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ANN-Based traffic volume prediction models in response to COVID-19 imposed measures

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ABSTRACT

Many countries around the globe have imposed several response measures to suppress the rapid spread of the COVID-19 pandemic since the beginning of 2020. These measures have impacted routine daily activities, along with their impact on economy, education, social and recreational activities, and domestic and international travels. Intuitively, the different imposed policies and measures have indirect impacts on urban traffic mobility. As a result of those imposed measures and policies, urban traffic flows have changed. However, those impacts are neither measured nor quantified. Therefore, estimating the impact of these combined yet different policies and measures on urban traffic flows is a challenging task. This paper demonstrates the development of an artificial neural networks (ANN) model which correlates the impact of the imposed response measure and other factors on urban traffic flows. The results show that the adopted ANN model is capable of mapping the complex relationship between traffic flows and the response measures with a high level of accuracy and good performance. The predicted values are close to the observed ones. They are clustered around the regression line, with a coefficient of determination ($R^2$) of 0.9761. Furthermore, the developed model can be generalized to determine the anticipated demand levels resulted from imposing any of the response measures in the post-pandemic era. This model can be used to manage traffic during mega-events. It can be also utilized for disaster or emergency situations, where traffic flow estimates are highly required for operational and planning purposes.

1. Introduction

In late 2019, an unexpected global pandemic started to spread around the world. The pandemic, which is called COVID-19, attacks the respiratory system of humans. During the first three months of 2020, the pandemic has reached almost all countries, affecting millions of lives, and overwhelming the healthcare systems of those countries. Many countries have adopted several policies, strategies, and measures to delay and control the spread of the pandemic, (Chen et al., 2021, Benita, 2021). The measures varied widely from one place to another, based on the assessment of local pandemic status. The pandemic spread and the imposed policies and measures have impacted numerous life aspects and regular daily activities. For most of the days in 2020, several countries observed a complete lockdown with strict movement restrictions, while other countries adopted partial movement restrictions (Dingil and Esztergár-Kiss, 2021). In 2021, many countries started to reduce the levels of restrictions (Das, 2022).

The pandemic proved that urban governance capacity and smart city construction play a significant role in preventing and controlling COVID-19 pandemic (Chu et al., 2021). The pandemic also proved that transport systems were highly vulnerable to those unexpected measures and restrictions. For instance, air traffic was severely affected as many international airports have ceased their operations completely (Suwamura et al., 2020, Manca et al., 2021, Nizetic, 2020, Santos et al., 2021). The land transport sector was also affected because of the lockdown and observed significant and sharp changes in travel behavior (Neuburger et al., 2021, Baris et al., 2021, Shakibaee et al., 2021). Public transportation services were either suspended or operated with very limited capacities (Vicker, 2021, Jenelius and Cebeauer, 2020, Wielechowski et al., 2020).

The State of Qatar has adopted a gradual approach to either restrict or release of certain activities during 2020-2021. Different response measures (either restrictions or release) were implemented with various levels. For example, 20% of the employees in public and private sectors...
were initially asked to work remotely. Based on the status of the pandemic, this percentage was incrementally increased to 50%, 80%, and 100% respectively. The percentage of remote work was gradually reduced as the pandemic status improved.

With respect to urban mobility in the State of Qatar, the pandemic and the implemented response measures that came along have significant impact on urban traffic demand. This impact makes the prediction of traffic demand under these unexpected measures extremely difficult. The level of congestion was reduced, and traffic volumes at junction and major arterials were reduced as well (Muley et al., 2021). In order to quantify this impact, there is a need to model this complex relationship between these unexpected contributing factors and changes in traffic volumes. Understanding such a relationship supports the process of planning and assessing the impact of fully or partially imposing some of the measures as traffic demand management strategies, and how to efficiently address any gap in the supply. Understanding this relationship can also be used to manage traffic demand for mega-events or emergency situations.

This study aims to investigate and assess the contribution of pandemic status and response measures in predicting daily traffic demand. Furthermore, the study illustrates the development of a reliable and robust prediction model to determine the daily traffic flows under a given set of measures so that evaluating the effect of various policies on urban mobility becomes an easy and reliable task. This study benefits from the nationwide implementation of response measures, so that their impact on traffic demand can be estimated with a high level of accuracy.

The added value of this study is derived from using real-life data that are observed in the reality in response to the pandemic. Within the context of large-scale or national social experiments, certain traffic demand changes are observed in response to deploying certain measures, such as school closure or promoting a given percentage of the remote work environment.

For instance, it could be argued that estimating traffic volumes can be derived from national transport models. However, it is extremely difficult to develop a well-calibrated model that can be used to predict the sudden and unexpected changes in traffic demand. Moreover, many issues should be addressed before using strategic transport model for such purposes, such as the lack of reliable revealed preferences surveys, the unexpected nature of the changes, the complexity of the imposed conditions, and the lack of previous or historical benchmarks with similar conditions. Since such conditions were never experienced or seen before 2020, validating transport models to reflect these conditions has its own issues, especially that it would have been impossible to be validated otherwise. In conclusion, this study provides a reliable alternative to estimate traffic volumes when unexpected events or measures exist.

The remaining sections of the paper are organized as follows, Section 2 emphasizes the motivations behind this study Section 3. presents a summary of relevant scientific articles and studies around the globe, where the impact of COVID-19 on travel behavior and other aspects of sustainable cities is investigated, including urban traffic prediction models Section 4. describes the research methodology, by identifying the type and nature of the collected data, how the data are collected, and the adopted ANN-based analysis and modeling methods Section 5. provides further details on the ANN-based modeling outcomes, where comparisons on the performances of different traffic demand prediction models are made Section 6. briefly discusses the policy implications that can be derived from this study. Finally, Section 7 sums up the key conclusions, along with recommendations for future work.

2. Study motivations

This study is motivated by the fact that the imposed measures have disturbed the daily routine activities, without any prior knowledge on how this disturbance would affect travel behavior or traffic demand. Therefore, there is a need to quantify the impact of the pandemic response measures on urban traffic flows through the development of a robust prediction model using artificial neural networks. The model should be capable of predicting urban traffic demand by utilizing the response measures and other available information.

Several studies have identified the impact of such measures on the transport sector by analyzing the effect on traffic demand and travel behavior (Dingil and Esztergár-Kiss, 2021, Patra et al., 2021), traffic safety (Yasin et al., 2021, Saladié et al., 2020, Lin et al., 2021, Shokouhyar et al., 2021), travelers' attitudes (Ceccato et al., 2021, De Vos, 2020, Kar et al., 2021, Brough et al., 2021, Zhang et al., 2021), and impact on air quality and environment (Singh and Chauhan, 2020, Nakada and Urban, 2020, Zangari et al., 2020, Benchrif et al., 2021, Polednik, 2021, Xin et al., 2021, Ferwati et al., 2018). However, this study differs from the existing literature by investigating the correlation between the pandemic’s response measures and urban traffic flows and then employing such a relationship in estimating traffic flows under different conditions in the future. For instance, sensitivity analysis can be done to determine the most effective measures in reducing urban traffic flows at an individual junction or a screen line when the target is to reduce traffic demand. Therefore, it is practical to eliminate measures that are not contributing toward reducing traffic demand. There was no comprehensive study in the literature to correlate the changes in urban traffic demand to the presence of the pandemic and the response measures that came along. This research fills this gap and uses real-life observed data to develop and model such as a correlation.

There are three specific concerns that are addressed in this study. The first concern is how to quantify changes in traffic demand in response to national crisis-imposed measures. The second concern is to assess the correlation between the pandemic perception by the public and traffic flows, if any. The third concern is to develop a model based on the pandemic experience that can predict traffic flows under given measures (such as online education or remote work environment) without relying on transport models that require extensive surveys, data collection, and data processing.

Many attempts were made to correlate traffic demand and seasonal variations, due to the significance and importance of such prediction for traffic engineers and transport planners. However, predicting traffic demand with the presence of unexpected factors (such as natural disasters or pandemics) has dragged less attention. This lack of attention can be attributed to the relatively short duration and locality of these factors. However, the COVID-19 pandemic is characterized by its global and long-lasting effect that has not been vanished as of February 2022. Moreover, there are no clear expectations on how it will be contained and fought. Many countries are still imposing a chain of measures without previous knowledge on how these measures are truly effective in reducing the pandemic spread or their impact on urban mobility.

3. Literature review

Due to the sudden and unexpected outbreak of the COVID-19 pandemic, and as a result of preventive measures, many activities that impact mobility were either restricted or suspended. Several attempts from different regions around the world were made to compare traffic demand levels in 2020 against their respective levels before the pandemic spread (i.e., before December 2019). One study in South Korea reported a statewide traffic demand reduction of 47.5% in 2020 when compared to their corresponding days in 2019 (Lee et al., 2020). The study also reported that the average daily traffic between January to March 2020 was less than the average daily traffic for the same period in 2019 by 10%.

A comparison of traffic flows in North Italy between February-May of 2019 and the same period in 2020 showed that the reduction in the number of vehicles at selected roadway sections in 2020 was up to 82% compared to 2019 (Marinello et al., 2021). Traffic flows in 2020 showed a reduced trend as well when a longer evaluation period was considered. Traffic flows in 2020 have experienced a reduction of 43% when...
compared to the same months between 2015-2019. An overall mobility drop of 30% was observed in Spain during the early days of COVID-19 compared to the same months between 2015-2019. The public transport ridership rates were dropped by 40-60% in Sweden between March-May in 2020 compared to the same period in 2019 across different regions in Sweden (Jenelius and Cebecauer, 2020). While there were no changes in the supply of this sector, these changes were attributed to the COVID-19 peak phase. A study in Poland showed insignificant relationship between public transport changes mobility and the number of newly confirmed COVID-19 cases (Wielechowski et al., 2020). However, the study stated that there was a significant correlation between public transport mobility and the stingency of anti-COVID-19 policies at both national and regional levels. Mobility data from Apple and Google revealed that mobility in Metro Malina during lockdown has decreased for all transport modes, where the public transportation sector experienced the largest reduction with an average of 75% (Hasselwander et al., 2021).

A stated preference survey was conducted to collect individuals' responses to various modes under different COVID-19 control policies (Chen et al., 2021). The results showed that these policies influenced the modal selection during the pandemic, where travel preferences were significantly associated with latent factors. An integrated Fermatean fuzzy model was presented with a multi-level decision-making hierarchy criteria to incorporate COVID-19 effect in planning to achieve resilient transport systems (Simic et al., 2022). The study concluded that COVID-19 changed the transport planning strategies and measures significantly.

Predicting traffic demand has numerous applications. Many scientific studies developed traffic prediction models to meet a wide range of planning applications and operational objectives. Examples can be found to predict Annual Average Daily Traffic (AADT) for rural highways (Fricker and Saha, 1986). AADT for non-freeway facilities was determined using spatial regression model, which provided better results when compared to ordinary regression model (Eom et al., 2006). The traffic volumes on low-volume roads were predicted using linear regression (Keenan, 2017) and logistic regression models (Apronti et al., 2016). Further, the daily and hourly traffic volumes were predicted using hierarchical clustering method and linear and logistic regression models (Caceres et al., 2018). Estimation of AADT for an entire road network was performed using MLR and Random Forest (RF) method (Pun et al., 2019).

Time series models were applied to predict traffic volumes. The application of time series to forecast average daily traffic volumes provided better results than standard method (Benjamin, 1986). The prediction was based on classified historical patterns and subsequent days data (Wild, 1997). Another study developed a short-term time series model to predict traffic volumes under given prevailing traffic conditions such as congestion or free flow (Vlahogianni et al., 2006). Further, the evolution of traffic in most of the cases was described with invariant time series models. However, the study showed that the models were able to assess the uncertainty in existing conditions when traffic data were available for long series (Solito et al., 2017). In general, time series models did not show sensitivity to unexpected changes in transportation systems, which is limiting their applicability.

Recently, artificial intelligence models based on Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machines (SVM) have gained popularity in predicting traffic volumes due to their improved prediction accuracy (Boukerche and Wang, 2020, Abu-Lebdeh, et al., 2016) and suitability for non-recurrent conditions (Chikarashi et al., 2020). They do not require advanced analysis of traffic patterns and are able to handle large amounts of historical data (Wang and Boukerche, 2021). Support vector regression was used to predict AADT (Castro-Neto et al., 2009) and traffic in case of poor weather (Bao et al., 2021). ANNs are applied to predict traffic on a motorway network 15-minute in advance, given either existing or historic information (Goves et al., 2016). Kalman Filtering Technique was applied to predict traffic for the following two days based on previous two-day data (Kumar, 2017). A hybrid model was developed to predict short-term traffic flow using a combination of linear autoregressive integrated moving average (ARIMA) method and non-linear Wavelet Neural Network (WNN) method coupled with fuzzy logic (Hou et al., 2019).

When comparing the different models, SVM had better performance compared to ordinary least square linear regression (Castro-Neto et al., 2009). The Long Short term Memory Neural Networks provided high accuracy of traffic demand estimation during hurricane evacuation (Roy et al., 2021). As for estimating AADT, neural network models were found superior than traditional regression models (Fu et al., 2017, Wu and Xu, 2019, Durak and Ramadan, 2019) and RF models (Wu and Xu, 2019). Similarly, Support Vector Regression and RF outperformed the traditional linear regression models for prediction of AADT across the entire network (Syfridis and Agnolucci, 2020). The deep neural network models produced better results for short-term prediction (5, 10, and 20 minutes) of traffic volumes before, immediately after, and after a disaster in terms of interpretability compared to SVM and RF (Chikarashi et al., 2020).

Recently, these advanced methods were applied to develop prediction models for COVID-19 pandemic. A Facebook Prophet model was applied to predict number of COVID-19 cases 90 days in advance. The impact of five government’s measures, implemented to control rate of infection, was also modelled on the growth rate of COVID-19 cases (Das et al., 2021). To derive evidence-based response measures to control spread of COVID-19 pandemic, a combined model using time series analysis and complex network theory was developed (Pan et al., 2021). A hybrid prediction model was presented to forecast the number of new COVID-19 cases by integrating machine learning, adaptive neuro-fuzzy inference system, and enhanced beetle antennae search
swarm intelligence metaheuristics (Zivkovic et al., 2021). Further, an IoT-SDN model was proposed to efficiently manage industrial systems during the pandemic (Rahman et al., 2021).

While there are several transport models, that can be potentially used to predict traffic demand with virtual inputs, it would have never been possible to assess the outcomes of these models based on real-life data. Simply because there was no such point in the recent history of any nation where it was possible to capture extended, large-scale, and true traffic demand as a result of different sets of measures. Thus, developing such a model that relies on real-life data which reflect the implemented measures has its own merits.

In summary, global changes in urban mobility and traffic demand during the COVID-19 pandemic can be attributed to the implementation of different preventive measures and the presence of the COVID-19 pandemic which demoted any unnecessary trips and out-of-home activities. Although several studies have quantified the impact of COVID-19 on mobility, none have attempted to take the opportunity in disguise to develop a robust and reliable mathematical model that can be utilized by transport planners and traffic engineers for traffic flows prediction purposes. As for the prediction technique, the literature reviews revealed that the use of ANN outperformed other prediction methods. Hence, it is selected for this study.

4. Research methodology

Traffic demand is dynamic and naturally fluctuates based on various seasonal and non-seasonal factors. However, the spread of the COVID-19 pandemic has created other unexpected factors that are affecting traffic demand. Since the objective of this study is to develop a model to predict daily traffic demand, a number of inputs that are relevant to traffic flows and the pandemic at the same time are suggested. This study has identified three main sets of factors that can potentially have an impact on traffic demand during the pandemic. The three sets are seasonal factors, pandemic status indicators, and response measures Fig. 1. summarizes the key factors under each of the assessed three groups in predicting daily traffic demand.

The first group of factors contains seasonal factors. Under typical conditions, traffic demand can vary for different types of the day (i.e., weekend vs weekdays), the hour of the day, and the month of the year. Traffic demand during special activities and national events can also be different. Traffic demand in the State of Qatar is rather sensitive to seasonal factors when compared to other parts of the world due to unique demographic and climate conditions (Land Transport and Planning Department (LTPD) 2020). Therefore, it is reasonable to use seasonal factors as an input to the traffic demand prediction model.

The second group of factors that could potentially have an impact on traffic demand during the pandemic is the pandemic status indicators. The relationship between traffic demand and the pandemic status can be perceived as a human factor. People have voluntarily changed their travel behaviors because of their awareness to the pandemic severity and the potential risks that come along.

The changes in personal travel behaviors and attitudes can be reflected on traffic demands, as a result of personal interpolation to the daily published statistics. It should be emphasized that the pandemic status factors are not derived from the imposed restriction measures, but rather from personal decisions to reduce, eliminate or prioritize certain trips.

The third group of factors is the response measures. Many measures were imposed based on the pandemic status, where certain activities are either restricted or suspended. The levels of restrictions were periodically revised and modified based on the pandemic status by the authorities. Therefore, each day during the study period has experienced different response measures at different restriction levels. The response measures along with their levels can be potentially used as an input as well, similar to the seasonal factors and the pandemic status indicators.

The study period started one week before diagnosing the first positive case in the State of Qatar, where no response measures were applied. The rest of the study period includes a set of different levels of...
staged response measures. The daily traffic data, along with the relevant data and information associated with the three different groups, were collected for the period between February 23, 2020 and December 31, 2021. The study period covers more than 22 months of daily data.

Once all the data are collected, they are tabulated in a database structure, and different models are created. All of the models are trained to predict the same dependent variable, which is daily traffic volume. However, the models are different based on their input factors. Each model has a different set of input groups. This approach was used to test the validity of independently using each of the three factor groups (i.e., seasonal factors, pandemic status, and response measures) as an input. This step is essential to identify which input group/s are the most relevant to develop a well-trained model that is capable of providing a reliable prediction. Although there are eight different possibilities to combine the input groups, it was found that the seasonal factor group shall be used. Therefore, there are four different models to consider.

An ANN approach is used to develop the four prediction models. The outcomes of each model are compared so that the final model is recommended. Different performance measures are used to test the accuracy of each model.

Finally, the recommended ANN model that outperforms the other three models is compared against the performance of Multivariable Linear Regression Analysis (MLRA) model, which is developed using the same inputs used to train the recommended ANN model. A graphical summary of the study approach is presented in Fig. 2. The following subsection provides more details regarding the collected data for inputs and output.

4.1. Traffic Demand Data

Daily traffic counts at 26 key junctions were initially considered for analysis. The selected key junctions are located within the urban part of the City of Doha. They are connecting major arterials. Historically, they experience heavy traffic demand. Most of the vehicles heading toward or leaving the City of Doha often pass through one or more of these junctions. The spatial coverage of the selected junctions is shown in Fig. 3. All the selected junctions are equipped with sensors to detect live traffic and adjust signal timing accordingly. As all junctions are signalized, they are controlled via SCATS system. Traffic counts are collected based on sensor data for every day between February 23, 2020 and December 31, 2021. The traffic counts are stored in 15-minute intervals. The raw data were obtained from the Public Works Authority (Also known as Ashghal) in the State of Qatar. The collected traffic flows from these intersections are used as a dependent variable for the analysis.

The collected traffic counts were processed. It was found that 10 sites (out of 26) are invalid due to different reasons. There are four junctions that did not have daily traffic counts for a significant number of days within the study period because of sensors’ failure. Construction activities at another six junctions have resulted in abnormal operational situations. Therefore, these 10 junctions are excluded from further analysis. Finally, daily traffic volumes at the remaining 16 signalized intersections are considered for further analysis in this research.

Despite the variation in traffic volumes, changes in demand distributions are less likely to occur (Muley et al., 2021, Aloi et al., 2020). This means that the hourly distributions throughout the day for different weekdays are similar, with the exception of reduced peaks. The monthly distributions of average daily traffic for every junction within the study period are presented in Fig. 4.

4.2. Seasonal Variation Factors

Due to the relatively long study period that is extended for almost two years (2020-2021), it is important to consider the variation in traffic flows due to seasonal factors. The daily and peak-hour traffic demands can fluctuate as a result of seasonal variation, as previously demonstrated in Fig. 4. Seasonal factors are introduced to describe the unique traffic pattern associated with those factors as inputs, such as working weekdays (Sunday – Thursday), weekends (Saturday, Fridays), and special occasions such as the Holy Month of Ramadan, Eid Holidays, National Day, National Sports Day, School Days, etc. (Land Transport and Planning Department (LTPD) 2020). The considered seasonal variables and their coding scheme is described in Table 2.

4.3. COVID-19 Pandemic Status Indicators

For the pandemic status, a set of indicators are published by the Ministry of Public Health. These indicators are published daily in both infographic and spreadsheet format (Ministry of Public Health in Qatar Nov, 2021, Qatar Open Data Portal 2022). The published indicators were considered in this study as input variables. Fig. 5, shows an example of the infographics that are shared with the public via different venues, including social media (Ministry of Public Health in Qatar Nov, 2021).

The assumption made here is that there is a potential that individuals might have voluntarily reduced their mobility activities and travel needs in response to the pandemic status. Even if a certain activity is not targeted by any measure, the travel behavior has changed as part of public awareness, caution, and risk of infection. Since those indicators are daily published to the public, they might be contributing to changes in traffic demand. Thus, this information can be potentially used as an input. However, contribution of this input group can be verified by assessing the model performance with and without having these data as inputs. A summary of the used pandemic status indicators can be found in Table 3.

4.4. COVID-19 Response Measures Data

The first COVID-19 positive case in the State of Qatar was registered on February 29, 2020 (Qatar Open Data Portal 2022). Several positive cases were registered afterward. Having the pandemic reached the State of Qatar, a series of preventive measures were proposed by the Supreme Committee of Crisis Management and implemented with different timelines, based on the national pandemic status. The first measure to significantly affect mobility was implemented on March 10, 2020, which was the complete closure of all educational institutions in the country. Many other measures were announced, where each measure has targeted one activity or more. Some measures have directly targeted mobility, such as limiting vehicular occupancy and shutting down public transport and metro services. While other measures did not directly target mobility, they still have an indirect influence on urban mobility and ride shares, such as closure of schools, and promoting remote work environment.

For this research, all the measures announced and implemented by the government are organized and sorted chronologically according to their effective date. Measures which are found to less likely influence urban traffic mobility (such as the use of masks in public and the installation of Ehteraz® mobile application on residents smartphones) are filtered out and excluded from being used as input variables. Out of all the measures, 47 measures are found to be associated with traffic and urban mobility during the study period. The overlapped measures are...
combined together and treated as one measure, since it is difficult to identify the impact of each measure individually. In total, there are 34 measures (combined or individual) that are found appropriate. These 34 measures are later used as part of the inputs to develop the ANN model. These measures are numerically coded for each day of the study period, based on their durations. It should be noted that the majority of the measures were implemented by the following day after their announcement. In 2020, the measures that took place between March 4 and June 14 were all of restrictive nature, aiming to reduce the spread of COVID-19 virus. However, a four-phase recovery plan was initiated on June 15, aiming to restore typical daily activities before the pandemic without compromising the pandemic status. As the second wave hit the country by the beginning of 2021, restrictive measures were imposed between March 26 to May 28. Those restrictive measures were gradually reduced. An accurate timeline describing the detailed pandemic status and all the implemented preventive and recovery measures can be found in Appendix A.

All the response measures were coded with a value between 0 to 1 depending on the level of restriction/release to represent the activity level. A value of zero represents the absence of an activity (i.e., full restriction) and 1 indicates that the activity is fully permitted. For instance, before the start of the pandemic, employment is assigned a value of 1.0, since 100% of the employees are working based on their routine work schedule from their respective workplaces. Similarly, a value of 0.2 is used when 80% of the employees are working remotely.

4.5. ANN-Based Prediction Models

To meet the objectives of this research, an artificial intelligence approach is used to develop the prediction models. ANN models are used to identify patterns and trends in complex relationships between the input and output variables (Ghanim et al., 2007, Ghanim et al., 2009, ...
In this study, the ANN technique is adopted because of the nature of the input and output data. ANN is a powerful prediction and classification tool that overcomes many of the issues other traditional methods encounter. For instance, many assumptions shall be met before regression analysis is performed. The errors should be random, and the predictors are independent. When regression analysis methods are used, these issues, along with normality and collinearity issues are often overlooked (Fox, 2015). The time series models are based on historic patterns and require subsequent data (Hastie et al., 2009, Madsen, 2007, Makridakis et al., 2009). The stationary assumption and uncorrelated random errors cannot be met with sudden changes in data over time (Madsen, 2007, Brockwell and Davis, 2009).

ANNs use non-linear and non-logarithmic statistical techniques to determine the outcomes based on a set of inputs. Inspired by nature, ANNs are based on the concept of layers, mimicking the biological process that occurs inside the brain (Bailer-Jones and Bailer-Jones, 2001). Typically, an ANN consists of three layers; input, hidden, and output layers. The normalized input vectors are stored in the input layer in the form of neurons, where each input vector is represented by one neuron in this layer. In each epoch (i.e., iteration), the signal from the input layer is transformed to the neurons located in the hidden layer. Each neuron receives a weighted signal from the input neurons. The number of neurons in this hidden layer depends on several factors, such as the number of input variables and the level of complexity of the input-output relationship (Hagan and Menhaj, 1994). The hidden neurons then transfer the received signal, after applying another transfer function and new weights to the neurons in the output layer, where each output vector is presented by an output neuron. Neurons in the output layer collect and process all the received signals to estimate the normalized output. The normalized output is then un-normalized and compared against each corresponding observed output. Neurons’ weights and biases are then adjusted based on the learning algorithm, aiming to minimize the error in estimated outputs. The adjustment process continues in each epoch until any of the termination criteria is met. The learning process is terminated if the maximum number of epochs is reached, the network performance target is achieved, or the check for validation errors increases by a pre-defined threshold. Once the learning algorithm is terminated, the final adjusted ANN model is applied to the testing dataset so that the performance of the prediction model can be assessed and evaluated.

5. ANN-based prediction models

5.1. ANN Architecture

In total, the input data have 678 records, where each record is representing one day of the study period. The output data have one vector that contains 678 elements, where each element is the observed total daily traffic volume for a specific day. To assure that a reliable and accurate model is developed, a total of 78 records (approximately 11.5% of all the available data) were randomly selected and removed from available 678 records and put aside as an independent stand-alone dataset. This dataset is used to check the independency of the final developed model, and to verify the model’s robustness. Therefore, input and output data from only 600 days are used to train the various ANN models described in Table 1.

The input and output data for the 600 days are further divided into three different datasets, training, validation, and testing datasets. In other words, each of the three datasets contains data from different days within the study period. It should be noted that each record in the database is randomly assigned to one of the three sub-datasets. The details of the datasets are as described below:

Training dataset: This dataset represents 70% of the available data (420 records). It is used during the learning process so that better mapping between the inputs and outputs is achieved. In each epoch, the weight and bias vectors are adjusted, aiming to minimize the cost
Validation dataset: This dataset represents 15% of the available data (90 records). This dataset is used to supervise the learning process so that overfitting can be avoided. Therefore, the trained model can be generalized and adapted to the patterns instead of memorizing them.

Testing dataset: This dataset consists of 15% of the records available in the structured database (90 records). They are used to assess the capabilities of the trained model in performing reliable and robust predictions. This is an independent dataset which is not involved in training or validation the ANN model. In other words, once the model is developed, it is tested using the records assigned to this dataset.

Fig. 6 illustrates the feed-forward ANN architecture, with $i$ neurons in the inputs layer, $j$ neurons in the hidden layer, and one neuron in the output layer.
The output layer. The $TF_1$ and $TF_2$ are the transfer functions between the input and hidden layer, and the hidden and output layer, respectively. In the learning process, the observed data for training and validation datasets are used to adjust the values of the weights and biases, aiming to minimize the cost function.

In this study, the feed-forward backpropagation ANN architecture consists of one input layer, where each neuron in this layer is associated with exactly one input vector. Only one hidden layer is used with 10 neurons. Since the ANN has only one output, the output layer has only one neuron. The signal is transferred from the input layer to the hidden layer using the log-sigmoid transfer function, and linear transfer is used to send the signal from the hidden layer to the output layer (Demuth and Beale, 1998, Haykin, 2004). The Levenberg-Marquardt backpropagation learning function is used to train the ANN model. The cost function to be minimized is the Mean Standard Error (MSE).

For a feed-forward ANN, the big-O notation for the training time complexity can be expressed as a function of the dimensions of the input, hidden, and output layers (i.e., $i$ number of inputs, a hidden layer of $j$ neurons, and $k$ outputs), the number of training samples $t$, and the number of training epochs, $n$. Mathematically, the big-O can be expressed as $\Theta(nt(ij + jk))$. Please note that the training time complexity increases as the number of hidden layers increase. As for the runtime complexity, it can be expressed as $\Theta(ij + jk)$.

5.2. Description of ANN-Based Models

The same architecture is used to train the four different ANN models listed in Table 1. However, the only difference is in the size of the input layer, which is determined by the dimension of the input groups used to develop each particular model. Other than that, all the models are using the same normalization function, transfer functions, learning algorithms, number of hidden neurons, objective function, termination criteria, etc.

Model 1 is developed using seasonal variables only. The underlying assumption in this model states that the variation in the traffic volume is only related to the change in seasonal factors, and no other factors are influencing traffic demand over time.

Model 2 is using COVID-19 statistics in addition to the seasonal data as input variables. This model is constructed under the assumption that the nationwide pandemic status indicators, in addition to the seasonal factors, are influencing the travel of individuals. For instance, it would be rational to assume that individuals are reducing their traffic needs as the pandemic severity increases, which is implicitly measured by the different pandemic indicators.

Model 3 is using the seasonal and response measures input groups only. The COVID-19 status inputs are excluded while training Model 3. This model aims to quantify the influence of response measures on the accuracy of the prediction model, with the absence of COVID-19 status inputs.

Finally, Model 4 is developed by using all three available input groups (i.e., seasonal variation, COVID-19 status, and response measures). This model is developed to assess the accuracy and robustness of the ANN model when all the inputs are used to train the ANN model.

It should be noted that all the models are using the seasonal variation inputs. As a matter of fact, other models were tested without the use of the seasonal inputs, and none of them resulted in reliable prediction, therefore, they were excluded from any further investigation.

5.3. Performance of the ANN-Based Models

The performances of all the ANN models shown in Table 1 are presented in this section. Despite the differences in their input variables, all of them are designed to predict the same output, the average daily traffic volume.

Each figure from Figs. 7 to 10 is showing the correlation between the observed and predicted daily volumes for each of the training, validation, and testing datasets respectively. It is clearly shown that each one of those ANN models behaves differently in mapping the input variables to the output. This is attributed to the different groups of inputs used to train each model, despite sharing the same architectures. The graphical results can be evaluated based on linearity trends, the coefficient of determination ($R^2$), the slope of the regression line, and the y-intercept value.

Fig. 7 shows the performance of the first ANN model (i.e., Model 1). Although the relationship between observed and predicted traffic demand is showing a positive linear trend, the relationship is noisy, and
many outliers can be spotted. For instance, the model is predicting the same numerical output value despite having different observed outputs. Such an observation indicates that while correct predictions can be made, false predictions can also be made. Therefore, using seasonal data only as inputs does not lead to a reliable or generalized ANN prediction model. Thus, more input data have to be used to improve the model prediction capabilities.

Fig. 8 shows the performance of the second developed ANN model (i.e., Model 2), which is trained using seasonal factors in addition to pandemic status indicators. Contrary to the expected, the prediction performed by Model 2 is noisier and shows more outliers than Model 1. Therefore, it can be concluded that the pandemic daily statistics are confusing the learning process instead of supporting it. Furthermore, it is suggested that more patterns might be needed to develop a converging and well-trained ANN model. It can be concluded that using COVID-19 pandemic status statistics did not improve the performance of the ANN model.

The performance of the third ANN model (i.e., Model 3) is shown in Fig. 9. This model uses seasonal and response measures data as inputs. Model 3 is showing a good match between observed and predicted values. For instance, the overall $R^2$ value for the testing dataset is 0.945, and the slope of the regression line is 0.9666, which is close to 1.0. Moreover, the data points are nicely clustered around the regression slope. They are less defused when compared to Model 1 and Model 2. All these remarks indicate that the use of response measures and seasonal factors, as a predictor of the daily traffic demand, is leading to reliable results.

The fourth ANN model (Model 4) is using all of the three input groups. The results shown in Fig. 10 are similar to the results of Model 3. However, there is more variance in the mapping of the predicted values to the observed ones. There are more outliers in this model than those existed in Model 3. These observations indicate that part of the inputs is distracting the learning process, despite the fair convergence. In other words, the use of COVID-19 statistics as an input did not improve the accuracy of the prediction model.

It can be concluded that the total average daily traffic can be predicted using an ANN Model. The best performance can be achieved by training the model with seasonal factors and response measures. Such a model can result in non-systematic differences between the predicted outputs and the targets without reflecting any fundamental or underlying concerns. In this study, it was found that ANN Model 3 was the best model to predict traffic flows. The model’s performance indicators are summarized in Table 4. The indicators used to assess the model validity are the Pearson correlation coefficient ($R$), the coefficient of determination ($R^2$), the Standard Error (SE) and Root-Mean Square Percentage Error (RMSPE).
The training complexity for Model 3 can be expressed as $\Theta(22 \times 420(41 \times 10 + 10 \times 1))$. The runtime complexity is $\Theta(41 \times 10 + 10 \times 1)$. The training time for each epoch in this model ranges from 0.028 to 0.241 seconds. The total training time was 3.163 seconds, with an average of 0.1506 seconds per epoch.

5.4. Testing the Selected ANN-Based Model

The stand-alone dataset with the 78 records is used to further validate the performance of Model 3 (i.e., the ANN model which outperforms the others). Since those records were not used in any phase of training Model 3, the prediction performance using this dataset provides an excellent indicator to the accuracy of the model. The results from applying Model 3 to this stand-alone dataset are shown in Fig. 11. The $R^2$ value of the regression between predicted and observed values is 0.9325. There is also a clear linearity trend with a slope that is approaching a value of 1.0. Furthermore, most of the points are clustered around the regression line. These results introduce another level of confidence on the reliability and accuracy of the developed model in estimating daily traffic demand.

5.5. ANN-Based Model vs Multivariable Regression Analysis

The performance of the selected model to predict daily traffic demand is compared against the performance of classical regression method, the Multivariable Linear Regression Analysis (MLRA). The MLRA model is developed using the same predictor variables used to develop the ANN-based models. The entire 600 records are used to develop the MLRA model since there is no need to divide the data into training, validation, and testing datasets. Furthermore, the developed MLRA model is applied to the independent stand-alone database that contains 78 elements. To avoid the collinearity issue, a stepwise approach is used to select the predictors that have significant coefficients. Nonetheless, it should be noted that independent variables did not meet all the underlining assumptions (linearity, normality, autocorrelation, homoscedasticity, and multicollinearity) to warrant the use of MLRA. However, the results are presented for comparison purposes only. The MLRA results are presented in Fig. 12. When the MLRA results are compared against the ANN-based Model 3, it is clear that the ANN model outperforms the MLRA model in mapping the average daily traffic demand to the same inputs.

6. Policy implications

The COVID-19 pandemic has a global effect that moved around the world in a fast pace. One proven aspect of its rapid spread is exposing the fragility of transportation systems to unexpected events. Air, sea, and land transport systems were negatively impacted by the different
implemented response measures in different countries. This study highlights the impact of the response measures on land transport, by assessing the changes in urban traffic demand. During the pandemic, the general trend was to experience traffic demand reduction when restriction measures were imposed. A reverse trend was also noticed when the level of restrictions is reduced, or when recovery measures are implemented.

The findings of this study reveal that changes in daily traffic demand as a result of the implemented response measures can be predicted. Although the intention of implementing the response measures did not target traffic demand as a management strategy, the measures were sufficient to significantly reduce or change traffic demand. The ability to predict short-term changes in traffic demand by analyzing real-life data can be utilized to assess the effectiveness of implementing these measures to manage traffic demand during special or mega-event, such as FIFA 2022 World Cup and Asian Games 2030.

Quantifying the changes in traffic demand can assist city and municipal authorities in promoting the use of other modes of transportation (such as public transportation or micromobility services) to balance between travel demand needs and traffic demand reduction. Moreover, the outcomes of this study can direct the relevant authorities to identify the effective response measure/s in reducing traffic friction which might arise due to unexpected future events.

The significance of using artificial intelligence (the use of ANN) in this study is demonstrated by having a generalized, adaptive, and reliable model to evaluate different cases and scenarios beyond the observed ones. Furthermore, this model can be utilized as a traffic demand management tool for routine and typical situations, as well as special events, or disaster and emergency situations.

7. Conclusions and recommendations

With the global and rapid spread of the COVID-19 pandemic, most countries around the world have responded differently to reduce the pandemic spread pace. Their reactions were reflected in the reality by imposing a set of preventive measures aiming to reduce the pandemic impact, improve the pandemic status, and avoid getting into multiple waves of the pandemic spread. Once the pandemic status is improved, other recovery measures were imposed by either reducing or canceling the level of previously imposed restrictions. Consequently, many life aspects were impacted by those response measures. Traffic demand is one of the affected aspects. This study investigates the effect of different response measures on urban traffic mobility, by developing an ANN model that uses different input groups to make a reliable and accurate traffic demand prediction. The developed ANN model uses seasonal and response measures variables as inputs to predict daily traffic demand at different key junctions that are surrounding the urban part of the City of Doha during the COVID-19 pandemic (i.e., in 2020 and 2021). Contrary
to the anticipated, the results revealed that using the published pandemic status statistics as an input did not contribute toward improving the accuracy of the prediction model. This shows that these statistics do not have substantial impact or influence on people’s travel decisions.

The developed ANN model is capable of providing reliable traffic demand estimates, where the relationship between observed and predicted values are linear, with a slope close to 1.0, and a coefficient of determination ($R^2$) of 0.9495 or higher for all of the training, validation, and testing datasets. The model was also applied to another independent dataset, where an $R^2$ value of 0.9325 is obtained.

There is no doubt that the COVID-19 pandemic has led to the largest isolation studies known to mankind (Choukér and Stahn, 2020). Both types of response measures (i.e., preventive and recovery measures) can also be treated as large-scale social experiments at the national or global level. Thus, environmental, social, and urban performance indicators before and after the pandemic can be reliable indicators that indeed reflect the true outcomes of relevant what-if scenarios. Rather than relying on mathematical or simulated models, the true outcomes are available. While it is possible to update strategic models based on changing the initial assumptions to replicate the otherwise hypothetical response measures, verifying the outcomes of different performance indicators for those models at the national level remains a dilemma. On the other hand, assessing the performance indicators at different response measures during the pandemic illustrates how the outcomes of these indicators should look like.

The developed ANN model can be employed to determine the expected changes in traffic demand after imposing different overlapping restriction policies. Moreover, the developed model can provide reliable outcomes of different what-if scenarios that reflect imposing different hypothetical policies. This model can also assist in identifying measures with significant impact on traffic demand, if needed. This functionality is useful in developing traffic demand management strategies for future major events which are going to take place in the State of Qatar, such as the FIFA 2022 World Cup, Doha Expo 2023, Asian Games 2030, the plans for hosting the 2032 Olympics, and other large events. The applications of the model can be further extended to develop and evaluate emergency response policies.

Although this study has provided an in-depth assessment of the

| Table 4  | Performance Measures for the selected ANN Model 3. |
|----------|--------------------------------------------------|
| Count   | R        | $R^2$    | SE     | RMSPE% |
| All     | 600      | 0.983    | 0.9761 | 289917.4 | 3.9%   |
| Training| 420      | 0.986    | 0.9792 | 291532.9 | 3.5%   |
| Validation| 90     | 0.977    | 0.9546 | 284035.7 | 4.4%   |
| Testing | 90       | 0.974    | 0.9495 | 281312.0 | 4.9%   |

Fig. 10. ANN Model 4-Observed vs. Predicted Daily Traffic Demand.

![Graph](image-url)
relationship between the COVID-19 response measures and urban traffic mobility, it has some limitations. One of the limitations of this study is targeting one aspect of urban mobility (i.e., urban traffic demand). However, there is a pressing need to extend the study scope further by investigating the impact of the pandemic on other aspects that are directly related to sustainable cities, such as emissions and air quality, traffic and public safety, public transport usage, non-motorized transport modes, and micromobility. Additionally, further investigations are required to ensure the transferability and applicability of the model to the national mobility indicators based on the results shown for urban mobility indicators in the City of Doha.

**Disclaimer**

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![Fig. 11. Performance of Model ANN-Based Model 3 on the Stand-Alone Dataset.](image1)

![Fig. 12. Performance of Multivariable Linear Regression Analysis for Model Development and Stand-Alone Datasets.](image2)

| COUNT   | R    | R²    | SE     | RMSPE% |
|---------|------|-------|--------|--------|
| All     | 600  | 0.804 | 0.6125 | 621092.7 | 41.3% |
| Assessment | 78   | 0.778 | 0.6051 | 658374.5 | 40.2% |

| COUNT   | R    | R²    | SE     | RMSPE% |
|---------|------|-------|--------|--------|
| All     | 78   | 0.966 | 0.9325 | 272810.9 | 6.1% |
DECLARATION OF COMPETING INTEREST

The authors confirm that there are no relevant financial or non-financial competing interests to report. The authors declare no conflict of interest.

APPENDIX A: Summary of Response Measures and their Timelines

Source: Information is compiled from official press releases made by the Government Communications Office, State of Qatar, as of December 31, 2021 (Government Communications Office (GCO) 2022).

| Measure ID | Action details                                                                 | Date Initiated | Date Suspended |
|------------|---------------------------------------------------------------------------------|----------------|----------------|
| —          | Pre-Pandemic.                                                                    | —              | 2/28/2020      |
| 0          | - First positive case was detected in the State of Qatar.                       | 2/29/2020      | 3/5/2020       |
| 1          | - The use of ID to travel within Gulf Cooperation Council is suspended, and passports are required for travel. | 3/6/2020       | 12/31/2020     |
| 2          | - Closure of all schools and universities until further notice.                  | 3/10/2020      | 9/1/2020       |
| 3          | - All residents to avoid gatherings in public places and avoid unnecessary travel. | 3/13/2020      | 9/1/2020       |
| 4          | - Closure of cinemas, theatres, children’s play areas, gyms and wedding venues, elderly avoid going out, Qatar Museums (QM) has closed all its museums and heritage sites to visitors until further notice. | 3/16/2020      | 9/1/2020       |
| 5          | - Doha metro temporary suspension.                                              | 3/18/2020      | 6/15/2020      |
| 6          | - 50% governmental employees to work from home.                                  | 3/22/2020      | 7/28/2020      |
| 7          | - Temporarily closing all restaurants, cafes, food outlets, and food carts.      | 3/23/2020      | 7/1/2020       |
| 8          | - Closure of in-person money exchange and transfer service offices.              | 3/26/2020      | 5/12/2020      |
| 9          | - Temporarily stop the temporary home services system provided by cleaning, catering, and other hospitality companies. | 3/27/2020      | 6/15/2020      |
| 10         | - The Ministry of Public Health (MOPH) has launched Remote healthcare services, shut down all the following outlets: outlets serving hot and cold beverages, coffee shops and cafes, companies and commercial shops to operate from 6am to 7pm, suspension of the hearings of the Court matters | 3/29/2020      | 6/15/2020      |
| 11         | - Suspend some non-emergency health services                                    | 3/30/2020      | 6/15/2020      |
| 12         | - 80% of public and private sector employees to work from home. All other employees have reduced working hours. | 4/1/2020       | 7/28/2020      |
| 13         | - Banned the movement of all types of scooters and ‘Jet Ski’ boats until further notice | 4/3/2020       | 6/15/2020      |
| 14         | - Close the shops and suspend all commercial activities on weekends.            | 4/9/2020       | 7/9/2020       |
| 15         | - No more takeaways: Cafes and restaurants can take only home-delivery orders.    | 4/22/2020      | 5/13/2020      |
| 16         | - Partial reopening of the Industrial Area with restricted entry.                | 5/6/2020       | 6/15/2020      |
| 17         | - New entry and exit procedures to certain districts in the Industrial Area.     | 5/11/2020      | 6/15/2020      |
| 18         | - Money exchanges in Qatar to reopen.                                            | 5/12/2020      | 12/31/2020     |
| 19         | - Restaurants and cafes in Qatar can resume takeaway services.                  | 5/13/2020      | 12/31/2020     |
| 20         | - Wearing face mask is compulsory when outside house, except inside private car. | 5/17/2020      | 12/31/2021     |
| 21         | - Halting most commercial activities until May 30.                               | 5/19/2020      | 5/30/2020      |
| 22         | - No more than two people are now allowed to be in the same vehicle.            | 5/19/2020      | 8/14/2020      |
| 23         | - Exceptions for three people are made for private vehicles driven by the family driver, or transportation in taxis. | —              |                |
| 24         | - Group exercising will not be allowed.                                          | —              |                |
| 25         | - Use of Ehteraz (a Governmental Mobile App) when leaving the house.             | 5/22/2020      | 12/31/2021     |
| 26         | - Removing entry and exit permits requirement to/from the Industrial Area.       | 6/15/2020      | 6/30/2020      |
| 27         | - Phase 1 of release measure started.                                            | 7/1/2020       | 12/31/2020     |
| 28         | - Phase 2 of release measures started, in addition to Phase 1.                   | 7/9/2020       | 12/31/2020     |
| 29         | - Cancellation of entry and exit points to and from the Industrial Area.         | 7/28/2020      | 12/31/2020     |
| 30         | - Phase 3 of release measures started, in addition to Phase 1 and Phase 2.       | 8/1/2020       | 12/31/2020     |
| 31         | - No more than four people (including the driver) are allowed to travel in a car, families are exempted. | 8/14/2020      | 12/31/2020     |
| 32         | - Phase 4-A of release measures started, in addition to Phases 1, 2, and 3.       | 9/1/2020       | 9/6/2020       |
| 33         | - 30% of students attend school.                                                 | 9/6/2020       | 9/20/2020      |
| 34         | - 50% students attend school, 66% for grade 12.                                  | 9/15/2020      | 12/31/2020     |
| 35         | - Phase 4-B of release measures started, in addition to Phases 1, 2, 3, and 4-A | 9/20/2020      | 12/31/2020     |
| 36         | - 100% of students attend school.                                                | 3/26/2021      | 4/08/2021      |
| 37         | - No indoor gathering, no more than 5 persons in open spaces                     | —              |                |
| 38         | - 20% public and private sector employees to work from home.                     | —              |                |
| 39         | - 30% capacity of malls, children under 12 not allowed to enter                  | —              |                |
| 40         | - 30% capacity of restaurants & cafes                                            | —              |                |
| 41         | - Closure of gyms, physical training clubs, including massage services, saunas, steam rooms, hot tubs, etc. | —              |                |

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| Measure ID | Action details | Date Initiated | Date Suspended |
|------------|----------------|----------------|----------------|
| 35         | - 30% capacity of museums and public libraries<br>- 30% capacity of barber shops and beauty salons<br>- Closure of amusement parks, swimming pools, water parks, and all entertainment centers<br>- 30% capacity of traditional and wholesale markets<br>- 30% capacity of cleaning and hospitality services<br>- Public transport capacity at 30% on weekdays and 20% on weekends<br>- Closure of driving schools<br>- Continuing max number of people in a vehicle as 4.<br>- Continuing the number of workers who are transported by buses to half the capacity of the bus.<br>- Closure of playgrounds, exercise equipment<br>- Blended learning in all schools<br>- 30% capacity of nursery and childcare facilities<br>- Reducing private health care facilities to 70%<br>- Closure of playgrounds, exercise equipment<br>- Continue indoor gathering, no more than 5 persons in open spaces<br>- 50% public and private sector employees to work from home.<br>- Postponing all exhibitions, conferences, and all events until further notice<br>- continuing 30% capacity of malls, children under 12 not allowed to enter<br>- Closure restaurants & cafes and all indoor food outlets<br>- Continue closure of amusement parks, swimming pools, water parks, and all entertainment centers<br>- Closure of museums and public libraries, cinemas, barber shops, and beauty salons<br>- Continue 30% capacity of traditional and wholesale markets<br>- Continue closure of gyms, physical training clubs, including massage services, saunas, steam rooms, hot tubs, etc.<br>- Limited cleaning and hospitality services<br>- Continue blended learning in all schools<br>- Closure of nurseries and childcare facilities<br>- Continue closure of playgrounds, exercise equipment<br>- Continuing max number of people in a vehicle as 4.<br>- Reduction of public transport capacity at 20% on weekdays and closure on weekends<br>- Continue closure of driving schools<br>- Continuing the number of workers who are transported by buses to half the capacity of the bus.<br>- Closure of private health care facilities<br>- Continue 30% capacity of malls, children under 12 not allowed to enter<br>- Continue 30% capacity of traditional and wholesale markets<br>- Continue 50% public and private sector employees to work from home<br>- 30% capacity of restaurants & cafes<br>- 30% capacity of museums and public libraries<br>- 30% capacity of traditional and wholesale markets<br>- Opening cinemas at 30% capacity<br>- 30% capacity of barber shops and beauty salons<br>- 30% capacity of cleaning and hospitality services<br>- Closure of playgrounds, exercise equipment | 4/09/2021<br>5/27/2021 |
| 36         | - No more than 5 persons in indoor gathering and no more than 10 vaccinated/5 unvaccinated persons in open spaces<br>- Continuing max number of people in a vehicle as 4.<br>- Continuing the number of workers who are transported by buses to half the capacity of the bus.<br>- Increasing public transport capacity at 30% on all days<br>- Reopening of driving schools at 30% capacity<br>- Increasing private health care facilities capacity to 80%<br>- 30% capacity of gyms, physical training clubs, including massage services, saunas, steam rooms, hot tubs, etc.<br>- 30% capacity of amusement parks, swimming pools, water parks, and all entertainment centers<br>- 30% capacity for blended learning in all schools<br>- 30% capacity of nursery and childcare facilities<br>- Continue 30% capacity of malls, children under 12 not allowed to enter<br>- Continue 30% capacity of traditional and wholesale markets<br>- Continue 50% public and private sector employees to work from home<br>- 30% capacity of restaurants & cafes<br>- 30% capacity of museums and public libraries<br>- 30% capacity of traditional and wholesale markets<br>- Opening cinemas at 30% capacity<br>- 30% capacity of barber shops and beauty salons<br>- 30% capacity of cleaning and hospitality services<br>- Closure of playgrounds, exercise equipment<br>- Continue 30% capacity of malls, children under 12 not allowed to enter<br>- Continue 30% capacity of traditional and wholesale markets<br>- Continue 50% public and private sector employees to work from home<br>- 30% capacity of restaurants & cafes<br>- 30% capacity of museums and public libraries<br>- 30% capacity of traditional and wholesale markets<br>- Opening cinemas at 30% capacity<br>- 30% capacity of barber shops and beauty salons<br>- 30% capacity of cleaning and hospitality services<br>- Closure of playgrounds, exercise equipment | 5/28/2021<br>6/17/2021 |
| 37         | - No more than 10 vaccinated persons in indoor gathering and no more than 20 vaccinated/10 unvaccinated persons in open spaces<br>- Continuing max number of people in a vehicle as 4.<br>- Continuing the number of workers who are transported by buses to half the capacity of the bus.<br>- Increasing public transport capacity at 30% on all days<br>- Reopening of driving schools at 30% capacity<br>- Increasing private health care facilities capacity to 80%<br>- 30% capacity of gyms, physical training clubs, including massage services, saunas, steam rooms, hot tubs, etc.<br>- 30% capacity of amusement parks, swimming pools, water parks, and all entertainment centers<br>- 50% capacity for blended learning in all schools<br>- 30% capacity of nursery and childcare facilities<br>- Continue 30% capacity of malls, children under 12 not allowed to enter<br>- Continue 30% capacity of traditional and wholesale markets<br>- Continue 50% public and private sector employees to work from home<br>- 30% capacity of restaurants & cafes<br>- 30% capacity of museums and public libraries<br>- 30% capacity of traditional and wholesale markets<br>- Opening cinemas at 30% capacity<br>- 30% capacity of barber shops and beauty salons<br>- 30% capacity of cleaning and hospitality services<br>- Closure of playgrounds, exercise equipment<br>- Continue opening cinemas at 30% capacity<br>- 30% capacity of museums and public libraries<br>- 50% capacity of traditional and wholesale markets<br>- 50% capacity of nursery and childcare facilities<br>- Continue opening cinemas at 30% capacity<br>- 30% capacity of museums and public libraries<br>- 50% capacity of traditional and wholesale markets<br>- Continue 30% capacity of barber shops and beauty salons<br>- 50% capacity of cleaning and hospitality services<br>- Closure of playgrounds, exercise equipment | 6/18/2021<br>7/08/2021 |
| 38         | - No more than 15 vaccinated persons in indoor gathering and no more than 30 vaccinated/15 unvaccinated persons in open spaces | 7/09/2021<br>8/05/2021 |
| ID | Measure |
|----|---------|
| 39 | No more than 15 vaccinated persons in indoor gathering and no more than 35 vaccinated/15 unvaccinated persons in open spaces |
| 40 | No more than 30 vaccinated persons in indoor gathering and no more than 50 vaccinated/10 unvaccinated persons in open spaces |

| Date | Action details |
|------|----------------|
| 8/06/2021 | Continuing public transport capacity to 50% on all days |
| 10/02/2021 | Reducing capacity of buses to 30% |
| 10/03/2021 | Increase public transport capacity to 75% on all days |
| 12/31/2021 | Increase capacity of driving schools to 100% |

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