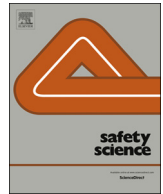




ELSEVIER

Contents lists available at ScienceDirect

Safety Science

journal homepage: www.elsevier.com/locate/safety

A multicriteria approach for risk assessment of Covid-19 in urban district lockdown

Valentino Sangiorgio^{a,*}, Fabio Parisi^b

^a Department of Civil, Environmental, Land, Building Engineering and Chemistry (DICATECh), Polytechnic of Bari, Bari, Italy

^b Department of Electrical and Information Engineering (DEI), Polytechnic of Bari, Bari, Italy



ARTICLE INFO

Keywords:

Risk of Covid-19 contagion
Multicriteria analysis
Calibration
Mathematical programming problem
Artificial neural networks
Apulian Region (Italy)

ABSTRACT

At the beginning of 2020, the spread of a new strand of Coronavirus named SARS-CoV-2 (COVID-19) raised the interest of the scientific community about the risk assessment related to the viral infection. The contagion became pandemic in few months forcing many Countries to declare lockdown status. In this context of quarantine, all commercial and productive activities are suspended, and many Countries are experiencing a serious crisis. To this aim, the understanding of risk of contagion in every urban district is fundamental for governments and administrations to establish reopening strategies.

This paper proposes the calibration of an index able to predict the risk of contagion in urban districts in order to support the administrations in identifying the best strategies to reduce or restart the local activities during lockdown conditions. The objective regards the achievement of a useful tool to predict the risk of contagion by considering socio-economic data such as the presence of activities, companies, institutions and number of infections in urban districts.

The proposed index is based on a factorial formula, simple and easy to be applied by practitioners, calibrated by using an optimization-based procedure and exploiting data of 257 urban districts of Apulian region (Italy). Moreover, a comparison with a more refined analysis, based on the training of *Artificial Neural Networks*, is performed in order to take into account the non-linearity of the phenomenon. The investigation quantifies the influence of each considered parameter in the risk of contagion useful to obtain risk analysis and forecast scenarios.

1. Introduction

Starting from the beginning of the 2020 year, the world has been an un-armed watcher in the spreading of a novel strand of Coronavirus, called SARS-CoV-2 (COVID-19), responsible of a severe respiratory syndrome. The spreading of the virus began in China but in few months a great number of foreign countries reported their first infection, due to the intensive network of connection and transportation worldwide (World Health Organization, 2020). The virus is particularly contagious, and the fatality ratio estimated for this disease is on average 1.38% (Verity et al., 2020). On the other hand, data shared by many countries show evidence that this fatality ratio can vary according to the age of the population and the health system efficiency of the affected cities.

Italy became the first Country after China in which the infection caused severe consequences, principally in Lombardia region. Because of the severity of contagion in Lombardy, the Italian government

defined the “red zone” of this region on March 8th. Successively, urgent measures to contain the spread of COVID-19 on the entire national territory was defined on March 11th. Despite the restrictive measures, from March 7 th to 18 th (after which the controls have been made more restrictive), many students and workers have left Lombardy to return to their regions and city of birth. This caused a spread of contagion throughout the national territory. The Apulia was one of the regions that suffered most infections caused by this return of off-site citizens. The region created a web-based platform to monitor the number of citizens returning from the red zones which recorded about 23,000 warnings (Regione Puglia, 2020). After the statement of the “pandemic” nature of virus, the Italian government imposed more restrictive lockdown conditions and effective controls also in southern Italy after March 22th preventing travel and leaving home unless special needs. As a result of the days before the lockdown, the number of infections has rapidly grown, and the fatality rate of the virus peaked at 9.9% on March 24th according to the data of ISPI (2020).

* Corresponding author.

E-mail addresses: valentino.sangiorgio@poliba.it (V. Sangiorgio), fabio.parisi@poliba.it (F. Parisi).

<https://doi.org/10.1016/j.ssci.2020.104862>

Received 5 May 2020; Accepted 27 May 2020

Available online 06 June 2020

0925-7535/ © 2020 Elsevier Ltd. All rights reserved.

In this context of quarantine, all commercial and productive activities was suspended, and all nations are experienced a serious crisis. To this aim, the understanding of when and how restarting the activities is fundamental for governments.

Many researches in the past investigated the development of pandemic forecasting by considering multiple parameters (Chretien et al., 2014). Different techniques have been tried such as optimized simulations (Nsoesie et al., 2013) or discrete time stochastic model for a Real-time forecasting (Nishiura, 2011). In addition, the study of Kucharski et al. (2014) demonstrate that social behaviour gives an important contribution in the transmission of some typologies of virus. Unfortunately, the strong infectious nature of the novel COVID-19 makes it necessary to consider additional aspects related to the characteristics of the urban districts. Population density, the concentration of the inhabitants and the habits of social aggregation become of basic importance in every urban district to identify the risk of contagion (Sohrabi et al., 2020).

The need to take multiple parameters for the risk evaluation into account is it is often addressed with multi-criteria methods in the scientific and technical community. In particular, the such approaches are very useful in risk assessment and management as specified in the review work of de Almeida et al. (2017). Multicriteria method are particularly effective thanks to its peculiarity of subdividing a complex problem into its basic components in order to obtain a hierarchical scheme of the phenomenon (Sangiorgio et al., 2020a, 2020b).

The multi-criteria approaches are typically supported by suitable calibration methodologies varying from simple calibrations based on applications to different case studies (de Luca, 2014; Sangiorgio et al., 2019) to more complex analysis involving Optimization (Sangiorgio et al., 2019, 2017, 2018), nonlinear analysis up to complex neural networks (Jiang and Ruan, 2010).

The ultimate goal of these approaches is to achieve different forecasting scenarios in order to identify the best mitigation strategies by considering different aspects of the problem. For what concern the application of multi-criteria methods and calibration procedures to obtain forecasting scenarios connected to the COVID-19, there are many aspects investigated in recent literature: i) macroeconomic scenarios are investigated in the studies of (McKibbin and Fernando (2020a), McKibbin and Fernando (2020b)) and (Atkeson, 2020), ii) the virus spreading is faced in confined environment (Rocklöv et al., 2020) or both at the regional (Johnson et al., 2020) or global level (Hellewell et al., 2020; Rodriguez-Morales et al., 2020); iii) and the risk of infection and potential death are investigated in several studies (Jung et al., 2020; Zhang et al., 2020; Anzai et al., 2020).

This paper proposes the calibration of an index able to predict the risk of contagion in urban district in order to support decision of administration and identify the best strategies during and after the lockdown condition at the regional level. The objective regards the achievement of tool to predict the risk of contagion in urban districts by considering social data, the presence of activities, companies, institutions and number of infections in the area. In addition, the index can be used to analyse different scenarios, based on different administrative policy, in order to forecast the related risks.

This ambitious objective is achieved by employing four synergistically related techniques: i) a multi-criteria approach (Saaty, 2008) is used in combination with the well-known risk factorial formula (Towhata, 2008; Sangiorgio et al. 2020a, 2020b) to structure the problem (in criteria and sub-criteria) and analyse every single aspect of the decision problem; ii) a data acquisition procedure to acquire pandemic and socio-economic data in 257 Apulian urban districts; iii) a calibration of the model is obtained by using the mathematical optimization and the *Generalized Reduced Gradient (GRG)* method by exploiting the collected data; iv) a comparison of the proposed index is carried out with a more refined analysis based on the training of an *Artificial Neural Networks (ANNs)* in order to verify the effectiveness of the multi-criteria approach.

ANNs are statistical learning techniques aiming at modelling a computing system that try to reproduce the human brain learning capability by replicating its structure made of interconnected neurons (Shanmuganathan, 2016). In particular, feedforward *ANNs* are one of the most used deep learning models (Goodfellow et al., 2016) and are usually structured with one or more hidden layers. The use of a feed-forward architecture implies the definition of: i) the architecture by defining the number of layers and the number of neurons; ii) a function that models the output of each neurons, called activation function; iii) a loss function and an optimization algorithm for this loss function. In this work, a feedforward *ANNs* is used to perform a regression task and a comparison with the index obtained with the GRG method.

In order to show the potential of the index, different administrative policies (after lockdown condition) are hypothesized in Apulia (Italy): 1) limited reopening of some commercial and productive activities and prohibited moves between different urban districts; 2) partial reopening of some commercial and productive activities and people movement control, 3) reopening of all commercial and productive activities and freedom of people movement. The resulting approach is used to analyse such different scenarios and obtain regional risk maps.

In addition, in comparison with previous studies, the influence of each parameter of the urban districts influencing the risk of contagion has been quantified. In this way it is possible to individuate the typology of companies or the activities at risk of contagion in every urban district. In addition, this paper presents risk analysis and forecasting scenarios in a southern Italy region.

2. Methodology

The proposed work is carried out in four phases: 1) definition of the problem and involved parameters, 2) data acquisition, 3) optimization-based calibration, 4) *ANN*-based procedure.

2.1. Problem definition

In the *first phase* the risk of Covid-19 contagion in urban districts is analysed to determine the involved parameters and classify them in *criteria*, *sub-criteria* and *intensity* (Fig. 1). In this phase the problem is structured according to the theory of the multicriteria approach (Saaty, 2008). In addition, by following the footsteps of existing risk assessment procedure (IEC, 2008) three well-known risk factors are defined and customized for the considered phenomenon: *Hazard*, *Vulnerability* and *Exposure* (Towhata, 2008; Sangiorgio et al. 2020a, 2020b).

In this work, the three factors are defined as *criteria* i (with $i = 1, \dots, 3$) for each of which a set of *sub-criterion* j (with $j = 1, \dots, n_i$) is defined to have an exhaustive analysis of the problem. The three *criteria* and related *sub-criteria* are described as follows:

- (1) the *Hazard* (with $i = 1$) considers the possibility of contagion and it is characterized by three *sub-criteria* ($n_1 = 3$) including *Infected people* ($j = 1$), *Not Immune People* ($j = 2$) and *Mobility* ($j = 3$);
- (2) the *Vulnerability* (with $i = 2$) evaluates the urban districts characteristics by contemplating fifty-six *sub-criteria* including *Population Density* ($j = 1$), and presence of crowded places such as *Food Stores/Pharmacies*, *Food Industries*, *Places of Worship*, *Retirement Homes*, *Construction Companies*, *Open Cafe/Restaurants*, etc. ($j = 2, \dots, 56$) (a comprehensive list of *criteria*, *sub-criteria* and *intensity* is showed in [Supplementary Table S1](#));
- (3) the *Exposure* (with $i = 3$) evaluates the typology of inhabitants, which can suffer fatal consequences by considering the *Age of Inhabitants* ($j = 1$) according to (Porcheddu et al., 2020).

In conclusion of Phase 1, weights of *criteria* and *intensity ranges* are defined as follows:

- v_i is the weight associated with each i^{th} *criterion*;

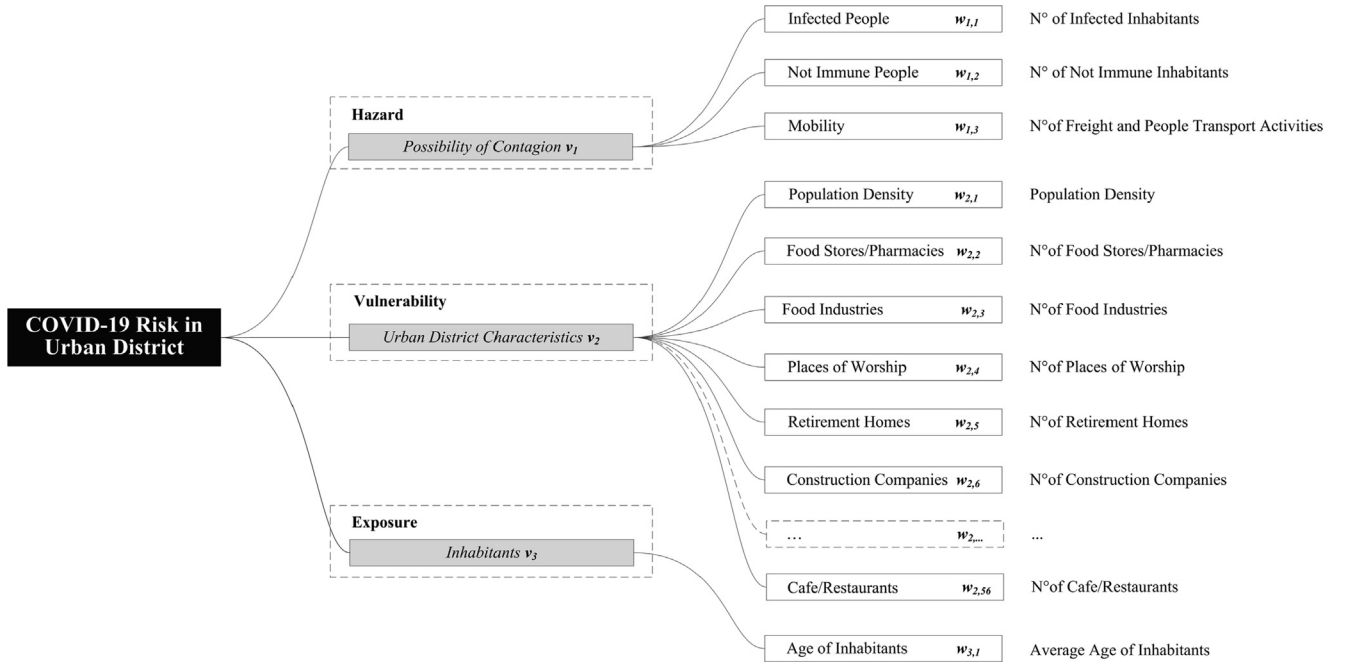


Fig. 1. Structure of the problem in *Criteria, Sub-Criteria and Intensity*.

- $w_{i,j}$ is the weight associated with each j^{th} sub-criterion related to the i^{th} criterion.

In addition, an *intensity* value $p_{i,j}$ (normalized to 1) represents the data acquired about the considered urban district considering the i^{th} criterion and the j^{th} sub-criterion. For instance, if the *Hazard* criterion ($i = 1$) and the sub-criterion *Infected people* ($j = 1$) are considered, $p_{1,1}$ represents the number of infected inhabitants in the studied urban district divided for the maximum number of infected inhabitants of all the considered urban districts.

A concise factorial equation is defined to evaluate the risk index ($R_{Covid-19}$) in urban district by aggregating the defined weights according to Sangiorgio et al., 2020a, 2020b; Towhata (2008) as follows:

$$R_{Covid-19} = v_1 \left(\sum_{j=1}^3 w_{1,j} p_{1,j} \right) \cdot v_2 \left(\sum_{j=1}^{56} w_{2,j} p_{2,j} \right) \cdot v_3 \cdot w_{3,1} p_{3,1}. \quad (1)$$

2.2. Data acquisition

In the *second phase*, an exhaustive dataset is obtained to provide the necessary information for the subsequent phases of calibration and validation. The database is developed by an automated data acquisition procedure to achieve a pandemic and socio-economic data collection. In particular, data are acquired for the Apulia region about $K = 257$ urban districts ($Ud = 1, \dots, K$) divided in six local government: 41 Bari, 10 Barletta-Andria-Trani, 20 Brindisi, 61 Foggia, 96 Lecce, 29 Taranto.

Data regarding all the intensities of sub-criteria are acquired from Italian civil protection (infected people of 24 th March 2020) and from The Italian National Institute of Statistics (ISTAT, 2020).

In addition, data regarding the effective infections useful for the calibration and expressed for every urban district (Inf^{Ud}) are achieved from data of the Italian Civil Protection and refers to the 8th April 2020.

Supplementary Table S2 shows all the acquired data classified for sub criteria (rows) and urban districts (columns).

2.3. Optimization-based calibration

In the *third phase*, the index $R_{Covid-19}$ is calibrated by exploiting nonlinear optimization technique, such as the GRG method and the real

data regarding the spreading epidemic in the 257 Apulian urban districts. It is worth noting that the Apulian region is a very effective area to calibrate the model for the particular condition of the epidemic beginning. Indeed, the return of 23,000 citizens from the red zones generated a uniform initial distribution of the virus on the territory. The consequent spread of the infection occurred on the basis of *Hazard, Vulnerability* and *Exposure* factors of urban district. To this aim, the calibration exploits data of infected people of the of 24 th March as the starting point of the infection and data of the 8th April 2020 to analyse the effect of the contagion and calibrate the model.

In particular, to obtain the weights v_i and calibrate the index, defined in Eq. (1), the $K = 257$ urban districts ($Ud = 1, \dots, K$) are considered in the Apulian region. The index of $R^{Ud}_{Covid-19}$ associated with the urban districts $Ud = 1, \dots, K$ is written in function of the column vector of weights $\mathbf{v} = [v_1, v_2, v_3]^T$ and $\mathbf{w} = [w_{1,1}, w_{1,2}, w_{1,3}, w_{2,1}, w_{2,2}, w_{2,3}, \dots, w_{2,56}, w_{3,1}]^T$ as follows:

$$R^{Ud}_{Covid-19}(\mathbf{v}, \mathbf{w}) = v_1 \left(\sum_{j=1}^3 w_{1,j} p_{1,j} \right) \cdot v_2 \left(\sum_{j=1}^{56} w_{2,j} p_{2,j} \right) \cdot v_3 \cdot w_{3,1} p_{3,1} \quad (2)$$

Subsequently, it is possible to define the function $F(\mathbf{v}, \mathbf{w})$, which evaluates the difference between the values of risk $R^{Ud}_{Covid-19}$ and the effective infections Inf^{Ud} registered on April 8th for each examined urban districts $Ud = 1, \dots, K$:

$$F(\mathbf{v}, \mathbf{w}) = \sum_{Ud=1}^K (R^{Ud}_{Covid-19}(\mathbf{v}, \mathbf{w}) - Inf^{Ud})^2 \quad (3)$$

To calibrate vector \mathbf{v} and \mathbf{w} it is assumed that the index of risk of infection $R^{Ud}_{Covid-19}$ should be as close as possible to the effective number of infections (normalized to one) registered for every considered urban districts on April 8th.

$F(\mathbf{v}, \mathbf{w})$ represents the quadratic sum of the differences between the proposed risk index and the effective consequences of the virus contagion phenomenon. Consequently, $F(\mathbf{v}, \mathbf{w})$ is selected as the objective function to be minimized by satisfying a set of constraints on vectors \mathbf{v}, \mathbf{w} :

$$\Gamma(\mathbf{v}, \mathbf{w}):$$

$$\prod_{i=1}^3 v_i = 1 \quad \text{for } i = 1, \dots, 3 \quad (4a)$$

$$v_i > 0 \text{ for } i = 1, \dots, 3 \tag{4b}$$

$$0 \leq w_{i,j} \leq 1 \text{ for } i = 1, \dots, 3 \text{ and } j = 1, \dots, n_i \tag{4c}$$

$$\sum_{j=1}^{n_i} w_{i,j} = 1 \text{ for } i = 1, \dots, 3 \tag{4d}$$

All the constraints are set to avoid negative or null values of the weights and to normalize to one the risk index according to (Towhata, 2008; Sangiorgio et al., 2020a, 2020b).

Now, in order to obtain the solution vectors \mathbf{v} and \mathbf{w} , the following Mathematical Programming (MP) problem is formulated:

$$\min F(\mathbf{v}, \mathbf{w}) \tag{5a}$$

$$\text{subject to } \Gamma(\mathbf{v}, \mathbf{w}) \tag{5b}$$

The problem is solved by using the GRG method and the results are showed in [Supplementary Table S3](#) and discussed in the [Section 3](#).

It is worth noting that, the proposed index is based on a factorial equation defined a priori. In order to verify the effectiveness of the factorial equation to describe the phenomenon, this approach is compared with another methodology capable of considering the non-linearities of the phenomenon. Among the existing approaches, ANN are particular effective to consider nonlinear interactions among the parameters of the problem. To this aim, an ANN is trained in order to analyse the complex problem risk of contagion by considering the same dataset and parameters of the first calibration.

2.4. ANN-based procedure

In the **fourth phase** a feedforward ANN is trained on data in order to predict an index to be compared with the results of the $R_{Covid-19}$ index calculated in the **third phase**.

The analysis considers, also in this case, the data of the 257 cities of Apulian Region as the input of the ANN: all the *intensity* value $p_{i,j}$ (with $j = 1, \dots, n_i$ and $i = 1, \dots, 3$) acquired during data collection phase are used as “predictors features”. Note that the number of infected people refers to the March 24th. Hence, the ANN is set to perform a regression task using the number of infected people registered on April 8th as the target or output variables.

The model is obtained in three steps (see [Fig. 2](#)):

- (i) Pre-processing step to collect data by normalizing and shaping them to feed the input layer of the network;
- (ii) Defining the architecture of the ANN, with an output layer composed by a single neuron. In order to obtain a normalized index comparable with $R_{Covid-19}$, with regression results ranging from 0 to 1, a “Sigmoid” activation function is chosen for the output neuron layer, instead of “ReLu” activation function used for other layers. The mean squared error is used as the “loss function” and the Adam optimization algorithm (Kingma and Bar, 2015) as the loss function optimizer;
- (iii) Training and validating of the model performed by an iterative procedure named “key-fold cross-validation” (with $k = 10$). In

particular, in this procedure, firstly the dataset is randomly split in ten sub-sets. Secondly, for every iteration, each one of the defined sub-sets is used as a “test-set”, while the remaining nine sub-sets are used as the training sets.

Note that the training/validation dataset is the same used for $R_{Covid-19}$. Analogously to the factorial equation, the obtained trained ANN is able to evaluate an additional risk index, for every urban district, ranging from 0 to 1 named $R_{ANN,Covid-19}^{Ud}$.

3. Results

3.1. Parameters influencing the spread of the virus on urban districts

By exploiting the first three phases of the procedure, we achieve the quantification of the influence of every parameter of the urban districts involved in the spread of the Covid-19. In particular, a total of 63 weights (\mathbf{v}, \mathbf{w}) are defined and calibrated by using the multicriteria approach and GRG method. The resulting influence is expressed in percentage and the description of results follows the parameters classification (considering *Exposure*, *Hazard* and *Vulnerability*) proposed in the **first phase**.

The most important parameters belong to the criterion of the *Exposure* and regards the age of inhabitants with a value of the 34%.

The *Hazard* has all three related parameters of intermediate importance: *Infected people* (13%), *Not Immune People* (13%) and *Mobility* (7%).

Moreover, the *Vulnerability* has few of the 56 related parameters resulting of high important and others which can affect less the effects of contagion: distribution of café and restaurant have a high influence each of the 13%, the number of available supermarket have an influence of the 7% and all the other parameters has an overall influence of 2%.

It is worth noting that in total *Hazard*, *Vulnerability* and *Exposure* have a very similar importance in the phenomenon with overall values of 33%, 33% and 34% respectively.

[Fig. 3](#) shows the influence of the most important parameters expressed in percentage and displayed in a pie chart. In addition, the [Supplementary Table S3](#) shows all the calibrated tabulated weights.

3.2. Forecasting scenarios by using $R_{Covid-19}$

In order to show the potential of the model, the proposed approach is used to obtain three different forecasting scenarios. In particular, three regional risk maps are achieved by applying to the studied region three different administrative hypothetical policy, respectively. The proposed index is easy to be computed by practitioners using data acquired from civil protection and ISTAT. In particular, the index is able to outcome a numerical value (ranging from 0 to 1) for every considered urban district to forecast the risk of contagion by using 56 input data including the actual number of infection and the characteristic of the district.

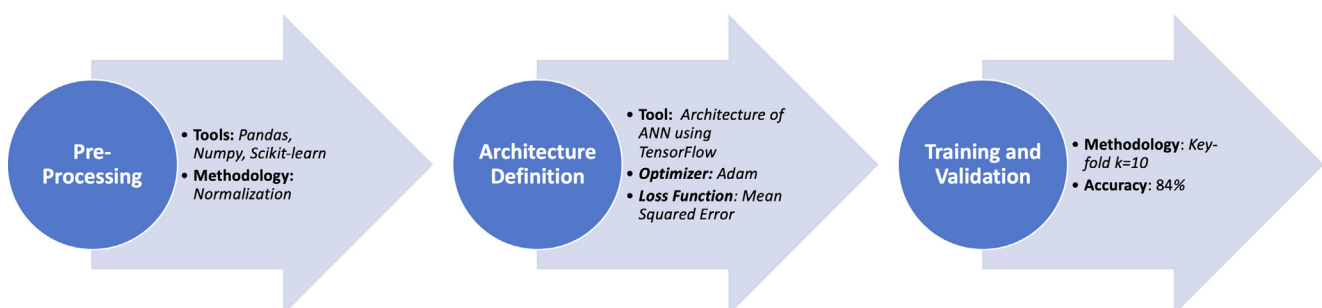


Fig. 2. Three steps of ANN model.

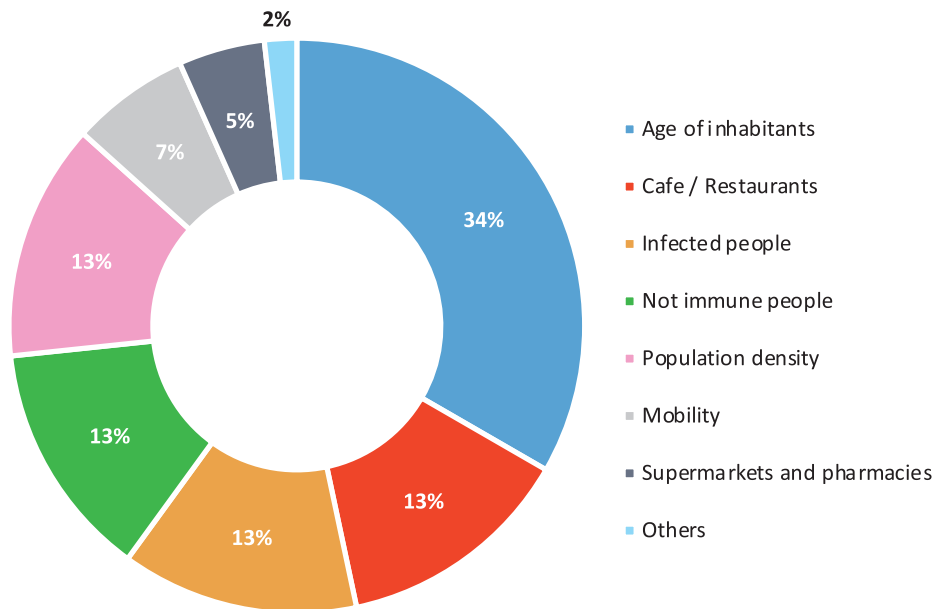


Fig. 3. Influence of each parameter in the risk of contagion for Covid-19.

The input data of all the 257 urban districts as already showed in [Supplementary Table S2](#). Moreover, the input data of the contagion are updated on 8th April 2020 and therefore the forecast is made for April 24th.

In addition, three scenarios are considered:

- (1) *Full Lockdown Condition* where only companies and institutions for primary needs are operative including *Pharmacies, Food-market, Food Industries, Pharmaceuticals enterprises*. In addition, the mobility is limited only for the workers of such basic needs.
- (2) *Lockdown Condition with the hypothesis of partial reopening* where only some risky activities, companies or institutions are kept closed including educational institutions, sports and recreation activities. In addition, *Mobility* and the *Cafè/Restaurants* are regulated allowing a halved flow of users compared to the full capacity.
- (3) *No Lockdown Condition with the hypothesis of full reopening* of all businesses, activities and institutions.

The proposed index $R^{Ud}_{Covid-19}$ is evaluated to forecast the risk of contagion for every one of the 257 urban districts by using Eq. (2) and [Supplementary Table S3](#). In addition, in order to better display the results, three qualitative ranges of risk are individuated: Low ($0 < R^{Ud}_{Covid-19} < 0.01$), Medium ($0.01 \leq R^{Ud}_{Covid-19} < 0.1$) and High ($R^{Ud}_{Covid-19} \geq 0.1$).

Fig. 4 shows the application of the index to generate three risk maps of the Apulian region, one for every scenario implemented in a

geographic information system (GIS).

As easily foreseeable, the big cities represent the zones most at risk in all scenarios. On the contrary, the risk in the other urban districts is not easily predictable and it depends from the local presence of specific companies, activities and institutes considered open in the various three scenarios. The higher level of risk is estimated for Bari in the hypothesis of *Full reopening condition* with $R^5_{Covid-19} = 0.8$. The lower level is registered in small cities such as Volturino or Castelnuovo della Daunia with almost zero risk in the hypothesis of *Full Lockdown condition* thanks to zero infections, very limited population mobility and low presence of activities in the territory. The obtained results suggest that for every urban district the local administrators can individuate a specific strategy useful to safeguard low risk and keep the economy active at the same time. Fig. 5 shows a generic example of an urban district where the low risk activities are represented in green circles and the risky activities are in red circles.

3.3. Forecasting scenarios by using Neural network

The model is trained and validated on the base of 257 urban districts data. For every urban district, 56 variables are provided to the model, including enterprises typologies and number of infected people. These data are the same used for the calibration of the third phase of [Section 2.3](#).

The trained model is able to compute the risk index $R^{Ud}_{ANN,Covid-19}$ on the basis of the same input data with the analogous shape of the

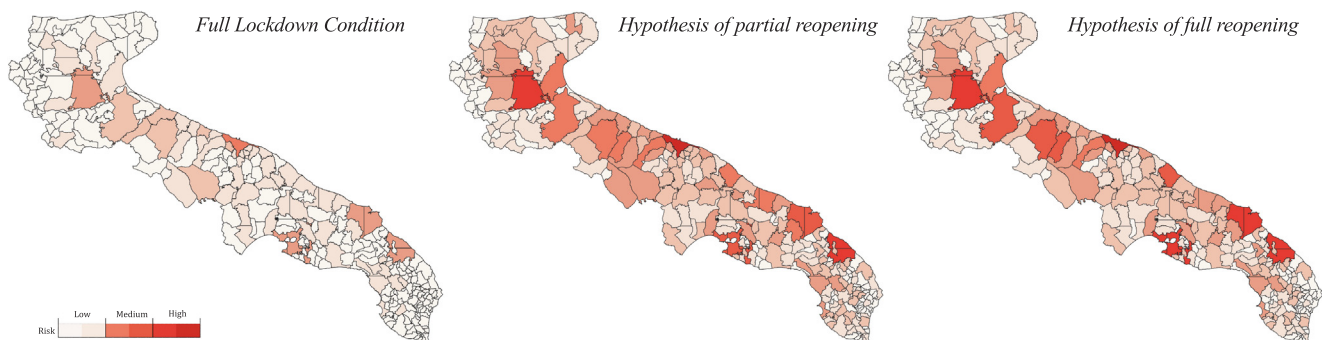


Fig. 4. Risk maps of contagion for Covid-19 for three regional scenarios.



Fig. 5. Example of the best choice for a generic urban district.

training/validation dataset used in the fourth phase of Section 2.4.

To obtain the forecasting scenarios for the Apulia Region, the model is provided with input data showed in Supplementary Table S1: input contagion data are updated to the 8th April, while operative enterprises data depends on the searched forecasting scenario and then on Full Lockdown, Lockdown with partial reopening or No Lockdown Condition.

As output of the forecasted scenarios the risk $R_{ANN,Covid-19}^{Ud}$ is obtained. An example of forecasted scenario is given in Fig. 6 for the full reopening scenarios.

3.4. Comparison of the two approaches

The result comparison shows that the two approaches are both effective to obtain forecasting risk scenarios by analysing the urban districts characteristics.

More precisely, for every forecasting scenario, an equal risk is identified with the two approaches for more than the 75% of investigated urban districts. Moreover, the 23% of the analyzed districts have irrelevant difference in risks since the indexes $R_{ANN,Covid-19}^{Ud}$ and $R_{Covid-19}^{Ud}$ remain in the same qualitative ranges of risk. On the contrary, relevant differences are detected only for the 2% of the investigated areas.

Moreover, Fig. 6 shows the comparison between $R_{ANN,Covid-19}^{Ud}$ and $R_{Covid-19}^{Ud}$ obtained for the “full reopening” forecasting scenario. In the right, an additional map shows the differences between the results of the two approaches. In particular, in 61 of 257 urban districts the two methods obtain slightly different risk values (not relevant and

represented in grey) and only 3 of 257 urban districts have slightly relevant differences that are represented in yellow. In no case there are differences from a zero or low risk to a high risk.

Summing up, the ANN-based procedure has a good accuracy but with this approach it is difficult to understand the importance of each parameter because the connections and the non-linear laws that regulate the phenomenon are not easily understandable. To this aim, ANN can be difficult to be used by administrations and government to define the best policy strategy in lockdown condition, even if it can be a very useful instrument for helping in the validation process.

On the other hand, index $R_{Covid-19}$ is able to achieve good forecasting scenarios by using a simple factorial equation and visible tabulated values. For these reasons, such a tool can be of great support for every urban district in order to identify all the activities, companies and institutions that represent a risk for the spread of the virus.

4. Conclusions

This paper defines and proposes the calibration of an index ($R_{Covid-19}$) that is devoted to predicting the risk of contagion in urban district by considering epidemic, characteristic and social data of the territory. The methodology is based on a multicriteria approach that starts on the well-known definition of the risk by means of three factors: hazard, vulnerability and exposure. Hence, the singled-out criteria and sub-criteria are considered in the definition of index $R_{Covid-19}$ by factorial formula that is calibrated by solving a mathematical programming problem.

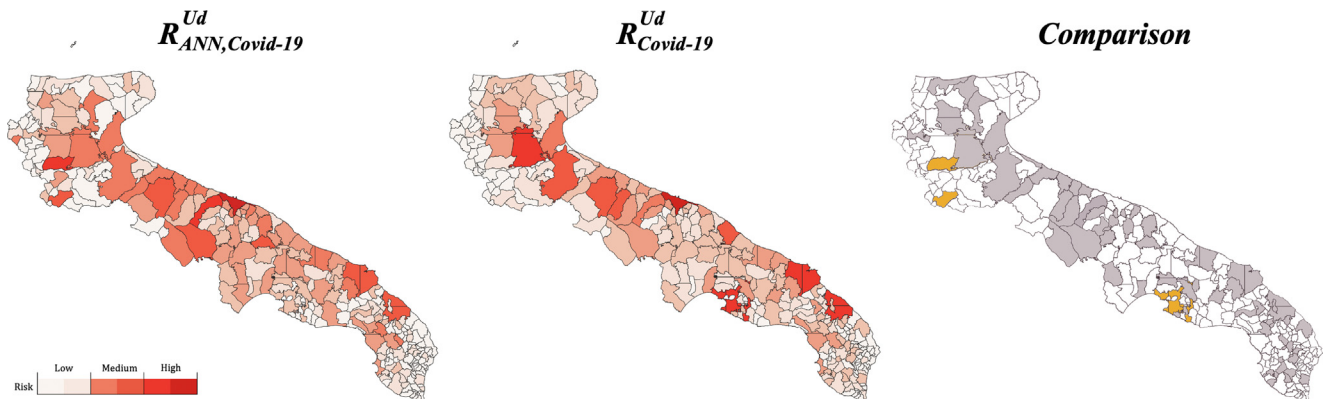


Fig. 6. Comparison between $R_{ANN,Covid-19}^{Ud}$ and $R_{Covid-19}^{Ud}$ results for the full reopening scenarios.

In particular, the calibration exploited a nonlinear optimization technique and the real data regarding the spreading epidemic of the Covid-19 in the 257 Apulian urban districts. Moreover, in order to verify the effectiveness of the factorial formula, the proposed $R_{Covid-19}$ is compared with the analysis obtained by training an ANN.

The comparison shows that both methods have the same efficacy. The ANN-based approach is able to obtain forecasting scenarios with a good accuracy, but it does not easily allow to assume different scenarios in order to evaluate the consequent risk consequent. On the contrary, the index $R_{Covid-19}$ is able to achieve good forecasting scenarios but using a simple factorial equation and visible tabulated values.

In conclusion, compared with previous research, the novelties of the proposed research are threefold.

For the first time, two models (the first based on the index $R_{Covid-19}$ and the second on ANN) are developed and calibrated by considering a set of urban districts to predict the risk of contagion including sociological and pandemic aspects in the analysis.

The second novel issue regards the quantification of the influence of each parameter of the urban district expressed in percentage: average age of inhabitants (34%) number of infected people (13%), immune people (13%), population density (13%), presence of café and restaurant (13%); citizen mobility (7%) and available supermarket (5%) are the most important parameters.

Thirdly, the research reaches the ambitious result of forecasting the risk in different scenarios assuming different administrative policies in the Apulia region.

Finally, the results of this research can be useful for local administrators and civil protection. Beyond this, also researchers and other government can exploit the proposed model to obtain maps of risk at different scales: urban, regional and national.

Future research will be focused on the implementation of the proposed strategy in a Decision Support System that will be able to fuse and elaborate the civil protection data in order to automatically provide the optimal solutions in presence of pandemic virus.

Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ssci.2020.104862>.

References

- Anzai, A., Kobayashi, T., Linton, N.M., Kinoshita, R., Hayashi, K., Suzuki, A., et al., 2020. Assessing the impact of reduced travel on exportation dynamics of novel coronavirus infection (COVID-19). *J. Clin. Med.* 9 (2), 601.
- Atkeson, A., 2020. What will be the economic impact of COVID-19 in the US? Rough estimates of disease scenarios (No. w26867). National Bureau of Economic Research.
- Chretien, J.P., George, D., Shaman, J., Chitale, R.A., McKenzie, F.E., 2014. Influenza forecasting in human populations: a scoping review. *PLoS One* 9 (4).
- de Almeida, A.T., Alencar, M.H., Garcez, T.V., Ferreira, R.J.P., 2017. A systematic literature review of multicriteria and multi-objective models applied in risk management. *MA J. Manage. Math.* 28 (2), 153–184. <https://doi.org/10.1093/imaman/dpw021>.
- de Luca, S., 2014. Public engagement in strategic transportation planning: An analytic hierarchy process based approach. *Transp. Policy* 33, 110–124.
- Goodfellow, Y., Bengio, Y., Courville, A., 2016. *Deep Learning*. MIT Press.
- Hellewell, J., Abbott, S., Gimma, A., Bosse, N.I., Jarvis, C.I., Russell, T.W., Munday, J.D., Kucharski, A.J., Edmunds, W.J., Sun, F., Flasche, S., 2020. Feasibility of controlling COVID-19 outbreaks by isolation of cases and contacts. *The Lancet Global Health*.
- IEC, I., 2008. ISO 31010—Risk Management—Risk Assessment Techniques. International Electrotechnical Commission: Geneva.
- ISPI, Italian Institute for International Political Studies, 2020. Covid-19 and Italy's Case Fatality Rate: What's the Catch?. <https://www.ispionline.it/en/publication/covid-19-and-italys-case-fatality-rate-whats-catch-25586>.
- ISTAT, 2020. <https://www.istat.it>.
- Jiang, H., Ruan, J., 2010. Investment risks assessment on high-tech projects based on analytic hierarchy process and BP neural network. *J. Netw.* 5 (4), 393.
- Johnson, H.C., Gossner, C.M., Colzani, E., Kinsman, J., Alexakis, L., Beauté, J., Würz, A., Tsolova, S., Bundle, N., Ekdahl, K., 2020. Potential scenarios for the progression of a COVID-19 epidemic in the European Union and the European Economic Area, March 2020. *Eurosurveillance* 25 (9), 2000202.
- Jung, S.M., Akhmetzhanov, A.R., Hayashi, K., Linton, N.M., Yang, Y., Yuan, B., et al., 2020. Real-time estimation of the risk of death from novel coronavirus (COVID-19) infection: inference using exported cases. *J. Clin. Med.* 9 (2), 523.
- Kingma, D. P., Ba, J., 2015 Adam: A Method for Stochastic Optimization. Proceedings of the 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA.
- Kucharski, A.J., Kwok, K.O., Wei, V.W., Cowling, B.J., Read, J.M., Lessler, J., et al., 2014. The contribution of social behaviour to the transmission of influenza A in a human population. *PLoS Pathog.* 10 (6).
- McKibbin, W.J., Fernando, R., 2020a. The global macroeconomic impacts of COVID-19: Seven scenarios.
- McKibbin, W.J., Fernando, R., 2020b. The economic impact of COVID-19. *Economics in the Time of COVID-19*, 45.
- Nishiura, H., 2011. Real-time forecasting of an epidemic using a discrete time stochastic model: a case study of pandemic influenza (H1N1-2009). *Biomed. Eng. Online* 10 (1), 15.
- Nsoesie, E.O., Beckman, R.J., Shashaani, S., Nagaraj, K.S., Marathe, M.V., 2013. A simulation optimization approach to epidemic forecasting. *PLoS One* 8 (6).
- Porcheddu, R., Serra, C., Kelvin, D., Kelvin, N., Rubino, S., 2020. Similarity in case fatality rates (CFR) of COVID-19/SARS-COV-2 in Italy and China. *J. Infect. Dev. Count.* 14 (02), 125–128.
- Regione Puglia, 2020. Coronavirus - Modulo di autosegnalazione <https://www.sanita.puglia.it/autosegnalazione-coronavirus>.
- Rocklöv, J., Sjödin, H., Wilder-Smith, A., 2020. COVID-19 outbreak on the Diamond Princess cruise ship: estimating the epidemic potential and effectiveness of public health countermeasures. *J. Travel Med.*
- Rodriguez-Morales, A., Tiwari, R., Sah, R., Dhama, K., 2020. COVID-19, an emerging coronavirus infection: current scenario and recent developments-an overview. *J. Pure Appl. Microbiol.* 14, 6150.
- Saaty, T.L., 2008. Decision making with the analytic hierarchy process. *Int. J. Serv. Sci.* 1 (1), 83–98.
- Sangiorgio, V., Martiradonna, S., Uva, G., Fatiguso, F., 2017, September. An information system for masonry building monitoring. In: 2017 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI) (pp. 230-235). IEEE.
- Sangiorgio, V., Pantoja, J.C., Varum, H., Uva, G., Fatiguso, F., 2019. Structural degradation assessment of RC buildings: Calibration and comparison of semeiotic-based methodology for decision support system. *J. Perform. Constr. Facil.* 33 (2), 04018109.
- Sangiorgio, V., Uva, G., Adam, J.M., 2020a. Integrated seismic vulnerability assessment of historical masonry churches including architectural and artistic assets based on macro-element approach. *Int. J. Architect. Heritage* 1–14.
- Sangiorgio, V., Uva, G., Aiello, M.A., 2020b. A multi-criteria-based procedure for the robust definition of algorithms aimed at fast seismic risk assessment of existing RC buildings. *Structures* 24, 766–782.
- Sangiorgio, V., Uva, G., Fatiguso, F., 2018. Optimized AHP to overcome limits in weight calculation: Building performance application. *J. Constr. Eng. Manage.* 144 (2), 04017101.
- Shanmuganathan S., 2016. Artificial Neural Network Modelling: An Introduction. In: Shanmuganathan S., Samarasinghe S. (Eds.), *Artificial Neural Network Modelling. Studies in Computational Intelligence*, 628. Springer.
- Sohrabi, C., Alsafi, Z., O'Neill, N., Khan, M., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, R., 2020. World Health Organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19). *Int. J. Surgery*.
- Towhata, I., 2008. *Geotechnical Earthquake Engineering by*, ed. Springer-Verlag Berlin Heidelberg, doi: 10.1007/978-3-540-35783-4.
- Verity, R., Okell, L.C., Dorigatti, I., Winskill, P., Whittaker, C., Imai, N., et al., 2020. Estimates of the severity of coronavirus disease 2019: a model-based analysis. *Lancet Infect. Dis.*
- World Health Organization, 2020. Coronavirus disease 2019 (COVID-19): situation report, 72.
- Zhang, Y., Yu, X., Sun, H., Tick, G.R., Wei, W., Jin, B., 2020. COVID-19 infection and recovery in various countries: Modeling the dynamics and evaluating the non-pharmaceutical mitigation scenarios. *arXiv preprint arXiv:2003.13901*.