al. 2007]. The Planning phase refers to the preview activities and aims at establishing a review protocol defining the research questions, inclusion and exclusion criteria, study sources, search string, mapping procedures and the control papers. These control papers are works that closely match with the objectives of the study and the inclusion and exclusion criteria used to define the selected papers. Thus, the control papers must be part of the selected works.

The Conducting phase consists of searching, selecting and analyzing the studies, in order to extract and synthesize their data. This phase executes the plan defined in the Planning phase. The last is the Report phase, which is characterized by the writing of the results to disseminate them. The main results from the first phase are presented below.
3.1. Research Questions

This mapping aims at answering the following research questions:

**RQ1.** When and where have the studies been published?

**RQ2.** Which contexts have been most approached in LSTM networks related to Time Series?

**RQ3.** Which LSTM models are being used to treat time series problems?

**RQ4.** What hyperparameters have been used in LSTM networks?

**RQ5.** What air quality characteristics have been most approached?

**RQ6.** What other neural network methods are being used in conjunction with LSTM?

**RQ7.** Are LSTM models effective in predicting Time Series?

3.2. Inclusion and Exclusion Criteria

Only 1 inclusion criteria (IC) and 8 exclusion criteria (EC) were created. The inclusion criterion is: (IC1) The study uses LSTM in data time series on air quality. The exclusion criteria are: (EC1) The study does not have an abstract; (EC2) The study is just published as an abstract; (EC3) The study is not written in English; (EC4) The study is an older version of another study already considered; (EC5) The publication is a tutorial, events annals, lecture log or secondary study; (EC6) It was not possible to access the study; (EC7) The study does not satisfy the inclusion criteria; (EC8) Does not use data about PM$_{2.5}$ or PM$_{10}$.

3.3. Sources

The search was applied to 7 electronic databases. However, it was not possible to export data from some databases used, so the results of the research of only two of them were used, which are:

- Scopus (http://www.scopus.com)
- IEEE Xplore (https://ieeexplore.ieee.org)

3.4. Keywords and Search String

The search string used in this study considered three areas: the LSTM neural network, Time Series and Air Pollution (see Table 1), and was applied to three metadata fields (title, abstract and keywords). The string has been refined about 7 times to fit the proposed study topic.

### Tabela 1. Keywords and Search String

| Area          | Keywords                                                                 |
|---------------|--------------------------------------------------------------------------|
| LSTM          | "LSTM", "long short-term memory", "prediction", "prescription"          |
| Time Series   | "Time Series", "forecasting", "forecast"                               |
| Air Pollution | "air", "pollution"                                                      |

**Search String:** ("LSTM" OR "long short-term memory") AND "Time Series" AND ("forecast*" OR "prediction" OR "prescription") AND ("air" OR "pollution")
3.5. Data Storage
The studies returned in the searching phase were cataloged appropriately. This helped to classify and analyze the studies for the next phase more clearly and intelligently.

3.6. Assessment
The mapping protocol was tested to verify its feasibility and adequacy, based on a pre-selected set of studies considered relevant for the investigation. The review process was conducted by the first author from this paper, who carried out its validation. About 37% of the studies were analyzed.

4. Conduction the Mapping
In this section, we discuss the main steps of this research, namely: search and selection, and synthesis and data analysis.

4.1. Search and Selection
Only articles from 2013 onwards were considered because as the theme is recent, no publications were found before this date. As a result, 155 publications were returned, of which 109 from Scopus, and 46 from IEEE Xplore.

A selection process for the returned publications was applied, which was divided into 3 stages. In the first, duplicates are eliminated based on examining the title and abstract, and the number of publications has been reduced to 123 (20.64% reduction). In the second step, the inclusion and exclusion criteria were imposed considering the title and abstract. 65 publications (52.84%) were eliminated. Some papers had a slightly confused title and abstract and made it difficult to apply the inclusion and exclusion criteria. This made it necessary to read the introduction of these studies to apply the criteria.

Finally, in the third step, the inclusion and exclusion criteria were applied considering the entire text, reducing the number of publications from 58 to 12 (79.31%). Unfortunately, many publications with excellent abstracts were eliminated because it is not possible to have access to the entire text. Attempts have been made to contact some of the authors of these excluded papers, but there was still no feedback.

From these steps, we selected 12 studies that were considered relevant, 9 + 3 control papers, for the next phase: Data Analysis. Table 2 shows the steps and results of the selection process. The selection process resulted in a reduction of about 92%, 12 out of 155. Table 3 lists these 12 studies that were considered relevant.

4.2. Synthesis and Data Analysis
In this section, answers to research questions are presented.

RQ1. When and where have the studies been published? – The selected publications were published between 2017 and 2020, being that in 2019 there is a higher occupancy rate (50% of publications). In relation to type of publication vehicle, 75% were published in Journals and 25% in Conferences, highlighting the IEEE Access with 25% of publications.

RQ2. Which contexts have been most approached in LSTM networks related to Time Series? – The main prediction problems were in relation to PM$_{2.5}$, Figure 1 shows the relationships of the predictions made in the studies. Standing out
| Step | Criteria                  | Analyzed Content       | Initial N. of Studies | Final N. of Studies | Reduction (%) |
|------|---------------------------|------------------------|-----------------------|---------------------|---------------|
| 1ª   | Eliminating Duplication  | Title and Abstract     | 155                   | 123                 | 20,64%        |
| 2ª   | IC1, EC3, EC5, EC6, EC7   | Title and Abstract     | 123                   | 58                  | 52,84%        |
| 3ª   | IC1, EC8                  | Entire Text            | 58                    | 12                  | 79,31%        |

| ID   | Reference                  | ID     | Reference                  |
|------|---------------------------|-------|---------------------------|
| [1]  | [Singh et al. 2019]       | [2]   | [Zhao et al. 2019]        |
| [3]  | [Riekstin et al. 2018]    | [4]   | [Li et al. 2020b]         |
| [5]  | [Lu et al. 2020]          | [6]   | [Qin et al. 2019]         |
| [7]  | [Wu and Lin 2019]         | [8]   | [Liu et al. 2019]         |
| [9]  | [Liu et al. 2020]         | [10]  | [Thaweephol and Wiwatwattana 2019] |
| [11] | [Park et al. 2017]        | [12]  | [Li et al. 2020a]         |

For making predictions of the lag effect of pollutants on respiratory diseases, and [Liu et al. 2019] for using predictions to treat haze-fog problems.

**RQ3. Which LSTM models are being used to treat time series problems?**
– Among the models used in the publications, 67% were the standard LSTM and 33% were a new version of the LSTM. In this one we highlight one of the control papers, [Zhao et al. 2019] by LSTM-FC, and also [Li et al. 2020b] by CNN-LSTM and [Li et al. 2020a] by AC-LSTM which is a variant of CNN-LSTM with a layer of attention mechanisms (attention-based layer).

**RQ4. What hyperparameters have been used in LSTM networks?**
– The hyperparameters used vary widely in each publication, among them the number of LSTM...
layers varied from 1 to 64, the nodes varied from 16 to 800 for each layer. Batch size was 2 to 108, epochs from 20 to 639. About the activation function, 42% opted for sigmoid, 25% opted for ReLu and 33% did not specify. 16% used optimizer Adam, and 16% also used RMSProp, highlighting [Park et al. 2017] who used Adagrad in addition to RMSProp and compared the performance between the two, in which it can be seen that RMSProp performed better.

**RQ5. What air quality characteristics have been most approached?** – Among the pollutants approached, PM$_{2.5}$ had a greater focus with a presence in 83% of the articles, followed by PM10 with 58%. In addition, 50% of the publications used other pollutants related to the Air Quality Index (AQI), such as [Thaweephol and Wiwatwattana 2019] which is able to correlate the growth of PM$_{2.5}$ with the other pollutants.

**RQ6. What other neural network methods are being used in conjunction with LSTM?** – CNN, RNN and SVR (support vector regression) are the most outstanding in relation to the networks that are being used together or for comparisons. Figure 2 shows all the models used. The paper [Li et al. 2020a] stands out for making comparisons with SVR, RFR (random forest regression), MLP (multilayer perceptron), RNN, LSTM, CNN-LSTM and presenting superior results to all of them.

**RQ7. Are LSTM models effective in predicting Time Series?** – All publications used metrics of moving averages of the error comparing the proposed model with other models. The metrics used were Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Pearson Correlation. The variations in error reduction goes from 7.45% to 500% as in the study [Park et al. 2017]. Another notable is [Qin et al. 2019] where Pearson correlation reaches 0.97, which is very close to the perfect one where 1 would be the perfect correlation between the real and the predicted value.

**5. Final Considerations**

This paper presented a systematic mapping that investigates the use of LSTM neural networks in time series data on air quality. 155 studies were investigated and 12 were
selected for further analysis. Despite the large number of publications returned from the search engines, it is possible that there are still publications that were not identified. A future work here is to enlarge the number of studies to get more accurate data or merge the data obtained by this research with others studies.

The contributions of this work are on showing and comparing the LSTM models used on time series prediction. In this context, we highlight the following conclusions: (i) A lot of studies in this area started to emerge after 2017, this shows a growing concern about air quality; (ii) Some studies already show that it is possible to create LSTM networks with unique characteristics for specific themes, thus improving their performance when compared to the standard model, as well as the creation of hybrid models using other neural networks together from LSTM as seen in [Zhao et al. 2019], [Li et al. 2020b] e [Li et al. 2020a]; (iii) Unfortunately, not all studies specified their network hyperparameters, but it is still possible to notice a preference in the activation function, sigmoid and ReLu, and in the optimizer, Adam and RMSProp; (iv) The effectiveness of LSTM models for predicting time series is remarkable in comparison with the statistical models in the literature and some other models of neural networks. Most of the studies obtained gains above 50% in the reduction of errors of the metrics MAE, MAPE and RMSE.

It is undeniable that concern with air quality is one of the areas that has grown the most in this area in recent years. And, as we can see, the use of LSTM models is, in fact, positively influencing the prediction of the main air pollutants. With the growth of IoT technologies and the advancement of artificial intelligence, it is promising to say that these improvements tend to become more and more optimized and with more accurate tools it is possible to improve the quality of life in relation to air quality.

Referências
Azzouni, A. and Pujolle, G. (2017). A long short-term memory recurrent neural network framework for network traffic matrix prediction. arXiv preprint arXiv:1705.05690.
Boné, R., Assaad, M., and Crucianu, M. (2003). Boosting recurrent neural networks for time series prediction. In Artificial neural nets and genetic algorithms, pages 18–22. Springer.
Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., and Bengio, Y. (2014). Learning phrase representations using rnn encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078.
Crone, S. F. and Kourentzes, N. (2010). Feature selection for time series prediction—a combined filter and wrapper approach for neural networks. Neurocomputing, 73(10-12):1923–1936.
Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8):1735–1780.
Hu, J., Wang, X., Zhang, Y., Zhang, D., Zhang, M., and Xue, J. (2020). Time series prediction method based on variant lstm recurrent neural network. Neural Processing Letters, pages 1–16.
Karevan, Z. and Suykens, J. A. (2020). Transductive lstm for time-series prediction: An application to weather forecasting. Neural Networks, 125:1–9.
Keele, S. et al. (2007). Guidelines for performing systematic literature reviews in software engineering. Technical report, Technical report, Ver. 2.3 EBSE Technical Report. EBSE.

Li, S., Xie, G., Ren, J., Guo, L., Yang, Y., and Xu, X. (2020a). Urban pm2.5 concentration prediction via attention-based cnn-lstm. *Applied Sciences*, 10(6):1953.

Li, T., Hua, M., and Wu, X. (2020b). A hybrid cnn-lstm model for forecasting particulate matter (pm2.5). *IEEE Access*, 8:26933–26940.

Li, Y., Zhu, Z., Kong, D., Han, H., and Zhao, Y. (2019). Ea-lstm: Evolutionary attention-based lstm for time series prediction. *Knowledge-Based Systems*, 181:104785.

Liu, B., Guo, X., Lai, M., and Wang, Q. (2020). Air pollutant concentration forecasting using long short-term memory based on wavelet transform and information gain: A case study of beijing. *Computational Intelligence and Neuroscience*, 2020.

Liu, Q., Zou, Y., and Liu, X. (2019). A self-organizing memory neural network for aerosol concentration prediction. *Computer Modeling in Engineering & Sciences*, 119(3):617–637.

Lu, J., Bu, P., Xia, X., Yao, L., Zhang, Z., and Tan, Y. (2020). A new deep learning algorithm for detecting the lag effect of fine particles on hospital emergency visits for respiratory diseases. *IEEE Access*, 8:145593–145600.

Park, J.-H., Yoo, S.-J., Kim, K.-J., Gu, Y.-H., Lee, K.-H., and Son, U.-H. (2017). Pm10 density forecast model using long short term memory. In 2017 Ninth International Conference on Ubiquitous and Future Networks (ICUFN), pages 576–581. IEEE.

Qin, D., Yu, J., Zou, G., Yong, R., Zhao, Q., and Zhang, B. (2019). A novel combined prediction scheme based on cnn and lstm for urban pm 2.5 concentration. *IEEE Access*, 7:20050–20059.

Riekstin, A. C., Langevin, A., Dandres, T., Gagnon, G., and Cheriet, M. (2018). Time series-based ghg emissions prediction for smart homes. *IEEE Transactions on Sustainable Computing*.

Singh, P., Narasimhan, T. L., and Lakshminarayanan, C. S. (2019). Deepair: Air quality prediction using deep neural network. In *TENCON 2019-2019 IEEE Region 10 Conference (TENCON)*, pages 869–873. IEEE.

Thaweephol, K. and Wiwatwattana, N. (2019). Long short-term memory deep neural network model for pm2.5 forecasting in the bangkok urban area. In *2019 17th International Conference on ICT and Knowledge Engineering (ICT&KE)*, pages 1–6. IEEE.

WHO, W. H. O. (2016). Ambient air pollution: A global assessment of exposure and burden of disease.

Wu, Q. and Lin, H. (2019). A novel optimal-hybrid model for daily air quality index prediction considering air pollutant factors. *Science of The Total Environment*, 683:808–821.

Zhao, J., Deng, F., Cai, Y., and Chen, J. (2019). Long short-term memory-fully connected (lstm-fc) neural network for pm2.5 concentration prediction. *Chemosphere*, 220:486–492.