Simulation Environment for Optimal Resource Planning During COVID-19 Crisis

Nenad Petrović

Abstract – **Recent COVID-19 outbreak has affected both human resources and economy around the world dramatically leading towards pandemic and serious global crisis. In this paper, a simulation environment leveraging the synergy of deep learning-based predictions and linear optimization for efficient resource planning is presented. The proposed solution shows satisfiable prediction performance and enables efficient resource exchange by reducing the trading costs.**

Keywords – **Deep Learning, Coronavirus, COVID-19, Linear optimization, Simulation.**

I. Introduction

The hottest topic since the first days this year was the discovery of new infectious disease *COVID-19* caused by *SARS-Cov-2* virus (also known as *2019-nCoV* or simply *coronavirus*) in China, which was behind several pneumonia cases in Wuhan's Seafood Wholesale Market [1]. One of the main differences from well-known influenza-alike viruses is the fact that even persons without any symptoms might be potential sources of infection [2, 3], which led to fast outbreak in China. A long and varying incubation period (2-14 days, exceptions of up to 27 days) [3] and high death rate in elder population [1, 2], making the situation even more difficult.

However, after just several weeks, the first cases were reported in other continents. It is believed that coronavirus reached Europe in the end of January, with the first case reported in France [4]. In next several days, the cases were reported in several other countries as well (Germany, Finland, Italy, Sweden) [4]. However, there were still just few cases in each of these countries and still did not seem so critical. Later, in mid-February, the number of cases in Italy has started to increase dramatically making it one of the world's worst-affected countries. Towards the middle of March, the COVID-19 was also detected in most parts of Europe which led to limited movement, lockdowns and closing borders in some of the countries. Therefore, the new disease turned from Chinese outbreak to worldwide pandemic in short time, which led to tragic consequences in many countries, huge number of lost lives, on the first place, but catastrophic financial losses and stagnation of economy as well [2]. Moreover, there is no specific treatment for COVID-19 proven by clinical trials yet [5]. For all these reasons, the world has reached the COVID-19 crisis.

In pandemic, it is of utmost importance to plan resources efficiently, but timely – either human, material resources or equipment. The protection of health and the economy of a country are linked tightly [6]. On the other side, it was shown that simulation is an effective approach contributing to the reduction of pandemic's consequences, especially at provincial and local level [7]. Therefore, in this paper, a software simulation environment is proposed aiming the efficient resource planning in current pandemic COVID-19 crisis.

In [8], an approach to prediction of COVID-19 spread based on simulation in Iran, which has been one of the disease's epicenters in the beginning, was presented. However, the work presented in this paper builds upon the approach from [9], that has shown as effective, leveraging prediction and linear optimization for optimal blockchain-based energy trading in smart grids. Analogously, in [10], linear optimization was used within smart city simulation environment for network resource planning together with deep learning and fading effect calculation.

II. Background

A. Linear Optimization

Linear optimization (known as *linear programming*) refers to mathematical method whose goal is to achieve the best possible outcome, relying on a mathematical model, where the requirements are represented by linear relationships [11]. It covers the techniques for optimization of a linear *objective function*, subject to linear equality and inequality *constraints*. The vector of variables determined as output of optimization is *decision variable*.

In this paper, linear programming is leveraged for optimal resource planning and exchange between cities during COVID-19 crisis. The implementation is based on AMPL[1], an algebraic modeling language for mathematical programming which enables writing linear programs using the syntax inspired by traditional algebraic notation. While it is not used for solving optimization problems, it provides interface to other programs responsible for that task. In this paper, CPLEX[2] based on simplex method [12] was used as a solver.

Nenad Petrović is with University of Niš, Faculty of Electronic Engineering, Aleksandra Medvedeva 14, 18000 Niš, Serbia, E-mail: nenad.petrovic@elfak.ni.ac.rs

[1] https://ampl.com/
[2] https://www.ibm.com/analytics/cplex-optimizer

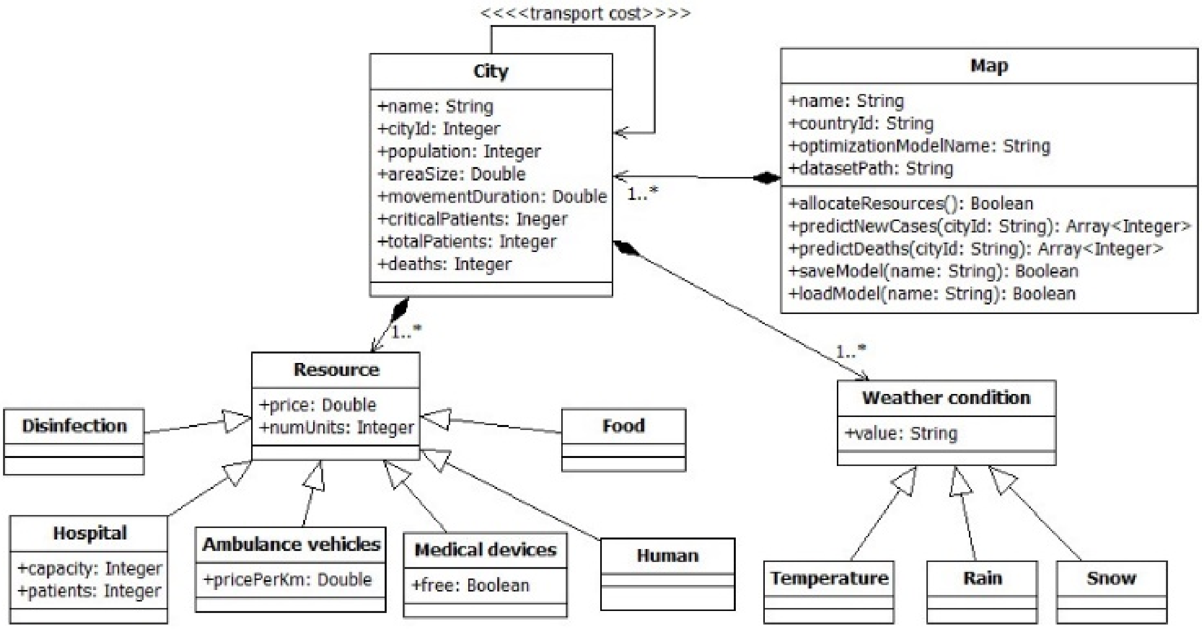

Fig. 2. Modelling environment notation as UML class diagram

B. Deep Learning

Deep learning includes various machine learning techniques based on artificial neural networks. *Artificial Neural Network* (ANN) is a group of computational units interconnected via weighted links known as *perceptrons.* Each unit contains one or more weighted input connections, a transfer function combining the inputs and an output connection [13]. Perceptron receives a signal, processes it and forwards the result to other connected nodes. Three types of layers exist in neural networks [13, 14]: 1) *input* - corresponds to the input variables 2) *hidden* – resides between the input and output layers 3) *output* - produces the output variables. A *deep neural network* (DNN) is an artificial neural network (ANN) which has multiple layers placed between the input and output layers [14].

In this paper, we make use of deep learning in order to predict number of new cases and deaths within city, necessary for resource demand estimation. The prediction model is trained on publicly available online data about COVID-19 spread and death cases from previous period. TensorFlow[3] for Python programming language with GPU-powered execution on CUDA-compatible graphics hardware was used for implementation.

III. Implementation

A. Solution Overview

First, user creates models of cities in terms of available resources (medical workers, equipment, vehicles, patients, disinfection) using a visual modelling environment run in web browser. A domain-specific notation is used for that purpose. The modelling tool implementation is based on JavaScript, HTML and CSS. Once the model is completed, it is augmented by the data about expected resource demands based on the results achieved relying on deep learning prediction model. Online public data about number of new infected people and deaths in countries and cities around the world on daily basis from various sources is aggregated, filtered and prepared for making new predictions. Moreover, AMPL .dat file generator constructs appropriate input for linear optimization process taking the previously created model and predictions that are produced as result of deep learning. After that the linear optimization according to the AMPL optimization model is performed, giving the output that represents optimal resource exchange which does not only help the affected cities from unnecessary distribution costs and spending, but also could lead to more lives saved. In Fig. 1, an illustration of the proposed solution is shown.

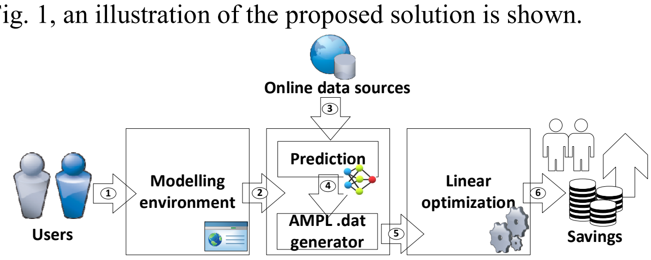

Fig. 1. Solution overview: 1-Model creation 2-Resource model 3-Aggregated and filtered data from online data sources 4-Predictions based on past data 5-AMPL data file 6-Optimization results

B. Modelling and Simulation Environment

A UML class diagram of the metamodel used for city resource modeling notation is given in Fig. 2. A map consists

[3] https://www.tensorflow.org/

of cities that are able to exchange resources during the crisis. The parameter describing the city connections is *transport cost*. Relevant parameters for cities are the number of citizens, its area size, number of hours allowed for movement. Moreover, relevant parameters for pandemic situation are the total number of cases and number of critical cases. Each city has six types of resources: 1) hospital buildings 2) ambulance vehicles 3) medical devices 4) medical workers 5) disinfection products 6) food. An important resource feature is its price. At each hospital, there is a limited capacity. At each moment, a number of places within the hospital can be occupied by patients. In case of COVID-19, respiratory equipment is crucial for saving lives in critical cases. For that reason, it is one of the most important resources exchanged between the cities, apart from disinfection products which can lead to reduction of new cases [15]. There is also possibility to set weather parameters like temperature, rain and snow.

The implementation of modelling and simulation environment is based on engine used for [9] and [16]. There are two views within the tool: (a) map view and (b) city view. Map view gives a global overview of the affected cities. City view is available for each city from the map, by double-clicking on it. In this view, it is possible to perform the resource allocation for further exchange on a local or global level. In case of foreign cities or countries included as donation/help or resource exchange partners, they can be added to the map and their resources set. In Fig. 3, a screenshot of the proposed tool is given.

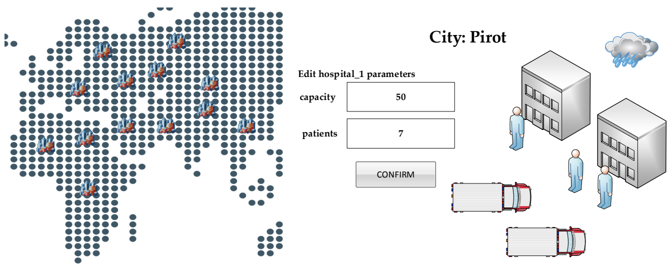

Fig. 3. Modelling and simulation tool screenshot: (a) map view (b) city view

Moreover, several simulation mechanisms are implemented. First, it is checked whether the number of respiratory devices is greater or equal to the number of critical patients:

$$num\_critical \leq num\_respiratory \quad (1)$$

After that, it is checked if the number of medical workers is enough to handle the number of expected new cases based on estimation of how many patients each medic can handle:

$$\frac{expected\_cases}{patients\_daily\_per\_medic} \leq num\_medics \quad (2)$$

A similar check like (2) is also done for ambulance vehicles.

Finally, it is checked if there is enough free space to place the patients in hospital:

$$expected\_cases \leq hospital\_free\_places \quad (3)$$

If one these conditions denoted fails, then an alert occurs in the simulation environment and corresponding resource exchange process based on the selected linear optimization strategy will be triggered.

$$if\,(condition_i \text{ } is\; false)\; then\; optimization(strategy_i) \quad (4)$$

C. Predictions Based on Deep Learning

The data aggregated from online sources was split into two disjoint sets – the training set (75%) and test set (25%). It consists of total eight variables, as it is shown in Table 1.

TABLE I
SPREAD PREDICTION DATASET

Id	Density [p/km^2]	Age [y]	Day [0..366]	T. [C]	Mh [h]	New [p]	D. [p]

City id represents the identification number of the considered area within the country. Number of persons per km^2 provides the information about population density within the area. Median age is the age that divides a population into two numerically equally sized sets, which might be of huge importance for prediction of death cases. Day refers to the ordinal number of a day (from 1 to 365 or 366). Temperature is the average daily temperature that day which could affect the movement of citizens that day. Instead of temperature, other weather parameters might be leveraged, such as rainfall. Movement hours is time frame during the day when the citizens are allowed to go outside and may vary across countries and cities, ranging from 0 (total quarantine) to 24 hours (regular situation). New cases refer to the number of new infected people identified within the area, as an average of 7 days which is approximately the average length of the incubation period [3]. Deaths is the number of people that died as consequence of COVID-19 disease that day. City id, density, age, day number, temperature and movement hours are treated as independent variables, while the number of new cases and deaths are dependent variables (predicted values). However, the information about population density, median age and movement hours are optional, but the predictions could also be made without them.

For training, publicly available data about the new cases and deaths on national level around the world was used from [17] together with data for cities in Serbia from [18].

D. Linear Optimization Model

There are several optimization models for different resource exchange strategies implemented within the tool (respirator, medical personnel, food, disinfection, vehicles and patients exchange), but only one of them will be described.

Let us consider a network of interconnected cities involved into resource trading, denoted as *C*. Travel cost *tc[i,j]* is assigned to each link between *city[i]* and *city[j]*. Each *city[i]* has predicted number of critical patients *cp[i]* and available respirator devices *r[i]*. For each critical patient, a respirator device is needed. Each *city[i]* has respirators of price *rp[i]*.

Moreover, each *city[i]* has amount of budget *b[i]* that is the maximum amount of money which can be spent. To each connection between cities, a decision variable x[i,j] is assigned to indicate the amount of respirators that will be sent from *city[i]* to *city[j]*:

$$x[i,j] \geq 0 \; \textit{if trading between } city_i \textit{ and } city_j \textit{ will be perfromed}, \quad x[i,j] = 0 \; \textit{otherwise} \tag{5}$$

However, there are several resource exchange constraints. First, the overall amount of available respiratory devices after exchange is always equal or greater than the number of critical patients.

$$r[i] + \sum_{j \in C} x[i,j] - x[j,i] \geq cp[i], i \in C \tag{6}$$

Moreover, the total cost of respirator acquisition should not exceed the available budget:

$$b[i] \geq \sum_{j \in C} tc[i,j] + x[j,i]rp[j], i \in C \tag{7}$$

Finally, the objective function minimizes the overall sum of costs, considering both the travel cost and respirator price:

$$minmize \sum_{i,j \in C} tc[i,j] + x[i,j]rp[i] \tag{8}$$

IV. Evaluation

For evaluation, a laptop equipped with Intel i7 7700-HQ quad-core CPU running at 2.80GHz, GTX1050 GPU with 2GB VRAM, 16GB of DDR4 RAM and 1TB HDD. In Table 2, the evaluation results in respirator device exchange scenario for different number of cities involved are given, considering the execution time for different processing steps – prediction and optimization (in seconds) and cost reduction (as percentage). According to the results, the processing time increases with the model size, but it does not exceed one second in the executed experiments. On the other side, the reduction of resource exchange costs depends on the problem instance itself and varies from case to case. When it comes to prediction performance, the relative error was 24%, while AUC score was 0.81.

Table II
Evaluation Results

Size [cities]	$T_{prediction}$ [s]	$T_{optimization}$ [s]	$C_{reduction}$ [%]
3	0.29	0.016	31
5	0.31	0.021	28
7	0.38	0.059	42
10	0.51	0.084	63

V. Conclusion

The proposed approach gives promising results, enabling the timely allocation of resources in a pandemic crisis situation. However, the tool is still a work in progress and more data about new COVID-19 cases in Serbia is needed for better prediction performance.

Acknowledgement

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