Classification of the social distance during the COVID-19 pandemic from electricity consumption using artificial intelligence

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Summary
Accurately quantifying the social distancing (SD) practice of a population is essential for governments and health agencies to better plan and adapt restrictions during a pandemic crisis. In such a scenario, the reduction of social mobility also has a significant impact on electricity consumption, since people are encouraged to stay at home and many commercial and industrial activities are reduced or even halted. This paper proposes a methodology to qualify the SD of a medium-sized city, located in the northwest of the state of Rio Grande do Sul (RS), Brazil, using data of electricity consumption measured by the municipality’s energy utility. The methodology consists of combining a dataset, and an average consumption profile of Sundays is obtained using data from 4-months, it is then defined as a high SD profile due to the typical lower social activities on Sundays. An supervised and an unsupervised artificial neural network (ANN) are trained with this profile and used to analyze electricity consumption of this city during the COVID-19 pandemic. Low, moderate, and high SD ranges are also created, and the daily population behavior is evaluated by the ANNs. The results are strongly correlated and discussed with government restrictions imposed during the analyzed period and indicate that the ANNs can correctly classify the intensity of SD practiced by people. The unsupervised ANN is used more easily and in different scenarios, so it can be indicated for use by public administration for purposes of assess the effectiveness of SD policies based on the guidelines established during the COVID-19 pandemic.

KEYWORDS
artificial neural network, COVID-19, energy demand, social distancing

1 INTRODUCTION
The first register of the infectious disease known as COVID-19, caused by the SRA-CoV-2 coronavirus, was on November 2019 according to Hong Kong’s South China Morning Post. This new coronavirus was first detected in the Wuhan region, China, and caused serious respiratory health issues in some of the affected. From
February 2020 onward, several COVID-19 epidemic centers were identified in Asia, Europe, Middle East, and North America, many non-traceable. These new hubs contributed to the rapid expansion of this infectious disease, and the first cases in African and Latin-American countries were then confirmed.5

Due to the “alarming severity and dissemination levels,” the World Health Organization (WHO) declared the COVID-19 as a pandemic on March 11, 2020. Five days later, the total number of affected countries was 143, according to a WHO report.5 Important issues that led to this are the highly airborne infectious nature of the virus, the fact the about 85% of infected do not develop strong symptoms after acquiring the disease, and around 15% of those infected require hospital treatment and a percentage of these may have an aggravated condition, requiring hospitalization in intensive care units (ICUs) and use of mechanical respirators.2,6 The residence time of these patients in ICUs in many cases exceeds 15 days. The coronavirus pandemic has affected all people in different dimensions of society, everyone has been impacted by the virus directly or indirectly, so several government in different locations around the world have decreed the collapse in their health systems.7

Many countries have created task forces, expert groups, advisory committees, science boards, to define measures and take actions to minimize the problems caused by the pandemic. One of the main strategies suggested by health agencies to fight the growth of infectious diseases is the social distancing (SD), which is defined as reducing the interaction between people in a community, because the lower the population’s mobility and social interactions, the higher is the probability for the contagion in that region to halt.5 SD is an important strategy when there are asymptomatic or oligosymptomatic infected individuals, but they are not yet identified, so they are not isolated. This measure should be applied especially in places where community transmission occurs, when it is not possible to trace the link between the cases, and the isolation of people with the virus is insufficient to stop transmission.8,9 Examples of SD include closure of schools and public markets, cancellation of events, office buildings and gatherings, in order to avoid crowding of people; essential services can be maintained.8

Besides the SD, other traditional public health measures such as quarantine, lockdown, and isolation are also currently being adopted and studied by different countries across the globe. Quarantine is the activity and movement restriction of a group of people who have been exposed to contagious disease, but are not sick. Isolation is a measure that aims to separate sick and non-sick people to prevent the virus from spreading, it can occur at home or in a hospital environment, depending on the person’s clinical condition. When SD measures, quarantine and isolation are insufficient, the lockdown may be necessary.8,10,11 One of the main challenges to the governmental authorities is how to monitor and enforce these policies, especially considering the plurality of population sizes, different cultures and socioeconomic statuses. This monitoring is crucial, so public agencies can better plan health policies, estimate the transmission rates of the virus, and determine the restrictions that must be imposed on the population.

Some researchers have studied the impacts of the COVID-19 pandemic on the world,5,7,12-14 others have seen how the profile of electricity consumption can help to diagnose or predict events of different natures.15-18 Chakraborty and Prasenjit12 described the impact of the COVID-19 pandemic on society and global environment and discussed possible ways in which the disease can be controlled. Milani14 studied the social and economic responses related to the COVID-19 pandemic in a large sample of countries. Niţetă13 discussed the effects of the COVID-19 pandemic on global air transport mobility; the results revealed that the pandemic gradually affected the air transport in Europe, where a peak in the reduction in the number of flights occurred in April. Dincer7 discussed that the increased use of fossil fuels has weakened people's immune systems, making them more susceptible to COVID-19. The author suggests using hydrogen energy as an option to improve human health and well-being.

Aquino et al19 made a review of the impact of SD measures on the COVID-19 pandemic and discussed the implementation of these measures in Brazil. They selected works from the PubMed, medRXiv, and bioRxiv databases and found that the SD measures adopted are effective, especially when implemented in conjunction with the isolation of cases from infected and quarantined individuals. Carvalho et al19 analyzed from software Joinpoint the effects of the SD measures on electricity consumption in Brazil, the analysis comprehended the period between January 1 and May 27, 2020, focusing on the COVID-19 pandemic. The daily load data were grouped into weeks and compared with the periods before and after the application of the SD decrees in Brazil. Statistically significant decreases were observed in the levels of the electricity consumption and the Joinpoint analysis for the calculation of energy consumption trends allowed the outline of more precise measures for Brazilian policy makers.

For the evaluation and implementation of SD measures, it is necessary to manipulate a large amount of data, so the use of artificial intelligence (AI) is a likely solution to optimize and automate this task.20 AI is widely known as an excellent tool to recognize patterns and handle multivariable problems, and it has already
been employed in applications related to public health. Kakodkar et al.22 used AI to better diagnose patients suspected to have contracted COVID-19. Neto and Bianchi21 presented an analysis about the individual consumption habits and their impact on the residential energy efficiency, based on the usage habits in the Brazilian residential class and the application of AI. In addition, combining different data sets is an useful methodology for predicting electricity consumption scenarios and making plans. Udaeta et al.22 presented a data combination strategy for energy planning and to prioritize resources for energy supply, using environmental, political, social, technical, and economic aspects. Mello et al.23 estimated the efficiency of electricity usage and correlated to the average temperature and the population’s income in different cities.

Therefore, there is a concern with the growth of individuals infected by COVID-19, as well as with the impacts of the pandemic on the world.5,7,12-14 One of the main strategies suggested by health agencies to fight the growth of infectious diseases in places where community transmission occurs, such as in Brazil, is the SD.5,8,9 To implement and conduct monitoring of SD measures, many countries and policy agencies use location tracking through collecting individual mobile data in order to find agglomerations and quantify the amount of population that is staying at their homes.5 However, this kind of tracking raises critical security and privacy concerns, and it may not even be the most effective solution in many places due to bad network coverage or low-income. For instance, the amount of population over 10 years old that owned a personal smartphone in Brazil was of 78.2% in 2017, according to an IBGE report.24 On the other hand, this report also showed that 99.5% of households were connected to the public electric network. In this context, considering that the evaluation of SD measures is important to control the pandemic, that most households are connected to a public electricity network, and that this issue involves the management of large data volumes, the use of AI and the combination of different electricity consumption data sets can be a relevant alternative to address this problem.

This paper proposes a new methodology to quantify the SD of the population of a medium-sized city, located in the northwest of the state of Rio Grande do Sul (RS), Brazil, from the electricity consumption data and the application of AI. The methodology initially consists of the combination of a set of electricity consumption data from the municipality’s energy utility in a period of 4 months (ie November 3, 2019, to February 2, 2020). Then, based on the hourly data measured, ranges associated with a low, moderate, or high degree of SD are determined, and the energy consumption profile of Sundays is used as reference for reduced mobility of people. Afterward, a supervised and an unsupervised artificial neural network (ANN) are trained to assess the degree of SD practiced by the inhabitants of the municipality in period of March 10 to April 30, 2020, during the COVID-19 pandemic. Both the training of the ANNs and the performance validation data of the proposed methodology are generated from actual data provided by the municipality’s energy utility. The simulations results are performed in the Matlab software and are also correlated to a series of sociopolitical events that occurred in the same period.

The rest of this paper is organized as follows. Section 2 presents the case study along with the characteristics of the city and measurements of energy consumption of inhabitants on Sundays and on weekdays. Section 3 proposes a data combination methodology for identifying the range of SD (ie. low, moderate, and high degree) using the average electricity consumption as metric. Section 4 describes the structure and training conditions of a supervised and an unsupervised ANN. Section 5 shows the simulations results and also makes a discussion of the correlation between the results of SD ranges and the policies taken by local authorities during the same period. Finally, Section 6 presents the paper’s main findings and conclusions, as well as the possibility of future works.

2 | CASE STUDY

The case study presented in this paper is based on Ijui city, which holds a population of about 90 000 people, located in the state of RS, Brazil’s southernmost region, as shown in Figure 1. Ijui is mainly a service and commerce city, although also has small industries. Electricity distribution in urban zones is done by the Municipal Department of Electric Energy (DEMEI); currently, about thirty-three thousand consumers are served.

By analyzing Ijui’s inhabitants social behavior and commerce hours, it is established that the city has a similar profile as other small- and medium-sized Brazilian cities. Local commerce normally opens Monday to Friday from 8 AM to 6 PM, with a lunch break from 12 PM to 1:30 PM; on Saturdays, hours are usually limited to 12 pm. Only essential services function on Sundays, such as hospitals, groceries, and drug stores. Sundays are also characterized by a higher prevalence of people staying in their homes due to the city’s low number of leisure activities. Thus, it possible to infer that, in a city such as Ijui, Sundays have a high degree of the SD.

To validate this hypothesis, the electricity consumption of every Sunday in a period of 4 months (from November 3, 2019, to February 2, 2020), before the COVID-19 pandemic, is analyzed. Figure 2 shows the hourly average energy demand from the data measured.
by the DEMEI. Average daily consumption of 16.37 MW is observed from the measured period, with an average deviation of 1.86 MW and an average SD of 2.56 MW. The blue area in Figure 2 shows the city’s typical business hours, wherein an average consumption of 15.46 MW is observed, with an average error and SD of 2.24 MW and 1.63 MW, respectively.

From this data, in order to obtain a consumption range, a confidence interval of 99.7% representing the typical behavior of energy consumption on Sundays is determined, and ± 3σ standard deviations are considered for both the lower and upper limit, of the hourly average from the typical curves of the period of November 2019 until February 2020. Sunday’s electricity consumption curve is defined as the profile of electricity consumption on a day with high degree of SD.

In order to propose the ranges of SD, similarly, the city’s electricity consumption is also evaluated during the weekdays for the same 4 months period (from November 3, 2019, to February 2, 2020). Figure 3 shows a daily average of 20.4 MW, with an average error and SD of 3.63 MW and 1.31 MW, respectively. The average consumption during business hours, highlighted in blue, is calculated to be 22.21 MW with a slightly higher SD of 1.41 MW.

3 | SOCIAL DISTANCING QUANTIFICATION THROUGH ELECTRICITY CONSUMPTION

This section defines three different ranges of SD based on the combination of the Sundays and weekdays electricity consumption data sets discussed in the previous section. The data presented in Figures 2 and 3 are combined, as shown in Figure 4, therefore a low, moderate, and high
SD ranges are determined, respectively, indicated by the colors red, yellow, and green. It is emphasized again that the electricity consumption typical of Sunday days, between 8 AM and 6 PM, is considered similar to a day with high degree of SD.

The low degree of SD is indicated by the red color, it is defined by the electricity consumption of the weekdays and its lower limit occurs by the lowest values ($-3\sigma$) of the average energy demand consumed. Analogously, the high degree of SD is indicated by green color, it is defined by the electricity consumption of the Sunday days and its upper limit occurs by the higher values ($+3\sigma$) of the averaged energy demand utilized. The moderate degree of SD is indicated by the yellow color, it represents the intermediate electricity consumption between the two situations considered (ie, Sundays and weekdays).

To validate the proposed SD ranges, a preliminary analysis is carried out using the energy consumption data on April 14, 2020, during the COVID-19 pandemic, called Scenario 1. In Figure 5, this scenario is plotted on the SD ranges, it is characterized by a high degree of SD, except for 1-hour during lunch time, when the consumption level enters the moderate SD range. Nevertheless, this lunch-hour behavior is considered to be an outlier.

The results obtained from Scenario 1 are also validated by decree No. 55.154 published on April 1, 2020, by the governor of the state of RS, which determined the total suspension of the activities of commerce, industry and services, keeping active only those essential activities, so in practice that day is considered of high degree of SD.

4 | ARTIFICIAL NEURAL NETWORK PATTERN RECOGNITION

ANNs have successfully been employed in different applications for pattern recognition. In this paper, two training methods for the ANNs are used: supervised and unsupervised learning. In the first method, a set of examples with inputs and their respective outputs is introduced to the network during the training phase and then the ANN generalizes the learning for other inputs that are not part of the training. For unsupervised training of ANNs, examples are not provided, so the training process classifies the data without human intervention.

For unsupervised learning, an ANN using an one-dimensional Kohonen map with competitive learning is applied, containing 1 layer with 3 output neurons and 11 inputs, as shown in Figure 6. The output of each neuron is a degree of SD – being low, moderate, or high – without any pre-established output order. The inputs correspond to 11 hours (ie, from 8 AM to 6 PM) of electricity consumption average data of every day analyzed, as shown in Figure 4), such that a degree of SD is then defined for each day according to the neuron that is activated. Thus, this ANN is a clusterizer, it groups the days according to consumption profile and has a competitive process in which the weights of the neurons are adjusted so that the neuron with the best response to an input pattern has its activation enhanced. For its implementation, a Python language program was created, and the Neurolab library was used.

For the supervised training case, the values of the energy consumption shown in Figure 4 from 8 AM to 6 PM are also used. A feedforward ANN with 1 hidden layer is used, as shown in Figure 7, with 11 inputs, 200 hidden sigmoid neurons and 1 softmax function output neuron, $w$ are the ANN weights, and $b$ are the biases. This type of ANN structure is usually employed when there is a need to classify the inputs into a defined set of categories. The softmax activation function is applied to format the data into a range between 0 and 1, being that 0 and 1 are defined as low and high degree of SD, respectively; all intermediate values (ie, moderate) are determined by the ANN.

A total of 200 neurons in the hidden layer are used, so the ANN can arbitrarily classify the input data. The training is performed using the conjugate gradient backpropagation method, and the data are divided into training (60%), validation (20%), and test (20%), the performance is evaluated through the confusion and
cross-entropy matrices. Figure 8 shows the confusion matrices obtained from the supervised ANN training, validation, and tests, in addition it presents a summary matrix. In these matrices, the columns represent the values 0 (ie, low degree of SD) and 1 (ie, high degree of SD), while the lines represent the target from the definitions and averages and standard deviations calculated in each of the two classes. Besides that, the last column represents precision, and the last line represents total sensitivity. The main diagonal (in green) of the confusion matrix represents the quantitative of the classified results each class correctly. Finally, the last cell (in blue) shows the general accuracy of the classification of the degree of SD. It is observed that the general precision obtained is 100%.

The results of both ANNs, supervised and unsupervised, were obtained by two researchers independently, without one having previously known the results obtained by the other.

5 RESULTS AND DISCUSSION

This section presents the simulations results of the application of both supervised and unsupervised ANNs to determine the degree of SD during the COVID-19 pandemic in the municipality of Ijuí located in the northwest of the state of RS. After an initial analysis from Scenario 1 presented in Section 3, the Scenario 2 was defined using data measurements from a total period of 7 weeks and 2 days, as shown in Table 1. Nevertheless, only the 38 weekdays of this period were considered, since these are the days with higher population mobility and activity, especially in small- and medium-sized cities.

The lines in the Table 1 are the measurement dates while the columns are 1-hour intervals during business hours. Before validating the results obtained by ANNs, the average hourly electricity consumption in MW of the inhabitants of Ijuí city was placed within the three SD ranges established in Figure 4. So, the electricity consumption was classified by the red, yellow, and green color scale, which are respectively low, moderate, and high degree of SD, as shown in Table 1. In sequence, these results are discussed and correlated to a series of sociopolitical events that occurred in the period of March 18 to April 30, 2020.

For a better visualization of the effects of sociopolitical events in the SD of the inhabitants of Ijuí city, the week before the publication of the first decree was included in the analysis, that is, the data collection started on March 10 extending to April 30, when the writing of this paper was began. The first COVID-19 pandemic-related measure adopted by the Ijuí city was the Municipal Executive Decree No. 6.975, which suspended all classes in private and public institutions at all education levels, on March 18. Table 1 shows that this decree did not cause a significant impact in the electricity consumption, the degree of SD was classified as low (ie, red color), which was expected since all other commercial and industrial activities remained unaffected.

The behavior of people in the municipality of Ijuí began to change as of March 20, when the color in Table 1 became predominantly yellow, with the degree of SD changing from low to moderate, also alternating at times to high degree of SD (ie, green color). This social behavior is correlated to the Municipal Executive Decree No. 6.978, of March 19, which suspended all activities in churches, clubs, or any kind of agglomerations; in addition, it imposed restrictions to the local commerce by reducing the maximum number of clients per establishment and determined the sanitation measures that should be taken.

A third Decree No. 6.987 was published on March 25, wherein other economic and social activities were
further restricted. Aside from limiting a maximum occupation of 50% in all public spaces, it also declared the State of Emergency in the city of Ijuí. However, the overall population did not alter significantly their mobility.

Thus, as Table 1 the moderate degree of SD (ie, yellow color) was kept for a few more days.

A fourth Decree took the opposite road and soften several of the previously established measures. Business
owners and workers exerted great pressure over the City Hall in reason of the Easter holiday being near, a date with noteworthy commercial activities. On Saturday, March 28, Executive Decree No. 6.999 was published and withdrew and/or lighten many of the restrictions that were imposed to commercial activities. The impact of the latter decree is easily observed in Table 1 where the electricity consumption began to rise on the next weekday, March 30, and even reached values similar to those from before public SD policies, a low degree of SD (ie, red color) was observed again.

Finally, on April 1, restrictions imposed by the State Governor were published; that is, the Decree No. 55.154 determined a total suspension of all service, commercial, and industrial activities – except for the ones considered as essential – in all the state of RS. Furthermore, it also established legal penalties and fines for those who break the rules. Thus, from that date, according to Table 1, people's behavior altered rapidly, SD changed from low to moderate on April 2 (ie, red to yellow color), and from the following day to a high degree of SD (ie, green color), which remained until the April 23, as shown in Table 1. After that day, some flexibility measures started to take place on the part of the municipal executive power. According to Table 1, the degree of SD of the people started to be predominantly moderate (ie, yellow color), eventually changing to a high degree of SD (ie, green color), thus remaining until the end of the period.

Therefore, from the analysis performed, it is possible to verify that the methodology proposed satisfactorily classified the degree of SD of the population of the Ijuí's city, using the electricity consumption profile of inhabitants. In sequence, the supervised and unsupervised ANNs were applied to recognize from the electricity consumption data provided by DEMEI the different ranges previously defined, which are, low, moderate, and high degree of DS, and then they were compared to the electricity consumption classification described in Table 1.

After training the supervised and unsupervised ANNs, the same Scenario 2 presented in Table 1 was used for validation. Figure 9 presents the simulations results very similar for both ANNs. The output data of the supervised ANN are in the range 0 (zero) to 1 (one), the value 0 represents the days of low degree of SD, the value 1 of high degree of SD, and intermediate values are classified by ANN representing the moderate degree of SD. For unsupervised ANN the output data are a range of SD, being low, moderate, or high, without any preestablished output ordem. In addition, the results are satisfactory, since they correctly classify the SD degree of the population and coincide with the results presented in Table 1, as well as with the decrees published by the municipal and state executive power.

This analysis can also be performed from direct comparison of both ANNs as presented in Figure 10. It shows the electricity consumption level in MW in the city of Ijuí along the day (from 8 AM to 6 PM), for the analyzed period (from March 10 to April 30, 2020). The colored bars on the right show the electricity consumption of inhabitants of the city of Ijuí, the darker the color, the lower the electricity consumption indicating that people are in their homes with a high degree of SD; the lighter the color, the greater electricity consumption indicating higher population mobility and activity, and in this case occurs a low degree of SD. The colored bars on the left show the classification of the days by the application of the supervised and unsupervised ANNs, in which red, yellow, and green are, respectively, low, moderate, and high degree of SD. It is possible to note that both ANNs present a very similar result.

It is noteworthy that the unsupervised ANN can be easier applied in different scenarios, it does not require data analysis and pre-classification. It only requires the definition of the number of classification groups and is independent from arbitrary threshold definitions. Therefore, the analysis of the degree of SD from the electricity consumption data in conjunction with an unsupervised ANN can be used by the public administration of the city in order to assess the effectiveness of the policies of SD of

![Figure 9: Demand for electricity consumption per hour of the analyzed period color-coded using the SD supervised and unsupervised ANNs](wileyonlinelibrary.com)
population from the established guidelines during the COVID-19 pandemic.

6 | CONCLUSIONS

In this paper, a methodology for assessing SD was presented, considering the electricity consumption of the population of a medium-sized city. The methodology initially proposed the combination of a data set on the electricity consumption of the municipality, and therefore energy consumption ranges associated with a low, moderate, or high degree of SD were determined. In sequence, a supervised and an unsupervised ANNs were trained to assess the degree of SD of the city's inhabitants. From the simulations results and comparison with the decrees published by the municipal and state executive power, it was observed that the supervised and unsupervised ANNs
immediately identified the degree of SD practiced by the city’s inhabitants, using only the information of the electricity consumption.

The unsupervised ANN is employed easier and in different scenarios in reason of not needing the data selection, analysis, and preclassification. In addition, there was no need to use methodologies that use data related to the privacy of the inhabitants, or that are based on the need to use mobile phone networks that are known, in several regions of our country, to not have adequate coverage. Therefore, the proposed methodology for analysis of the SD from the electricity consumption data in conjunction with an unsupervised ANN can be used by the city’s executive power to assess the effectiveness of the population’s DS policies based on the guidelines established during the COVID-19 pandemic. As future work, it is suggested the application of this methodology in other small- and medium-sized cities, as well as extending this methodology to cities of other sizes to quantify the population’s DS degree.

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DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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