A Data-Driven Optimization Model for Medical Resource Allocation during the Pandemic

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ABSTRACT

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The outbreak of Covid-19 in recent years has once again brought the critical issue of medical resource allocation during a pandemic to the forefront of research and public attention. The dynamic and rapid nature of the pandemic has posed significant challenges in accurately predicting the demands for medical resources and developing effective strategies for their distribution. In this study, we aim to address these challenges by studying the medical resource allocation problem during a pandemic and proposing a data-driven optimization methodology that combines mathematical programming and machine learning techniques.

To tackle the problem of demand prediction, we utilize a Long Short-Term Memory(LSTM) model to predict medical resource demand using historical pandemic time series data. Building upon the demand predictions, we develop a linear programming model to optimize the allocation of medical resources. The objective is to maximize the total accessibility of hospitals within each region while also ensuring a balanced distribution of accessibility across all regions. We also conducted a case study on the application of this framework to the Quebec, Canada, pandemic hospitalization case scenarios. The dataset we utilized consisted of hospitalization case numbers from 16 regions in Quebec, along with the geographical locations of 15 regions and their corresponding healthcare facilities. The prediction performance is evaluated by mean absolute error(MAE) and root mean square error(RMSE), which yielded average values of 3.079 and 5.491, respectively. And after optimizing, the total accessibility of all regions is 4.503. The results indicate the effectiveness of our proposed method in accurately predicting future hospitalization numbers and determining the necessary increase in bed capacity for each region, showcasing its potential to assist in resource planning and allocation during a pandemic.

Keywords: Data-Driven Optimization; Medical Resource Allocation; Long Short-Term Memory; Linear Programming

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Chapter 1

Introduction

A pandemic commonly refers to an epidemic of contagious diseases that spreads rapidly over a whole nation or one or more continents at the same time; for example, pandemics include smallpox, Black Death in history, and HIV/AIDS at present[1]. In the past decade, the most significant pandemic that emerged around the world is Covid-19. Covid-19 is an infectious respiratory disease that is caused by a virus called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The virus was first identified in December 2019 in Wuhan, China, and was first isolated from the lower respiratory tract of the Covid-19 patient sample[2]. Statistical results from the epidemiological studies demonstrated that SARS-CoV-2 is highly contagious and exhibits large variability —— the virus has developed multiple strains and has affected over 200 countries worldwide. Moreover, Covid-19 has infected approximately 6 million people and has caused the death of 365,000 individuals worldwide until the end of May 2020[3]. Although the pandemic seems to be ending, within less than one month, 5.3 million new confirmed cases and over 48,000 deaths were reported (January 23 to February 19, 2023). As of February 2023, over 757 million Covid-19 cases and over 6.8 million deaths have been documented globally[4].

Most hospitals are overloaded as the number of Covid-19 patients raised rapidly. Although the majority of infected cases could recover themselves, there was still a large number of severe cases that needed medical treatment and hospitalization. The high number of patients would place a sustained and great demand for medical resources on the current health system and might overwhelm the medical health infrastructure. Take the situation in the United States as an example, the medical demands created by the Covid-19 pandemic were well beyond the capacity of the hospital and medical infrastructure. Based on the numbers from the American Hospital Association, there was under 68,400 intensive care unit (ICU) bed that was available for adult patients in the community hospital of the whole state. Additionally, the limited hospital beds, ventilators, personal protective equipment (PPE), and trained respiratory therapists presented critical concerns to the health systems and those issues needed to be addressed immediately[5]. Thus, the urgent problem was to resolve the shortage of hospital space and medical resources to satisfy the large health demand. In this thesis, we developed a data-driven optimization framework that could manage the hospital beds efficiently and increase the capacity of the hospitals based on past hospitalization data from different regions. The framework we constructed would focus on predicting the weekly hospitalized case numbers and allocating hospital beds using machine learning and optimization techniques. A case study about Quebec pandemic scenarios was also conducted, which applied this framework.

1.1 Principles of Medical Resource Allocation

Generally, there was a shortage of medical resources to satisfy the large demand from patients during the pandemic; therefore, an efficient allocation plan was needed to properly manage these resources and maximize their usage. In a situation where medical resources are limited, the questions of who gets those resources and how the resources can be divided ethically and equally become significant. Ethical principles need to be followed for allocating scarce medical resources, and those principles were traditionally classified into four categories: treating people equally, favouring the worst-off, maximizing total benefits, and promoting and rewarding social usefulness[6]. Each of the four values can be operated in different ways in real-life medical settings; thus, evaluating one specific value as a single criterion alone was not sufficient to determine who receives the scarce medical resource. Multiple ethical values and frameworks are needed in the pandemic setting to fairly allocate health resources. Therefore, in the scenario of Covid-19, more specific ethical recommendations were designed based on the complex context. The new ethical values include six instructions: maximize benefits; prioritize health works; do not allocate on a first-come, first-served basis; be responsive to evidence; recognize research participation; and apply the same principles to all Covid-19 and non-Covid-19 patients[5].

Among these principles, maximizing total benefits, especially maximizing the number of lives or life years saved, was the most crucial[5]. This principle was typically regarded as the highest priority during a pandemic period, and we also considered maximizing total benefits as the primary goal in this research. Maximizing benefits is composed of both saving maximum numbers of lives and maximizing the quality and length of the patients' post-treatment life. Given the limitations of time and information during the Covid-19 pandemic, it is more reasonable to prioritize maximizing the number of patients who survive treatment; after that, maximizing the length of life will be considered.

1.2 Challenges for Medical Demand Allocation under Pandemic

The pandemic is an epidemic that propagates rapidly and infects people in different regions across international boundaries. The intervention and control of pandemic propagation are critical as their efficiency determines the outcome of the infection. On the one hand, inefficient healthcare emergency coordination and epidemic control can result in an increase in the number of infected people and the rate of mortality. On the other hand, sophisticated and well-developed strategies and frameworks that properly organize infected patients and provide them with timely clinical management and medical treatment can reduce the infectious rate of this disease and lead to the breakdown or deceleration of the virus chain. Thus, it is critical to design rational interventions and create efficient instructions to control the spread of the disease.

The two main factors that are necessary for controlling the infection include broad-scale diagnostic tests and sufficient health protection. In the current Covid-19 setting, multiple diagnostic test method has been developed rapidly in the past year to enable rapid broad-scale diagnostic of the disease, for example, SARS-CoV-2 detection by a real-time revese-transcripase-polymerase-chain reaction from nasopharyngeal swab and SARS-CoV-2 protein detection by short-time antigen testing. However, the available in-stock healthcare equipment, which includes diagnostic tools, personal protection products, and medical treatment resource, was not adequate to satisfy the overwhelming demand for diagnosing and treating Covid-19 during the pandemic. The question of how to properly manage the limited medical resource arises, and in this particular project, we focused on how to manage the hospital beds, as an important and measurable index of medical resources, effectively, when the hospitals were reaching full capacity and were facing large public health demands under Covid-19.

Predictions on the disease propagation and the medical demand need to be made to allocate the limited health resources rationally and efficiently. These predications can help the medical institution and government to better organize the resource in advance so that the health system would not be completely overwhelmed and more patients can receive proper medical treatment. Hence, the urgent problem now becomes forecasting medical equipment demands and the number of hospitalized cases in the future based on the current knowledge of the Covid-19 disease and its epidemiological statistical data.

Under the Covid-19 condition, the medical supply chain exhibited two distinct characteristics that increased the complexity and difficulty of solving the medical demand forecasting problems. First, the information related to immediate medical demand was limited[7]. To prediction the number of hospitalization patients in the future with high accuracy, the information on the exact number of infected/hospitalized patients from each region needs to be up to date. The prediction would also be more valid if the statistical data on the patients' number was reported and updated everyday. However, most platforms did not provide that information in detail, and the data on the available medical equipment was limited, which creates obstruction and confounding factors in making predictions of the medical demand in each region. There were various reasons that were causing the delay and generalities of the information on medical demands, which included the limited number of staff in the health care system and the delay in documentation from the manual operation aspect. The property of the Covid-19 infectious disease itself might also play a role; in particular, the varied incubation period of Covid-19 resulted in a time delay for disease information, and the medical needs could not be immediately reported.

Second, the infection was highly contagious and displayed great variation between individuals. Infection and mortality rates, clinical symptoms, and individual patients' customs typically varied across different areas. The high contagious rate and various infectious patterns with different virus strains of Covid-19 made it difficult to predict the disease. Moreover, the large variety of symptoms in Covid-19 patients was another factor that made making predictions on the number of hospitalized patients even harder. Covid-19 patients exhibited a broad range of symptoms, from no symptoms, mild symptoms with fever, cough, myalgias, and gastrointestinal symptoms, to severe symptoms with acute respiratory distress syndrome that needed more delicate medical treatment with the utilization of mechanical ventilator and endotracheal intubation. Thus, it is difficult to determine the proper medical treatment each patient needs just after one simple diagnostic test[8]. As a result, medical services and clinical treatment provided by the hospitals in each area with each patient were also different, which made the prediction even harder[9].

1.3 An Optimization Framework for Temporary Healthcare Facility Location Problem

The pivotal challenges of allocating medical resources during the pandemic were quickly identifying the urgent demand and constructing a corresponding allocation plan, which was crucial to providing timely medical treatment to patients and relieving the pressure on hospitals.

In this study, we presented a framework to allocate medical resources to different hospitals of different regions in a given city to maximize the total benefits, using a time series prediction model and an optimization model. The objective of our research was to properly manage the available medical resources to satisfy the large need for hospitalization and balance the utilization of hospital space in different regions. We developed a system that calculated the number of specific medical resources that needed to be increased with a combined allocation plan, which could provide insight for the government to manage medical resources more efficiently during the pandemic.

We proposed a long short-term memory(LSTM) model to forecast the medical resource demand, which is well-suited for making predictions based on time series data and avoiding the problem of vanishing gradients. In addition, we applied a linear programming method for the optimization model, which aimed to maximize the accessibility of patients with the minimum difference in the accessibility between each region. We forecast the demand within weekly intervals, which would serve as the input in the optimization model, to propose a feasible allocation plan. More importantly, we used the real-life data of the Covid-19 pandemic from April 2020 to June 2022 from Quebec, Canada, to evaluate the performance of the proposed framework (shown in the Result section) to test the validity of the framework. The success in forecasting the medical demand would give insight to the health care system and the government to help them properly allocate the medical resource and relieve the pressure from large medical demand.

1.4 Contribution

The main contribution of this thesis was to develop a data-driven medical resources allocation framework to maximize overall accessibilities across regions given high volatile demands during the pandemic. We integrated a machine learning-based demand prediction model and a linear programming resource allocation model to optimize the allocation plan. Furthermore, we conducted a case study on applying this framework to Quebec pandemic hospitalization case scenarios, which could provide insight for the government to manage medical resources during the Covid-19 pandemic efficiently and be referred to future scenarios when other severe infection outbreaks occur.

1.5 Thesis Outline

The remainder of this research is structured as follows. In section 2, a review of previously relevant literature is presented. In section 3, the problem that needs to be solved is stated. In section 4, the problem is described along with our proposed framework, which presents a data-driven optimization model in which a machine learning prediction method, LSTM, and a linear programming formulation are included. Section 5 contains the case study on Quebec, Canada. In section 6, the conclusion and future works are discussed.

Chapter 2

Literature Review

When a pandemic occurs, it creates a significant influence and an immediate burden on the medical system, which leads to a dramatic increase in the demand for healthcare, including medical treatment and health equipment supply. In order to control the spread of the pandemic and minimize the mortality of the disease, it is urgently necessary to solve the problems of the overloaded capacity of hospitals and insufficient inventory of medical resources that are inevitable during the onset of the pandemic. With the prevalence of Covid-19, there has been wide research on medical demand forecasting and healthcare resource allocation utilizing various methodologies in recent years. Due to the large differences in the number of confirmed cases and hospitalized patients across different regions within various time periods, the demand for medical resources varies significantly. Therefore, it is necessary to establish a model that can accurately predict the demand of different regions during the pandemic.

In this research, we suggested a data-driven optimization framework to allocate supplementary medical resources efficiently to different regions in a given area. Our framework was divided into two sections, including medical demand forecasting and allocation optimization, so the literature review mainly focuses on these two aspects by analyzing the framework other research groups used to solve these problems. These two parts would be further divided into subsections by different methods.

In detail, our proposed methods contained a time series model to predict the demand for medical equipment and hospital beds in specific, using historical time series data on the number of Covid-19 hospitalization in different areas. Afterwards, the allocation problem of medical equipment was solved with a linear programming method. Together, the objectives of this framework were to increase and balance the accessibility of hospitals for Covid-19 patients in each region. Later on, this model may also apply to other scenarios when the healthcare system is facing a large demand for medical treatment to allocate the equipment efficiently.

2.1 Medical Demand Forecasting Model

Medical demand forecasting is a crucial process that involves predicting the future demand for health services, healthcare needs and rates of utilization of services based on previous knowledge acquired through a systematic process[12]. By forecasting, healthcare providers can better meet the needs of their patients, improve the quality of care, and ultimately improve health outcomes, which is especially essential during the pandemic period to achieve the goal of maximizing benefits with limited medical resources.

However, since the background of research varies, which includes social-cultural factors and also differences in the spread of disease and the demand for medical treatment in each region and country, the method used to study medical demand forecasting may be different. In a complex situation, especially with the emergence of the pandemic, there are many factors that are influencing the spread of the disease and the distribution of medical resources and treatment. Thus, there is no a role of thumb approach to make medical predictions under complicate scenarios, so hybrid methods have often been utilized to forecast aggregate or specific health conditions in the past[13]. Another significant risk factor during the prevalence of the pandemic is the scarcity of medical supplies, which is also regarded as supply chain risk. They can be categorized into operation and disruption risks, and epidemic outbreaks are one kind of disruption risk which belongs to low-frequency-high-impact events[10]. More importantly, epidemic outbreaks present particular threats to the supply chain, distinguishing them from other disruption risks. These threats include (1) the presence of long-term and unexpected scaling disruption, (2) disruption propagation in the supply chain and epidemic outbreak propagation in the population, and (3) disruptions in the infrastructure of logistics, demand, and supply[11]. Since epidemics typically begin as small-scale that rapidly spread, timely and accurately forecasting demand during such pandemics presents a significant challenge. Various demand forecasting models have been proposed to facilitate better supply chain management during epidemic outbreaks. In specific, three methodologies based on their respective approaches are commonly used in the situation of epidemic which includes, machine learning, mathematical models, and SIR/SEIR models.

Together, in this subsection, we would mainly review previous prediction models about medical demand, which includes artificial intelligence-based model, statistic based model, stimulation-based model, and time series model, and how those studies may give insight into constructing our model of optimizing medical resource allocation during Covid-19.

2.1.1 Artificial Intelligence-Based Model

In recent years, the field of Artificial Intelligence (AI) has experienced rapid development with the flourish of information and computational technologies. AI's strong ability of automative analysis has allowed it to handle complex data and has been widely utilized across diverse domains, including the medical demand prediction aspect that we were focusing on. Various engineering groups have applied AI to process data in depth; the apparent advantages of the usage of AI techniques would be that it eliminates artificial errors and bias, simplifies repetitive data work, and increase the efficiency of the project, while its disadvantages would be the high preliminary cost and work effort for its construction. Here, we reviewed the research on the medical demand forecasting model using AI.

Peipei Liu[14] has provided a dynamic neural network model to forecast the intermittent demand for medical consumables with a short life cycle. They proposed a neural network model as their basic forecasting model, as well as an optimal model, which adapts the minimum description length(MDL) to select optima neurons in the neural network. This sMDL-NN model avoids underfitting and overfitting and enhances the generalization capacity of zero-demand data.

Shilpa J. Patel et al.[15] have developed a machine learning model for predicting demand for hospitalization for pediatric asthma by only using the data available at the time of triage. They examined the performance of four common machine learning approaches, including decision trees, LASSO logistic regression, random forests, and gradient boosting machines. As a result, gradient boosting machines worked more precisely than the other three methods.

Da-Young Kang et al.[16] have developed an artificial intelligence algorithm to predict the medical service demand in emergency medical services. They used feedforward networks to classify the demand for critical care, which trained the output by the Softmax Classifier. Moreover, they applied the Adam optimizer to improve the accuracy of the prediction. This AI algorithm based on deep learning could better deal with a large number of input variables, which was validated in this model as well.

Shuojiang Xu et al.[17] have proposed a machine learning method with big data to forecast the demand for medical devices. They used the search index on the Internet as the input, combined with the historical demand to build the prediction model. The result shows that online search queries could improve the accuracy of the forecasting model, and SVM performs well when the number of observations is limited.

Rohaifa Khaldi et al.[18] have developed a feedforward neural network(FFNN) model combined with an ensemble empirical mode decomposition(EEMD) technique to forecast the weekly arrivals of patients to the emergency department. The EEMD technique was used to divide the signal of weekly visits into sub-signals, which entered into the FFNN model to make the prediction. With the combination of these two methods, learning stochastic noises could be avoided, improving the performance of the prediction model.

Zhaozhi Qian et al.[19] have developed a Covid-19 capacity planning and analysis system(CPAS), a machine learning-based system, to generate a plan to manage ICU resources of hospitals across the UK. This system comprised an aggregated trend forecaster, which used a compartmental epidemiological model combined with a framework of Bayesian hierarchical modelling and Gaussian process to predict the overall trend of hospital admission, along with an individualized risk predictor, which used an auto machine learning tool to predict ICU capacity. CPAS could manage nationwide ICU resources during the pandemic.

Marcel Goic et al.[20] have developed an ensemble model to predict the demand for ICU beds under Covid-19. They built a compartmental model to describe the patient flow, which is widely used in epidemics research. They also introduced several autoregressive neural networks and artificial neural networks to capture dynamic variations, following a trimmed mean approach to generate the prediction output. Moreover, they directly used the number of symptomatic cases as the primary input.

While AI techniques hold numerous advantages, there are some limitations other than their cost when applying them to the field of medical demand forecasting. The quality of data plays a crucial role in the accuracy of AI predictions, and any deficiencies in input data could adversely affect the results. However, in reality, public historical data is generally low in quality due to the chaotic management and errors with manual data collection, which makes it not suitable for the construction of accurate AI models, particularly during the pandemic. When the public health system is under tremendous burden, obtaining timely and comprehensive data becomes challenging, which could potentially introduce delays in analysis and compromise the reliability of predictions.

2.1.2 Statistic-Based Model

Statistic-based data analysis and model construction are one of the most traditional methodologies for information processing and demand forecasting, and it has been widely accepted and utilized as the fastest and easiest approach for making the medical prediction. We here reviewed different research that has utilized statistic-based model to make medical predictions and their implications in the current Covid-19 pandemic.

Krisjanis Steins et al.[21] have developed a forecasting model for predicting the number of emergency medical services. Compared to the current SOS alarm forecasting model based on a moving average with seasonality weights method, this model was based on the zero-inflated Poisson regression approach to predict when and where the emergency call will occur. This ZIP model improved the accuracy of the result and revealed the factors that influenced the emergency calls as well. The overdispersed data is not suitable for the ZIP regression approach.

During the Covid-19 pandemic, the World Health Organization WHO, which is the most prestigious and reliable health agency for public health services, has also developed a statistic-based model that can easily predict the number of confirmed cases and supply needs. WHO[22] has developed Essential Medical Supplies Forecasting Tool Covid – ESFT model. They used a simple exponential growth method to estimate the expected cumulative cases and forecast essential supply needs. This method is best suited for estimating short forecast periods, of about six weeks or less, in the early stages of an outbreak.

Johannes O. Ferstad et al.[23] have developed a model that estimates the number of people requiring hospitalization and forecasts the demand for Covid-19 related hospital beds. This model used the initial hospitalization or confirmed cases numbers and the doubling time as the inputs, then used a simple exponential model to estimate the total number of COVID-19 people in each US county who required hospitalization.

The University of Washington's Institute for Health Metrics and Evaluation (IHME)[24] has developed a forecasting tool that provides a cumulative death rate forecast and a state-by-state health service needs forecast. They used a curve-fitting tool to fit a mixed effect non-linear regression model to obtain the cumulative death rate function related to time. Then, an individual-level microsimulation model was applied to estimate hospital service utilization, which used the death rate estimated from the model as an input.

Oilson Junior et al.[25] proposed a mathematical model to predict the demand for PPE in Brazilian hospitals during the pandemic. They applied naïve statistical modelling, which used historical data on the consumption of PPE by hospitals, current protocols for their uses and epidemiological data as the inputs to obtain the PPE demand forecast as well as the indication of the safety stock for each PPE.

Although statistical methods have been extensively used in healthcare research for their reliability and wide acceptance, these methods often rely on specific assumptions and are sensitive to outliers, which may limit their suitability for real-world scenarios. The traditional statistical models' low adaptation to complex situations and rapid-changing environments make them hard to handle the chaotic pandemic circumstance. Moreover, unlike AI models and other advance methodologies, statistical models cannot evolve quickly with the newly collected data, and there are also risks of errors with manual analysis. Thus, when we use statistical models in medical demand forecasting problems, their applicability in dynamic and complex healthcare settings should be carefully considered.

2.1.3 Simulation-Based Model

Simulation-based modelling is typically used for engineers and designers to construct and examine digital models and forecast their efficiency in real-life settings. The model elaborately investigates the maximum load of a digital and its physical model that can withstand and design the optimum working condition. This type of modelling could also be applied in the field of medical research forecasting, and the most known model is the SIR model and the SEIR model. The SIR model divides the analyzed population into three compartments, including Susceptible, Infectious, and Recovered, and the SEIR model contains one more Exposed compartment. The SIR/SEIR model is one of the most common infectious disease models, which can reflect the practical phenomena observed in incubation periods and is widely used in the epidemic model.

Thus, here we reviewed the research applying SIR/SEIR modelling in consistent with other simulation-based modelling to explore their potential in the Covid-19 pandemic.

World Health Organization WHO[22] has developed an Essential Medical Supplies Forecasting Tool Covid – ESFT model to help governments, countries, and hospitals forecast essential supplies for Covid-19. They used the SIR model to estimate the expected cumulative cases to forecast essential supply needs. This tool is more suitable for a short-period prediction, specifically 12 weeks or fewer.

Kristian Lum et al.[26] have developed a Covid-19 Hospital Impact Model for Epidemics (CHIME) & Personal Protective Equipment(PPE) Estimation tool to assist hospitals with hospital capacity and emergency medical supplies management. This model used the SIR model to forecast the expected daily number of Covid-19 patients who are hospitalized, the number in the ICU, and the number of new admissions. After that, they transferred patient projection into PPE projection by separating the PPE into two types and proposing a contact-based and stuff-based consumption model.

A collaboration between Oxford Policy Management, the University of Oxford, and the Covid-19 International Modelling Consortium[27] has developed an age-structured, compartmental SEIR model to estimate the trajectory of Covid-19 based on different scenarios and assess the potential impact of the various behavioural change strategies as well as treatment and vaccines. It can estimate the demand for hospital and ICU beds at various levels of the health system, the quantity of tests, personal protective equipment, ventilators, and other supportive tools needed in treating the diagnosis and treatment of patients, and the cost of equipment needed.

Yuxuan He et al.[28] presented a modified SEIR model to forecast the time-varying emergency medical demand for public health emergencies. They separated people into the common and vulnerable groups to enhance prediction accuracy due to the different infection, recovery and mortality rates between these two groups. Demand for prophylactic relief was also considered in this model.

Eugene Furman et al.[29] used theory from time-varying queueing models to propose a prediction framework to forecast the amount of PPE required over a defined period during the Covid-19 pandemic. This was achieved by grouping patients with similar hospital experiences into distinct categories and subsequently determining their expected length of stay (LoS) in the hospital and the PPE requirements for each interaction between the patient and healthcare worker.

Kali Barrett et al.[30] introduced a data-driven simulation model to predict the PPE demand for a region. A discrete time, dynamic, parallel, individual-level health state transition model based on epidemiologic data and clinic practice patterns was applied to estimate the PPE demand for the Ontario healthcare system. Additionally, the authors introduced the concepts of “touchpoints” and “PPE bundles” to estimate the amount of PPE required per patient.

Simulation models are intuitive and provide a clear visualization of the entire prediction process, allowing for a better understanding of the impact of different strategies on the outcomes. However, building simulation models requires a substantial amount of data and a theoretical foundation, which can be challenging for demand prediction during a pandemic when all the data is newly collected and the available information is limited. Additionally, the results of simulation models always rely on initial assumptions. Considering the complex situation of the Covid-19 pandemic, it would be hard for the researchers to make reliable initial assumptions with the scarce information and any errors or biases within the assumptions may largely affect the accuracy of the result.

2.1.4 Time Series Model

Time series prediction is a method to forecast upcoming trends of the given historical dataset with temporal features[31]. Time series data typically exhibit four components: trend, seasonal effect, cyclical, and irregular effect, which are essential in understanding the underlying patterns and dynamics of the data[32]. One of the main assumptions in time series analysis is that the future behaviour of a time series will resemble its past behaviour. Therefore, by analyzing past data, we can make predictions about future events.

Traditionally, researchers have employed various methods for time series analysis, which are auto-regressive moving average (ARMA), auto-regressive integrated moving average (ARIMA), LSTM, artificial neural network(ANN) models, etc. In the following subsection, some research about these models will be reviewed in detail.

- **Long Short-Term Memory Method**

Erdinc Koc et al.[33] have developed a multilayer long short-term memory(LSTM) network for forecasting demand for medical equipment and the number of confirmed cases of Covid-19. This framework consisted of a normalization layer, a multilayer LSTM network, a dropout layer, a fully connected layer and a regression layer, while an adaptive moment estimation algorithm was introduced in the neural networks to train the LSTM network. They used Covid-19 data from Turkey in experimental studies and separately predicted the number of intensive care beds, respiratory equipment and confirmed cases.

Sajad Shafiekhani et al.[34] have proposed an LSTM model to predict confirmed Covid-19 hospital admission numbers. They employed the Adaptive Moment Estimation(ADAM) optimizer to update the weight and bias in this structure. Moreover, they set the initial learning rate, learn rate drop period, learn rate drop factor, and gradient threshold as 0.005, 125, 0.2 and 1, respectively, to train this model. altonThe dataset was divided into 75% for training and 25% for testing purposes. The results of the study demonstrated the LSTM model's ability to accurately predict the number of confirmed cases in both ICU and non-ICU settings.

Muhammad Iqbal et al.[35] have utilized an LSTM model to predict Covid-19 cases in Pakistan. They have used the Percentage of Positive Patients, which represents the ratio of the number of daily positive tests and the total tests conducted per day, as the input to ensure the accuracy of the prediction model because of the lack of test kits in Pakistan. The dataset consisted of 80 days of training data and 24 days of testing data. The researchers conducted experiments with different configurations, including varying the number of hidden nodes, epochs, and batch size, to identify the optimal performance of the LSTM model. The mean absolute percentage error (MAPE) was used to evaluate this model. The results revealed that the model achieved the best performance with 20 hidden nodes, 100 epochs, and a batch size of 15.

Junling Luo et al.[31] have applied time series models to predict the daily confirmed cases of Covid-19. They introduced an LSTM and an XGBoost model to predict the time series data of America as well as to compare the capability to interpret the complex trend in time series. They used the confirmed cases number as the input. Moreover, the dataset was separated into 90% training and 10% testing data. The experimental result showed that LSTM outperformed XGBoost in predicting the Covid-19 time series data under their assumptions.

Luyu Zhou et al.[36] have evaluated several time series forecast models, including LSTM, bidirectional long short-term memory (Bi-LSTM), generalized regression unit (GRU), and dense-LSTM, for the prediction of confirmed cases and deaths during Covid-19. The cumulative confirmed cases and death cases from a total of 12 countries were utilized as the inputs. Partitioning for the dataset is set to 70% and 30% for training and testing. The results have shown that Bi-LSTM, which can learn information from previous and future, performed better on high-frequency data. Furthermore, the LSTM model has the highest prediction accuracy.

Dalton Borges et al.[37] have presented an Integrated Multivariate Prophet-LSTM method to forecast ICU bed demand during Covid-19. This approach incorporated various factors, including traditional time series components, daily Covid-19 cases, vaccination rates, non-pharmaceutical interventions, social isolation index, and regional hospital bed occupancy, to capture the complex dynamics of ICU demand. The methodology combined the strengths of the Prophet model in capturing time series components and linear relationships with the LSTM model's ability to capture non-linearities and correlations. A comprehensive dataset from Brazil was utilized to evaluate the proposed model, and its performance was compared to traditional time series methods like ARIMA and KNN. The results demonstrated that the Prophet-LSTM approach outperformed other methods in accurately forecasting Covid-19 ICU demand.

- **Other Method**

Wang-Chuan Juang et al.[38] have applied time series analysis to forecast monthly emergency department(ED) visits for demand prediction. They collected monthly ED visit data from January 2009 to December 2016 for a time series autoregressive integrated moving average analysis(ARIMA), among which the data from 2016 was used to validate the accuracy of this model. They determined the components of ARIMA by some tentative order selection algorithms. Finally, the predicted accuracy of this model was evaluated via the mean absolute percentage error.

Yihuai Huang et al.[12] have proposed a hybrid time series prediction model to forecast the demand for medical services. They applied an ARIMA model to build the basic prediction model while introducing a self-adaptive filtering model to optimize the parameters of the ARIMA model to improve the prediction accuracy. This model makes a balance between prediction accuracy and calculation complexity.

Tasquia Mizan et al.[39] have proposed a novel approach to reduce patients' waiting time by developing a multi-target time series forecasting model. In the training phase, they compared the performance of five different models, including three problem transformation models (proposed ensemble of pruned progressor chain, stack of single target and ensemble of regressor chain) and two algorithmic adaptation models (regression forest and support vector regressor) to select the most accurate model. Subsequently, the chosen model was applied to predict the three target variables, namely patient arrivals, workload and miss turn-and-around(miss-TAT) rate.

Mahdieh Tavakoli et al.[40] have simulated the patient flow and applied a time series method to predict the future entry of patients at a hospital in Iran during the pandemic, aiming to provide insights for medical demand management. The Arena software was used to simulate the patient flow process. Then, the seasonal auto-regressive integrated moving average(SARIMA) method was employed to predict the entry of outpatients, emergencies and inpatients. They collected 10 months of historical data as the input and separated it into 70% for training and 30% for testing, enabling the forecasting of patient entry data for the future 30 days. The predicted output was then combined with the Taguchi method and data envelopment analysis(DEA) model to simulate worst-case scenarios, facilitating preparedness recommendations for future medical demand.

Sinaga H et al.[41] have compared two time series techniques to forecast the medical disposable supply demand at a hospital in Indonesia. The moving average method and exponential smoothing method were employed, using an input of 180 days of data. The researchers specifically compared the simple moving average models with 3-point and 4-point moving average, and the single exponential smoothing models with smoothing parameter α set to 0.1 and 0.3. The evaluation of the models was based on the RMSE. The results revealed that the exponential smoothing model with α = 0.1 achieved the highest level of accuracy among the models compared.

2.1.5 Remark

After conducting a comprehensive literature review on methodologies and modelling used for medical demand prediction, we have selected the LSTM model in our study for several reasons. Firstly, our research mainly focuses on forecasting the hospitalization numbers for the upcoming week, which will be utilized in optimizing medical resource allocation. Given the availability of daily hospitalized case data from official websites during the pandemic, LSTM's ability to handle time series data makes it well-suited for our purposes. Secondly, pandemic-related data often exhibit delays, incompleteness, and significant fluctuations due to factors such as vaccination efforts and policy changes. LSTM's capability to effectively handle noisy or incomplete data enhances its suitability for capturing the dynamic nature of medical demand during uncertain times. Thirdly, LSTM's inherent ability to capture long-term dependencies in sequential data further supports its efficacy in predicting complex and evolving medical demand patterns. Together, those reasons render LSTM one of the best suitable models to make medical demand predictions based on the currently available data.

2.2 Medical Resource Allocation Optimization Model

When a pandemic occurs, it brings immense pressure on the healthcare system, resulting in scarce medical resources and overcrowded hospitals. To address these issues, multiple strategies can be implemented, including: (1) increasing supply resources by adding manpower, number of beds, equipment and space; (2) controlling demand sources by implementing feasible strategies; (3) exploiting management skills and operational research models for the efficient allocation of medical resources[42]. Of these, the third alternative appears to be more efficient, as it can facilitate the realization of the first two approaches while guiding for addressing similar issues in the future. In this subsection, we will review existing research on medical resource allocation models.

2.2.1 Single-Objective Optimization Model

Yuxuan He et al.[28] proposed a linear programming model to optimize the distribution of emergency medical relief under the concern of both physical and psychological. The objective of this model is to minimize the physical fragility of infected individuals, which is related to the priority of common and vulnerable groups and infected rates. They also proposed an extended allocation model that adopted a suffering coefficient which reflected the additional psychological suffering due to the distribution delay based on the original model.

João Flávio de Freitas Almeida et al.[43] have developed a two-step optimization model to address a location-allocation problem in second-level healthcare by mathematical methods. For the first step, they developed a mixed-integer linear program(MILP) model to select the location of medical facilities concerned with minimizing the weighted sum of demand and distance between patients and facilities. Another MILP model was utilized to make the allocation plan for the medical equipment with the target of minimizing the distance between patients and equipment. This model mainly focuses on distance and reaction time; the cost is not in the scope.

Tamara de Melo Sathler et al.[44] have proposed an integrated model to tackle the location-allocation problem of medical specialties centers(MSCs). They developed a MILP model to determine the optimal locations of MSCs and allocate medical equipment to maximize population demand for specialized medical care and exams while avoiding the need for supplementary resources, and the additional resources were only considered if necessary. The model was constrained based on the available state budget and capacity limitations.

Jayalakshmi D S et al.[45] have presented a system to optimize the allocation of medical test examples to testing laboratories under Covid-19. A MIP based brand-and-bound algorithm was established to obtain the optimal result, which integrated a baseline greedy model and clustering technique to identify relevant clusters and optimize transportation costs. This model efficiently distributed test samples among labs within a state by taking into account factors of timeliness, resource availability, and transportation costs.

Shaojen Weng et al.[46] have built a simulation model aimed at optimizing resource allocation in emergency departments (EDs) using data from a medical center in Taiwan. The objective of the model is to minimize the National Emergency Department Overcrowding Scale (NEDOS) value, which measures congestion in the ED. The NEDOS value is calculated based on various factors such as waiting time, number of sickbeds, number of hospitalized and emergency patients, and other parameters, using a regression equation. A higher NEDOS value indicates a higher level of congestion. The output of the model is an allocation plan for physicians, nurses, and sickbeds. The analysis of the results demonstrates that implementing new allocation strategies can improve the overall performance of EDs by approximately 8%.

2.2.2 Multi-Objective Optimization Model

Yang Liu et al.[47] has developed a bi-objective optimization model to determine the optimal temporary medical service locations and medical service allocation plan. The objectives of this model were to maximize the number of expected survivals and minimize the total operational cost, which was in conflict and could not be directly solved by the MIP solver. To address this, the authors developed an iterative method based on the ε-constraint method, which transformed the bi-objective model into a single objective sub-problem. The proposed method enabled the identification of Pareto-optimal solutions that provide a tradeoff between the objectives.

Zhenyu Chen et al.[48] have developed a bi-objective optimization model for an emergency medical resource allocation problem. The model incorporates a two-dimensional material flow, encompassing the vertical allocation between two echelons and the horizontal allocation within each echelon. The objectives of the model are to allocate medical resources efficiently and fairly. The ε-constraint method is employed to transform the bi-objective problem into a single objective formulation. Moreover, the objective functions were designed to minimize the mean and variance of unsatisfied demands in different outbreak regions, which are equivalent to maximizing allocation efficiency and fairness.

F Ben Abdelaziz et al.[49] has developed a multi-objective stochastic program model to assign beds to hospital departments. They considered mathematical programming to minimize the cost of the creation and management of new beds and the number of nurses and physicians working in these hospitals. To solve this stochastic program, the researchers utilized a combination of a chance constrained approach, a recourse approach, and a goal programming approach, which ultimately transformed the multi-objective stochastic program into a certainty equivalent program. This model considered interactions between different hospital units in a country.

Wenting Zhang et al.[50] has developed a genetic algorithm based multi-objective optimization(MOO) approach for healthcare facility location-allocation problems in highly developed cities. They developed four mathematical optimization models to satisfy the four conflicting objectives associated with building new healthcare facilities. Then, they yield a set of Pareto solutions to identify the most practical tradeoffs between the objectives.

Tasquia Mizan et al.[39] have proposed a mathematical model to reduce patients' waiting time in healthcare facilities. The model is designed to optimize medical resource allocation and workload distribution through a multi-objective MILP(MOMILP) approach. The model takes into account the parameters of patient arrivals, workload, and miss-turnaround time (miss-TAT) rate as inputs, which were from a forecasting model. The objectives of the model are to minimize waiting time, service delay, miss-TAT rate, and workload while maximizing on-time service. To solve the model, the researchers applied two techniques: weighted-sum and ε-constraint.

Bahareh Kargar et al.[51] have designed a novel MOMILP model for a liver transportation and allocation problem considering both efficiency and equity. This model was proposed to maximize the survival rate of patients and minimize transportation costs and time. To solve the model, they first reformulate the objective functions into linear forms using a combination of min-max operator and binary variable multiplication techniques. Then, a possibilistic programming approach was applied to transform the original model to an equivalent auxiliary crisp model to address the problem of fuzzy numbers better. Finally, a new interactive fuzzy goal programming method was developed to obtain the optimal Pareto solutions.

2.2.3 Remark

In our study, we adopted a linear programming model to solve the medical resource allocation issue. The primary aim of our model is to maximize accessibility by adding hospital beds, the sole variable in the optimization model, which is well-suited to the framework of the linear programming model. Moreover, this choice was driven by the simplicity and practicality offered by linear programming, as it allowed us to efficiently incorporate multiple constraints while pursuing our objectives. Leveraging the predicted hospitalization data from our forecasting model, along with the original supply of hospitals and geographical information, we were able to design a computationally efficient solution that didn't impose excessive hardware requirements. By employing linear programming, we could effectively address the resource allocation challenge and enhance the overall accessibility of medical services.

Chapter 3

Problem Statement

3.1 Introduction to the Problem

In the past few years, the emergence of the Covid-19 pandemic has placed a challenge on the healthcare system worldwide. Based on the estimation from statistical research, the mortality of Covid-19 ranges from 0.25% up to 3.0% before vaccination, which is substantially higher in comparison with seasonal influenza [52]. Additionally, the high variability and contagiousness of the SARS-CoV-2 has resulted in a vast number of infected patients. However, historical data has suggested that 80% of patients who are infected with Covid-19 exhibit non to mild symptoms; there was approximately 20% of infected patients who need advanced medical treatment and hospitalization, which creates a tremendous demand for medical treatment.

This large demand for medical resources has placed a heavy burden on the health infrastructure. The medical resource supply has been extremely limited during the pandemic period, and this phenomenon has been well-documented in literature from different countries. The shortage of medical resources includes scarcity of hospital beds, personal protective equipment (e.g., gloves, N95 mask, protective coverall), trained therapies, other medical workers, and so on. In one of the most developed countries, the United States, it is only estimated be a total of 85,000 adults ICU beds in the whole state, including the undercounting beds from the American Hospital Association data[53]. The number of respiratory therapists and critical care staff who are able to operate is also extremely limited. Based on medical law, the existing number of respiratory therapists can only manage a maximum of 10,000 patients daily, which is the same number of confirmed cases weekly at peak in the U.S., take account the fact that lots of patients are not documented and cannot receive proper medical treatment [5]. The scenario is much worse in developed countries; poor healthcare infrastructure, extreme shortage of medical workers per population, and scarcity of medical supply and ICU facilities, are all essential reasons[54].

Thus, how to organize the limited medical resource ethically and efficiently with a large number of hospitalized patients is an urgent problem that needs to be solved. Considering the high transmission of mortality of the Covid-19 pandemic, ethical and rational principles that are suited for the pandemic need to be followed to properly allocate scarce health resources. In specific, in the thesis, we would be focusing on maximizing the benefits, which can be simply explained as saving most lives and most life-years with quality as the main principle to be assessed.

3.2 Allocation Challenges

In short, the problem we were facing could be viewed as a location-allocation problem for the healthcare facility. In this kind of problem, accessibility, the ratio of supply and demand, is a critical factor that refers to the relative ease by which the locations of activities. It typically measures the relative ease by which work, school, shopping, recreation, and health care, can be reached from a given location[55, 56]. To better assess the accessibility of medical sources during the pandemic, measurable variables that represent the supply and demand need to be determined at the start of the research. Among the number of healthy trained therapies and the number of patients who need advanced treatment, the amount of personal protective equipment supply and needs, the number of hospital beds and the number of hospitalized patients are the best pair of variables to represent the supply and demand for medical treatment as they both could be easily measured and the data could be accessed publicly online.

Thus, we treated hospitalization cases as the medical demand and hospital beds as the health supply, aiming to optimize accessibility by determining the optimal number of additional beds. However, each region typically had more than one hospital, we were unable to determine the specific allocation of cases within the region and we could not ascertain the individual requirements for each hospital. To simplify the model, we make the assumption that each region was served by a single hospital positioned at the midpoint of all hospitals within the region to analyze the problem.

In the traditional resource allocation model, the statistical data for demand is typically manually estimated and the generated allocation plan for the supply is mostly static, which is not suited for the uncertainty and dynamic of the pandemic. During the ongoing pandemic, updating time series data of the confirmed and hospitalized cases has been a crucial resource for people from different fields. The historical data could be used by researchers to investigate the epidemiology of the disease; the government could analyze the real-time data to organize the patients and control the propagation of the disease efficiently; the public could be informed about the circumstance of the disease to better protect themselves. It was relatively easy for us to obtain the data of hospitalization case data each day in each region of Quebec. Therefore, we could construct data-driven optimization models to forecast the medical demand and allocate the resource efficiently as the time series data of hospitalization cases is accessible online. Different from the traditional resource allocation framework, the data-driven model leverages the historical and real-time data to generate allocation plan that are dynamic and adapt rapidly to the change of the pandemic.

Overall, the data-driven model could better estimate future medical demand and enhance the overall efficiency and effectiveness of health resource allocation. To forecast the medical demand and compute a distribution solution, we employed machine learning techniques to predict hospitalization demand based on historical time series data. The data comprised information about the geographical locations of regions and hospitals, the demand from each region, and the initial number of beds at each hospital. The problem then became how to allocate the limited health resource, hospital beds, to hospitals in each region more efficiently to maximize the overall benefits. Merely matching the number of beds to hospitalized cases is insufficient for effective optimization, which may lead to an excessive allocation of beds in some hospitals, resulting in wastage, while others remain underutilized. In short, we need to maximize accessibility for hospitalized cases while minimizing the inequity of accessibility between each region. Thus, in the constructed framework in this thesis, the allocation was the process of balancing the usage of hospital beds in each hospital and considering adding or transferring hospital beds to the existing hospitals to satisfy the principles of medical resource allocation and utilize the limited medical resource efficiently and effectively.

3.3 Objectives and Significance of the Research

The objective of the proposed data-driven optimization framework was to satisfy the increased hospitalization demand caused by the pandemic by predicting the medical demand, number of patients who need hospitalization, and allocating the limited medical resource, number of hospital beds, efficiently and effectively. Moreover, the general goal of the thesis was to maximize the benefits based on the principle of allocating medical resources.

The significance of this research was that we constructed a data-driven framework that applied the time series data on the hospitalized cases from each region of Quebec, Canada. The data-driven framework adapted to the rapidly changing circumstance of the pandemic and could make reliable predictions. The validity of the framework was also evaluated by the future dataset from each region, which imply that it could be used as a reference the forecast the spread of the disease and the allocation of medical resource. The government and health facilities could apply this model to manage the limited medical resource during the Covid-19 pandemic effectively and efficiently. More importantly, the framework could also be utilized in the future, when other severe epidemics or pandemic outbreaks occur.

Chapter 4

Medical Resource Allocation Optimization Framework

4.1 Framework for Medical Resource Allocation Problem

In this research, we present a framework to model the problem as a time series capacity allocation problem. More specifically, we use time series data as input for an LSTM model to predict the future hospitalization case number. The predicted data will then be utilized in a linear programming model to determine the optimal number of newly added hospital beds number and the allocation plan, with the objective of maximizing the overall accessibility of all regions involved.

Figure 1. Framework for Medical Resource Allocation Problem

4.2 Long Short-Term Memory Model for Medical Demand Prediction

Long short-term memory (LSTM) is a type of recurrent neural network (RNN) architecture used in deep learning. It was proposed by Hochreiter and Schmidhuber in 1997[57]. It is an efficient algorithm for building a sequential time series model.

RNN is one of the artificial neural networks where connections between nodes form a directed graph along a temporal sequence, allowing RNN to exhibit temporal dynamic behavior. RNNs can use their internal status (memory) to process variable-length sequences of inputs[58-60]. However, RNNs have long-term dependencies problems. They will be gradient vanishing and gradient explosion when learning long sequences. To address these challenges, LSTM networks were introduced. LSTM networks were specifically designed to overcome the long-term dependencies problem associated with RNNs.

LSTM networks are well-suited for classifying, processing, and making predictions based on time series data. The working principle of LSTM architecture is based on the long-term information reminder approach. This architecture contains hidden units called memory cells[33]. The LSTM structure generally includes layers of forget, input, and output gates. These layers determine whether an entry is significant and what information to delete or save[57, 61, 62]. By incorporating specialized memory cells and gating mechanisms, LSTM networks are able to effectively capture and propagate information over extended time intervals, enabling more robust learning and prediction performance. By utilizing the memory-enhancing capabilities of LSTM, we can improve the model's ability to capture temporal dependencies, leading to more accurate and reliable predictions in various applications.

4.2.1 Long Short-Term Memory Network

LSTM structure consists of repetitive sequential blocks, as shown in Figure 2. The general processing steps of this structure are as follows[61-64].

1. Firstly, using the information x_t and h_{t-1} to determine what information is to be deleted from the cell state. These operations are carried out using (f_t) in Equation (1) in the forgotten layer:

$$f_t = \sigma(w_f x_t + w_f h_{t-1} + b_f) \tag{1}$$

where sigmoid is used as the activation function. The output of the LSTM is denoted as h, while' w represents the weight matrix and b corresponds to the bias vector.

2. The next step is to determine the new information to be stored in the cell state. First, the information is updated using the sigmoid function i_t. Secondly, the tanh function is applied

to generate candidate values C_t, which will introduce new information into the cell state. These operations are formulated by Equations (2) and (3):

$$i_t = \sigma(w_i x_t + w_i h_{t-1} + b_i) \quad (2)$$

$$C_t = tanh(w_c x_t + w_c h_{t-1} + b_c) \quad (3)$$

Then, new information is created using Equation (4):

$$C_t = C_{t-1} * f_t + i_t * \tilde{C}_t \quad (4)$$

3. In the last step, output data are decided using Equations. (5) and (6):

$$o_t = \sigma(w_o x_t + w_o h_{t-1} + b_o) \quad (5)$$

$$h_t = o_t * \tanh(C_t) \quad (6)$$

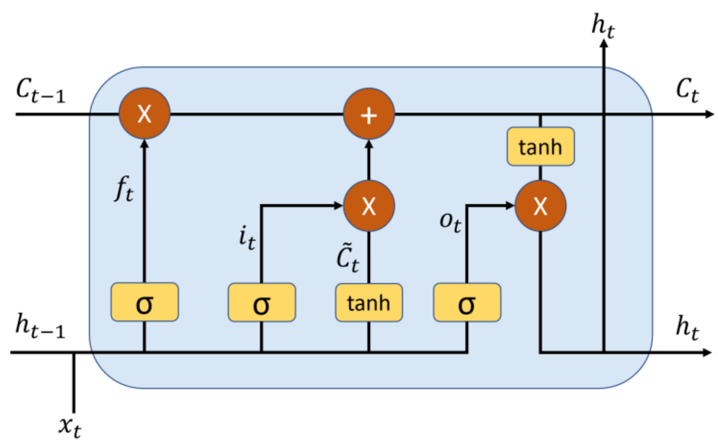


Figure 2. LSTM Structure

4.2.2 Medical Demand Forecasting Model

In this research, the LSTM model was employed to predict medical demand during the pandemic. We specifically focused on hospital bed demand, a critical parameter in the following optimization model, so we utilized the daily hospitalization case number as the input data to train our LSTM model. The choice of using the daily hospitalization number as input was motivated by its direct correlation with the demand for hospital beds. By capturing the temporal trends in the hospitalization data, the LSTM model was able to learn and predict the future demand for beds more accurately.

In order to enhance the computational efficiency during training, a normalization process was applied to the input data. Specifically, the min-max method was employed to normalize the data, ensuring that it is scaled within a range of 0 to 1. After that, the ADAM(Adaptive Moment Estimation) optimizer was employed to train the data, which is designed to combine the advantages of AdaGrad and RMSProp methods[65]. ADAM enables efficient stochastic optimization that only requires first-order gradients with little memory requirement. In the training phase, other parameter settings are presented in Table 1. Finally, the trained weights of the test data were utilized to forecast the number of hospital beds, which would be imported into the optimization model as the input.

Table 1. Training Parameters and Values

Parameter	**Value**
Learning Rate	0.001
Drop Ratio	0.2
Hidden Units	16
Epochs	30
Step Size	5
Batch Size	32

4.3 Optimization Model for Medical Resource Allocation Problem

In our optimization model, we assume a place where there are *m* regions and *n* healthcare facilities. Each healthcare facility is located at the midpoint of the hospitals within its respective region. It is important to note that *m* may not be equal to *n* due to the absence of healthcare facilities in certain regions or the unavailability of facilities for ill patients caused by the contagion, which means patients in such regions need to seek healthcare facilities located in other regions. We also assume that patients in one region could visit hospitals in other regions.

To determine the demand for each region, denoted as D_i, we utilize the number of hospitalized cases in each region which is predicted from the forecasting model. Additionally, we consider the initial supply of each healthcare facility, represented by SO_j, which corresponds to the number of hospital beds.

In our optimization model, we introduce two key decision variables. The first decision variable x_j, represents the newly added hospital beds. If the x_j is zero, it indicates that no hospital bed is allocated to the healthcare facility in that region. Conversely, if the x_j is larger than zero, it means that x_j hospital beds will be distributed to the hospitals within that region.

The second decision variable y_i, represents the accessibility of each region. It refers to the relative ease with which healthcare facilities can be reached from each region. A higher accessibility value indicates that the healthcare facilities in a region are well-equipped to meet the demand for medical services, considering the available supply of hospital beds. Conversely, a lower accessibility value suggests that the demand for healthcare resources exceeds the available supply, indicating a potential need for resource reallocation.

The set, parameters and decision variables we used to formulate the linear programming model are defined in Table 2.

Table 2. Notations of the mathematical model

Index	Description
i, k	the index of the region
j	the index of the hospital
Sets	**Description**
M	the set of regions
N	the set of hospitals
Parameters	**Description**
$m \in \mathbb{Z}^+$	the total number of regions
$n \in \mathbb{Z}^+$	the total number of facilities
$D_i \in \mathbb{Z}^+$	the demand in the i-th region
$SO_j \in \mathbb{Z}^+$	the original supply capacity of the j-th hospital
$dis_{ij} \in \mathbb{R}^+$	the distance between the i-th region and j-th hospital
$\beta \in \mathbb{R}^+$	the coefficient of the distance decay function
$\alpha \in \mathbb{Z}^+$	the maximum value of the total increased supply capacity for all regions
$\gamma \in \mathbb{R}^+$	the maximum value of the difference between each region
Variables	**Description**
x_j	is the increased supply capacity on the j-th hospital
y_i	the accessibility at region i

4.3.1 The Mathematical Model and Formulation

The following formulations are used to model the medical resource allocation problem.

$$Maximize\left(\sum_{i=1}^{m} y_i\right) \tag{7}$$

$$y_i = \sum_{j=1}^{n} \frac{(SO_j + x_j) f(dis_{ij})}{\sum_{k=1}^{m} D_k f(dis_{kj})} \tag{8}$$

$$f(dis_{ij}) = dis_{ij}^{-\beta} \quad (\forall\, i \in M, \forall\, j \in N) \tag{9}$$

$$|y_i - y_k| \le \gamma \quad (\forall\, i, k \in M, \ \ i \ne k) \tag{10}$$

$$\sum_{j=1}^{n} x_j \le \alpha \quad \alpha \in \mathbb{Z}^+ \tag{11}$$

$$\alpha \le \sum_{i=1}^{m} D_i - \sum_{j=1}^{n} SO_j \tag{12}$$

$$x_j \ \ge 0 \quad (\forall\, j \in N) \tag{13}$$

The objective function (7) maximizes the total accessibility for all regions. This objective function is designed to ensure that medical resources are efficiently distributed to meet the demands of all regions during the pandemic.

In our model, accessibility is measured by the supply and demand ratio. To calculate accessibility y_i for each region, we employed equation (8)[50], which incorporates the original supply capacity of the hospital(SO_j), the newly added supply capacity of the hospital(x_j), the medical demand of the region(D_i), and a distance decay function($f(dis_{kj})$). The contribution of the supply at each facility j to the accessibility at region i is firstly discounted by the distance decay function. Additionally, the contribution is further discounted by the quantity of all demands and their respective locations[55].

Equation (9) is a general distance decay function[50]. β is the travel friction coefficient in this function. In previous studies, researchers have set different values and conducted sensitivity analyses for β within a specified range. Zhang et al.[50] set β as 0.8 in their studies on optimizing healthcare facility allocation problems in Hongkong. Wang et al.[55] have performed a sensitivity analysis on β in their equal accessibility problem choosing values within the range between 0.6 and 1.8, ultimately selecting $\beta = 0.6$ for their optimization. Moreover, Luo et al.[66] have tested seven values of β from 1.0 to 2.2 to compare two measurement methods of spatial accessibility. For the travel friction coefficient, people tend to travel further to the hospital when β is smaller, leading to smaller gaps in accessibility between regions[55]. And a larger β value means that patients are more unwilling to take long travel time to healthcare facilities[66].

Constraint (10) states that the accessibility between each region should be relatively balanced. By limiting the disparity in accessibility between regions, we strive to ensure that all patients have equal opportunities to access healthcare services, regardless of their geographic location. The threshold γ represents the maximum allowable difference in accessibility between any two regions. It can be determined based on policy considerations, resource availability, or other relevant factors. A smaller value of γ indicates a stricter requirement for balancing accessibility, while a larger value allows for more flexibility.

Constraint (11) ensures that the total number of additional hospital beds does not exceed the limit α, which represents the maximum capacity expansion allowed. The value of α is determined by the difference between the total hospitalization demand and the initial supply of hospital beds as the constraint (12). Constraint (12) ensures that α remains within a feasible range, limiting the expansion of capacity to a realistic and manageable level. Constraint (13) guarantees the decision variable x_j to be non-negative, which ensures that the number of hospital beds added to each facility does not fall below zero, reflecting practical constraints on resource allocation.

4.3.2 Worked Example

In this part, we present a worked example for the proposed linear programming optimization model. This example contains three regions and two facilities; other inputs are shown in Table 3. We oversimplified this problem to explain the optimization process clearly.

The first facility is located in the first region; the second facility is located in the second region, while there is no capacity that could be provided for the third region, which means patients in the third region should visit the hospital in the other two regions. The patients in these three regions that need to be hospitalized will be distributed to those two hospitals. The original capacity of the hospitals is not enough to accommodate patients. Therefore, the number of added hospital beds will be calculated by the model presented in the model part to satisfy the demand.

After calculating, the α, the maximum value of the total increased supply capacity for all regions, is 23. We firstly set $\gamma = 0.2$; the optimization result is $x_1 = 6$, $x_2 = 17$, which means hospital1 should add six beds, and hospital2 should add seventeen beds to satisfy the demand from these three regions, under the constraint that the accessibility between each region is less than 0.2. Moreover, the accessibility of the three regions is 0.743, 0.675, and 0.550, respectively.

Table 3. Inputs of the worked example

Region(i, k)	**Coordinate**	**Demand(D_i)**
1	(1,0)	15
2	(0,2)	10
3	(2,1)	5
Facility(j)	**Coordinate**	**Original Supply(SO_j)**
1	(0,0)	5
2	(0,1)	2
β=0.5		

In this model, γ is an important parameter influencing optimization results. When we set different γ, the different results are as below.

Table 4. Results comparison for different values of γ

ϒ	**x_1**	**x_2**	**y_1**	**y_2**	**y_3**
0.4	23	0	1.134	0.818	0.764
0.3	16	7	0.973	0.759	0.676
0.2	6	17	0.743	0.675	0.550
0.1	0	11	0.409	0.391	0.310

Chapter 5

Quebec Case Study

In the previous chapter, we proposed an LSTM method to predict the demand for hospitalization and a linear regression model to allocate hospital beds during the pandemic. In the chapter, we implement our methodology on a real-world case study from Quebec, Canada, Covid-19 dataset.

Quebec is the largest province by area and contains the second-largest population in Canada. Due to the broad land, it has been typically divided into 17 administrative regions[67]. Under the Covid-19 pandemic, Quebec once became the province with the most confirmed cases in Canada. The first case was diagnosed on February 28, 2020, and within a short period of time, the virus spread throughout the province. Until February 2023, the Quebec government announced over 1 million confirmed cases and 18,000 deaths related to Covid-19[68].

5.1 Data Description

Our objective is to predict the number of hospitalizations to confirm each region's demand in Quebec, then develop an additional hospital bed allocation plan for each hospital. To accomplish this, the dataset we need is separated into two parts: historical hospitalization cases and information about hospitals.

The historical hospitalization data for each region in Quebec was collected from Quebec's government website[69]. This website provided daily updates on the number of confirmed Covid-19 cases, deaths, and hospitalizations in each region. The advantage of using this dataset is that it directly provides the number of hospitalizations, eliminating the need to estimate hospitalizations from confirmed cases using hospitalization rates. This ensures more accurate and precise results. For our analysis, we used data from April 2020 to May 2022 to forecast the number of hospitalizations for the following week. After May 2022, the government only collected data on weekdays, which could introduce errors in our predictions and optimization due to the lack of weekend data. Therefore, we did not include hospitalization data after May 2022 in our analysis. The dataset was divided into training and testing sets, with 25 months allocated for training and one month for testing.

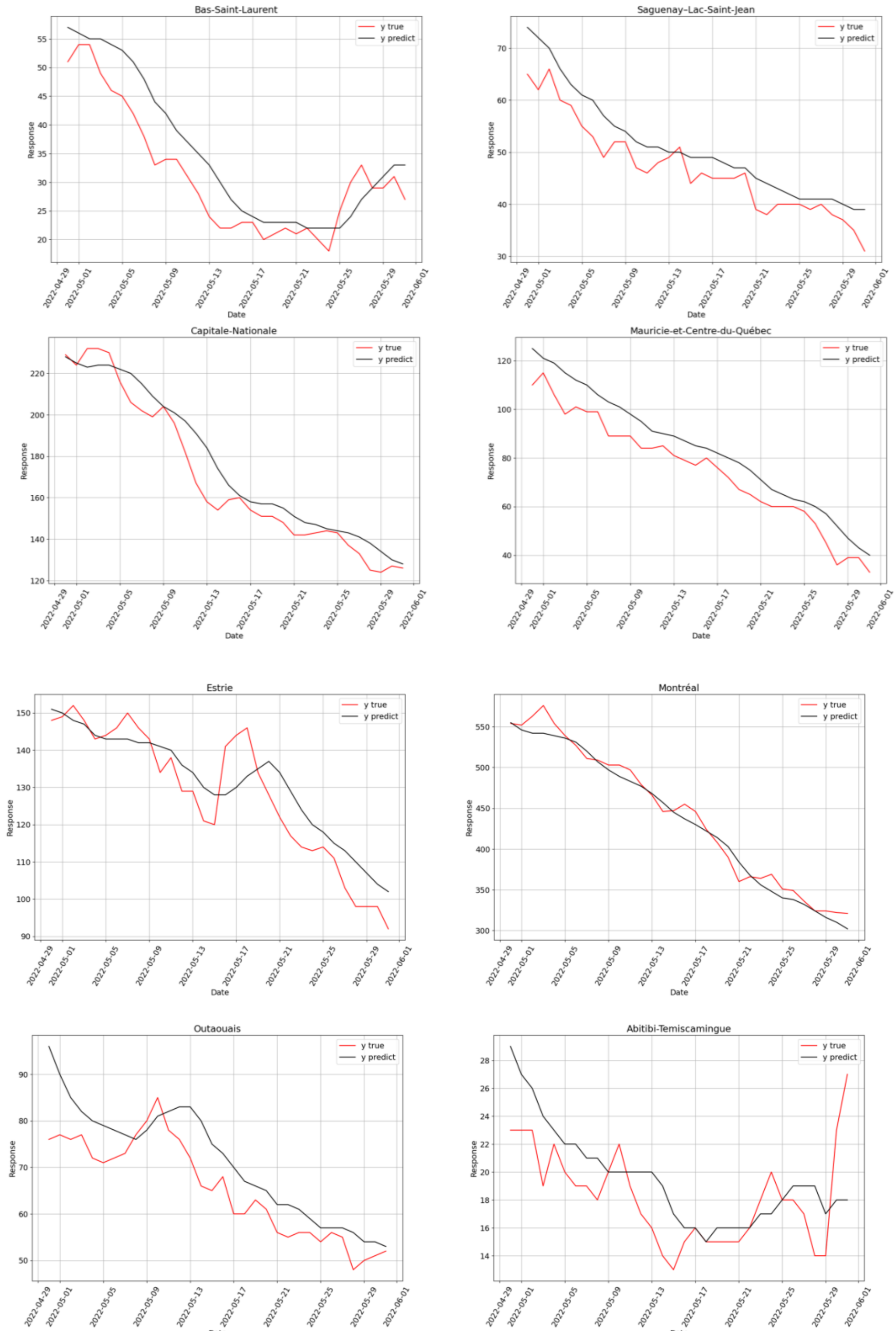
Regarding hospital information in Quebec, the original number of hospital beds in each region is retrieved from the Indexsante website[70]. This website provided information on the number of functional stretchers in the emergency rooms of each hospital in each region. Since infectious patients requiring hospitalization typically present severe symptoms, such as trouble breathing and persistent pain in the chest, and would visit emergency facilities for medical service[71]. In this case, the number of functional stretchers in the emergency room was considered equivalent to the number of hospital beds. The coordinates of hospitals and regions are obtained from Google Maps, with latitude and longitude represented by x and y coordinates, respectively. As we lacked specific information on individual hospital demands and only had overall demand for each region, we aggregated all the hospitals in each region. And we designated the midpoint of all hospitals within the region as the coordinate for this region's hospital.

5.2 Demand Prediction

5.2.1 LSTM Model Prediction Results

In the section, we have applied the LSTM model to predict the hospitalization numbers for the upcoming week across regions within Quebec. Each regional dataset encompassed a duration of 782 days, spanning from April 2020 to May 2022, providing hospitalization case numbers. The figures in the first 751 days were used for training, and the last 31 days were used for testing. And this process was repeated individually for each region under examination. During the training phase, the Adaptive Moment Estimation (ADAM) optimization algorithm was employed. The training process consisted of 30 epochs, with a step size of 5 and a batch size of 32 was utilized. It is important to note that these LSTM models are implemented using Python 3.10 on the Google Colab.

Below graphs show the results for each region in which the red lines present actual hospitalization case numbers while the black lines show predicted numbers.



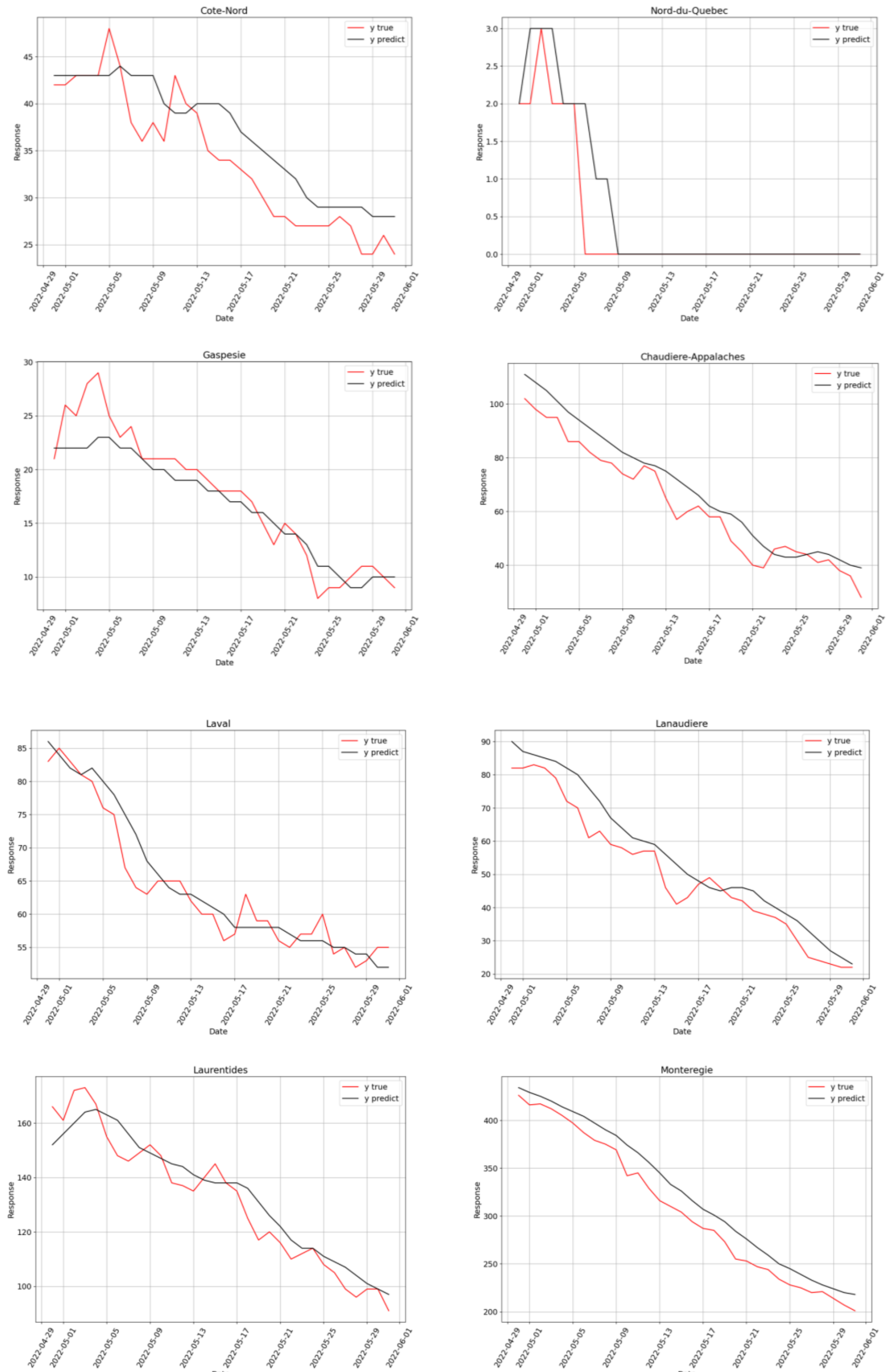


Figure 3. Comparing the actual value and predicted value of hospitalization numbers using LSTM for 16 regions in Quebec, the dataset from April 2020 to May 2022

And the predicted hospitalization numbers for the following 7 days of each region are shown in the table below.

Table 5. Prediction results for 16 regions' hospitalization numbers in Quebec for the following 7 days

Regions	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Total**
Bas-Saint-Laurent	33	33	33	34	36	37	38	244
Saguenay–Lac-Saint-Jean	39	39	39	39	39	40	41	276
Capitale-Nationale	130	128	127	128	129	129	129	900
Mauricie-et-Centre-du-Québec	43	40	39	40	40	40	40	282
Estrie	104	102	102	103	104	105	105	725
Montréal	310	302	296	290	284	276	270	2028
Outaouais	54	53	52	53	54	55	55	376
Abitibi-Temiscamingue	18	18	18	19	20	19	20	132
Cote-Nord	28	28	27	28	29	30	30	200
Nord-du-Quebec	0	0	0	0	0	0	0	0
Gaspesie	10	10	10	9	9	9	9	66
Chaudiere-Appalaches	40	39	38	38	38	38	37	268
Laval	52	52	52	52	51	50	50	359
Lanaudiere	25	23	23	23	23	23	22	162
Laurentides	99	97	97	97	97	97	96	680
Monteregie	220	218	218	217	218	220	220	1531

5.2.2 Performance Measures for LSTM Model

The performance metrics of the prediction results are shown in Table 6. We present the MAE and RMSE for each prediction, and the average of them is presented as well.

Table 6. The performance of the LSTM model for Quebec's regions dataset

Region	MAE	RMSE
Bas-Saint-Laurent	1.304	2.546
Saguenay–Lac-Saint-Jean	2.435	4.135
Capitale-Nationale	6.457	10.546
Mauricie-et-Centre-du-Québec	4.491	7.955
Estrie	4.001	6.596
Montréal	3.427	6.144
Outaouais	1.108	2.421
Abitibi-Temiscamingue	0.825	2.218
Cote-Nord	0.825	2.218
Nord-du-Quebec	0.125	0.433
Gaspesie	0.729	1.586
Chaudiere-Appalaches	3.038	5.106
Laval	2.344	3.057
Lanaudiere	3.350	5.254
Laurentides	4.910	9.726
Monteregie	9.898	17.914
Average	**3.079**	**5.491**

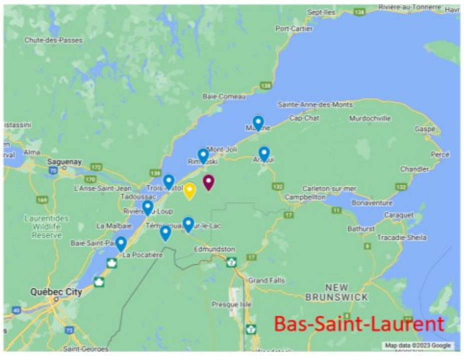
5.3 Linear Programming for Medical Resource Allocation Problem

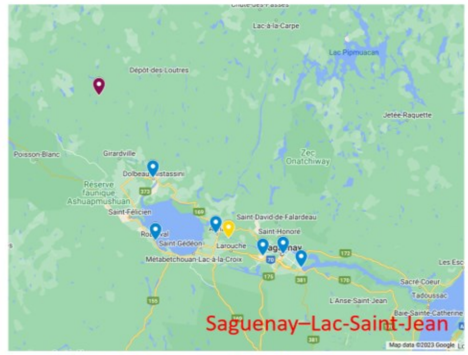
In our previous proposal, we presented a framework for the distribution of medical resources during the pandemic. In this section, we focus on addressing the issue of additional hospital beds using the Quebec hospital dataset. The problem involves various parameters and variables, which are defined in Table 1. Specifically, we consider the geographic coordinates (latitude and longitude) of regions and hospitals, as well as the initial number of hospital beds, as inputs for this allocation problem. Additionally, we incorporate the predictions generated by our LSTM model as the parameter $D_i \in \mathbb{Z}^+$, representing the demand for each region. To solve this linear programming problem, we utilize the Gurobi optimizer, a widely used tool for such purposes, in the Google Colab.

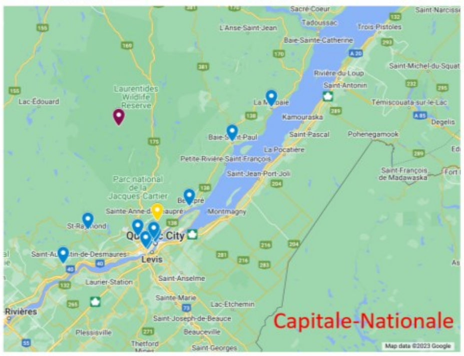
For our modelling assumptions, we treat each region as a point with its geographic location obtained from Google Maps. Regarding the hospital locations, we assume that each region has one hospital, and its coordinates are determined as the midpoint of all hospitals within that region, as previously mentioned. The distance between each region and its hospital is calculated as the linear distance.

There are 17 regions in Quebec. Because the region Mauricie and Centre-du-Québec are combined as one region in the hospitalization dataset, we only have the data of 16 regions in this framework. Moreover, it is important to note that there is no hospitalization case in Nord-de-Quebec from the result we predicted by the LSTM model, and there is no hospital available in this region either, so we opted to ignore this region in our optimization model.

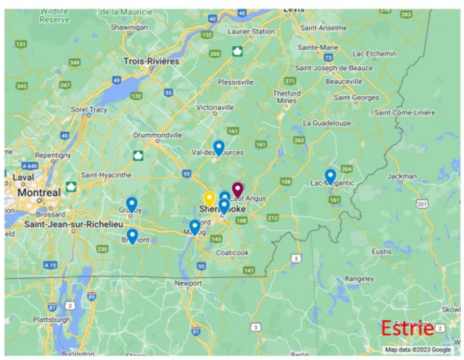
To illustrate the distribution of hospitals within each region, we provide Figure 4, which showcases the geographical representation of regions and hospitals. In the figure, the purple node represents the position of a particular region, the blue nodes represent hospitals within that region, and the yellow node represents the midpoint of all hospitals in the region. Additionally, Figure 5 presents the distribution of all regions and hospitals, with nodes of the same color denoting corresponding regions and the midpoints of hospitals.

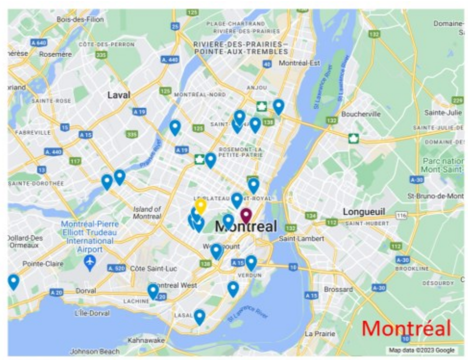

Bas-Saint-Laurent

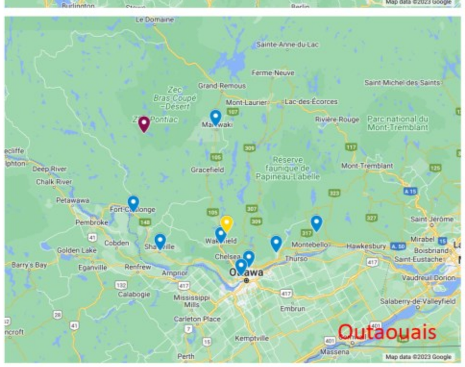

Saguenay–Lac-Saint-Jean

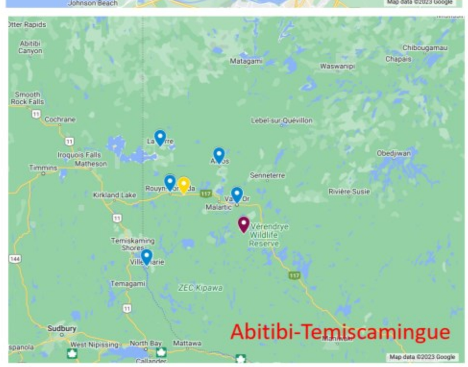

Capitale-Nationale


Mauricie-et-Centre-du-Québec


Estrie


Montréal


Outaouais


Abitibi-Temiscamingue

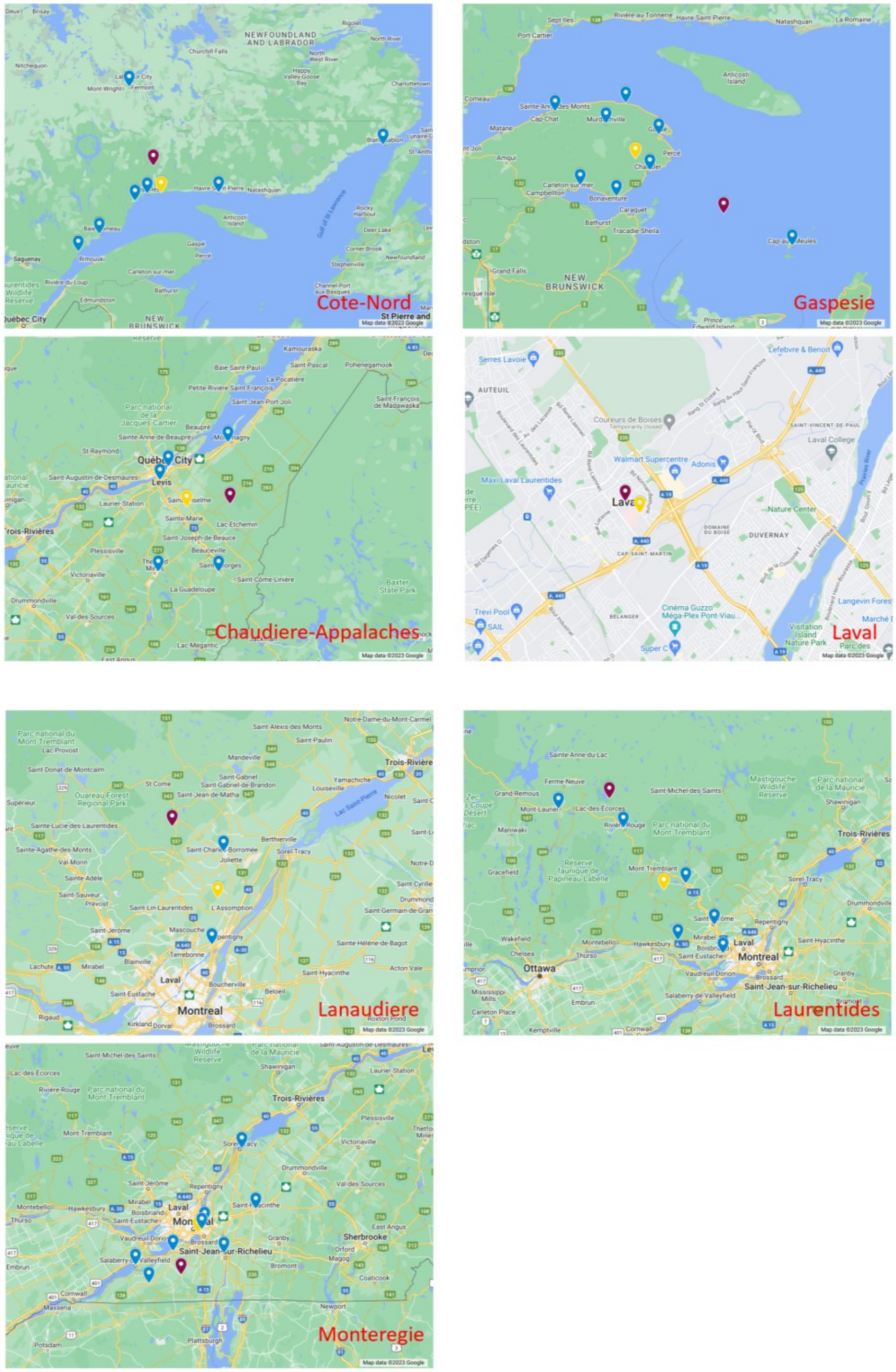


Figure 4. The distribution of hospitals in each region in Quebec

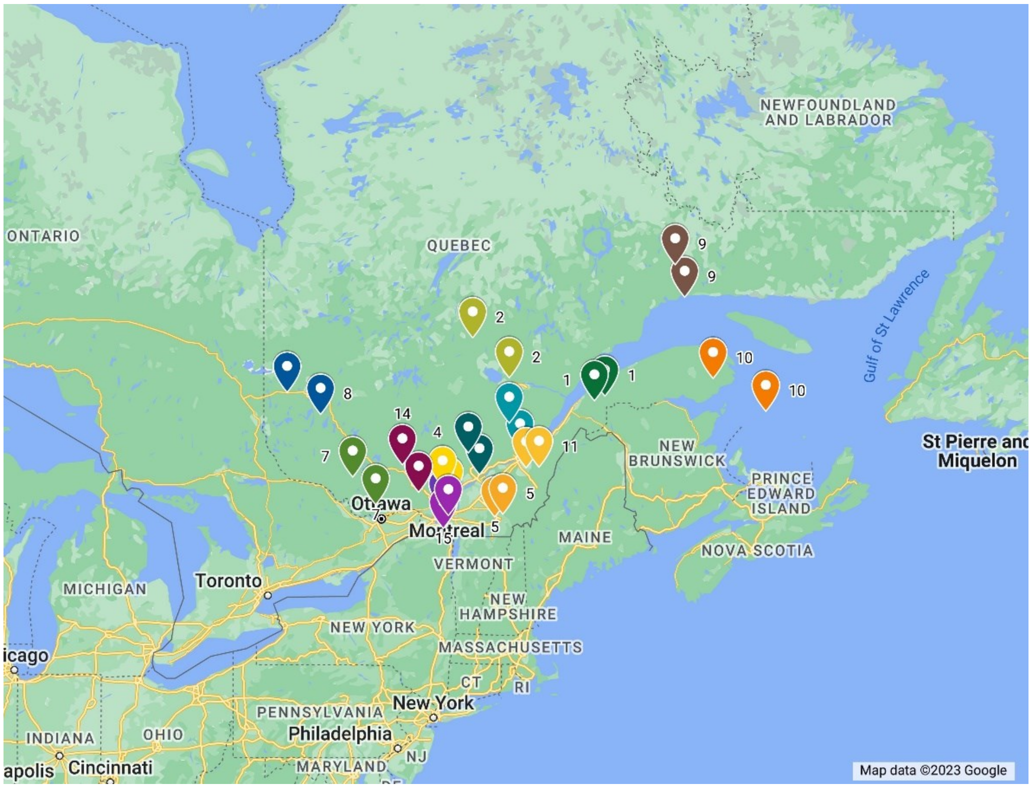


Figure 5. The distribution of regions and hospitals in Quebec

5.3.1 Optimization Result

The primary objective of our model is to maximize the overall accessibility of regions in Quebec. Accessibility, defined as the ease of reaching a location, is measured by the ratio of supply to demand. [55, 56]. To account for the impact of distance, we incorporate a distance decay function, which discounts the supply and demand based on their respective distances. In our case, we have set the coefficient β of the distance decay function to 0.5, considering the specific characteristics of Quebec.

Determining the parameter γ in constraint (10), which represents the difference in accessibility between regions, required a trial process. In this model, we set γ to 0.2 and observed the resulting optimization outcomes, as presented in Table 7. The variable x indicates the number of additional hospital beds to be allocated in each region, subject to the specified constraints, while y represents the accessibility level of each region.

Table 7. The optimization results of the Quebec dataset

Regions	x	y
Bas-Saint-Laurent	414	0.375
Saguenay-Lac-Saint-Jean	1072	0.288
Capitale-Nationale	0	0.375
Mauricie-et-Centre-du-Qubec	2440	0.375
Estrie	1127	0.375
Montreal	204	0.375
Outaouais	0	0.207
Abitibi-Temiscamingue	0	0.188
Cote-Nord	4	0.198
Gaspedie-iles-de-la-Madeleine	811	0.175
Chaudiere-Appalaches	0	0.328
Laval	207	0.375
Lanaudiere	0	0.318
Laurentides	0	0.249
Monteregie	0	0.303
Total	**6279**	**4.503**

5.3.2 Sensitivity Analysis on γ

Constraint (10) plays a crucial role in confining our model by determining the difference in accessibility between regions. However, it is essential to strike a balance with the parameter γ to avoid allocating an unrealistic number of additional hospital beds to a single region in order to meet the demand. To tackle this challenge, we conducted several experiments by varying the value of γ, leading to different optimization outcomes. These varied results are shown in Table 8.

Table 8. Comparison of optimization results with different γ

Regions \ γ	1		0.5		0.2		0.1	
	x	**y**	**x**	**y**	**x**	**y**	**x**	**y**
Bas-Saint-Laurent	2797	1.418	1138	0.843	414	0.375	191	0.234
Saguenay-Lac-Saint-Jean	3482	0.701	5141	0.656	1072	0.288	746	0.186
Capitale-Nationale	0	0.863	0	0.807	0	0.375	0	0.234
Mauricie-et-Centre-du-Qubec	0	0.661	0	0.592	2440	0.375	264	0.205
Estrie	0	0.628	0	0.529	1127	0.375	952	0.234
Montreal	0	0.604	0	0.526	204	0.375	0	0.234
Outaouais	0	0.443	0	0.378	0	0.207	0	0.137
Abitibi-Temiscamingue	0	0.418	0	0.356	0	0.188	1110	0.134
Cote-Nord	0	0.539	0	0.409	4	0.198	0	0.142
Gaspedie-iles-de-la-Madeleine	0	0.452	0	0.343	811	0.175	2966	0.134
Chaudiere-Appalaches	0	0.771	0	0.629	0	0.328	0	0.207
Laval	0	0.582	0	0.506	207	0.375	50	0.220
Lanaudiere	0	0.572	0	0.499	0	0.318	0	0.187
Laurentides	0	0.510	0	0.499	0	0.249	0	0.157
Monteregie	0	0.545	0	0.468	0	0.303	0	0.186
Total	**6279**	**9.705**	**6279**	**8.041**	**6279**	**4.503**	**6279**	**2.832**

Chapter 6

Conclusion and Future Studies

In this section, I summarize the thesis, provide conclusions and discuss future directions.

6.1 Conclusion

The outbreak of Covid-19 in recent years has once again brought the critical issue of medical resource allocation during a pandemic to the forefront of research and public attention. The dynamic and rapid nature of the pandemic has posed significant challenges in accurately predicting the demands for medical resources and developing effective strategies for their distribution. Existing research has primarily employed machine learning and mathematical programming methods to address these problems. However, we believe that by integrating these two approaches, we can achieve improved outcomes for both methods.

In our study, we conducted an investigation into the problem of allocating medical resources during a pandemic. To optimize the allocation plan, we proposed an approach that combines mathematical programming and machine learning techniques. Our research employed a data-driven optimization methodology that incorporated an LSTM model, which used historical time-series data to forecast future demand in conjunction with a linear programming model. Furthermore, our study aimed to maximize the overall accessibility of hospitals for each region within a place while also ensuring a balanced accessibility distribution across all regions.

Our research is mainly focused on addressing the increased demand for hospitalization during a pandemic by adding extra hospital beds. We utilize historical hospitalization data to construct our prediction model, enabling us to forecast future hospital bed demand. These projected needs are then incorporated into the optimization model, considering relevant geographic data of different regions and hospitals to determine the number of additional hospital beds required and their allocation across the regions. We implement our framework to a real-world case study from Quebec, Canada. The prediction performance is evaluated by mean absolute error(MAE) and root mean square error(RMSE). The average values of 16 regions are 3.079 and 5.491, respectively, which are acceptable. And we optimized the allocation plan to maximize the total accessibility of all regions, resulting in a value of 4.503. The results reveal that our proposed method is capable of predicting future hospitalization numbers and calculating the required increase in bed capacity for each region, showcasing its potential to assist in resource planning and allocation during a pandemic. Thus, the constructed framework in this research could be applied as a reference for medical resource management in future scenarios where other epidemic outbreaks occur.

6.2 Future Direction

For our proposed framework, ensuring a sufficient quantity of historical input data is crucial to maintain the accuracy of our prediction model. One of the significant drawbacks of this study was the historical data used for model construction was limited. In some regions, the numbers for confirmed and hospitalized patients per day were missing. The initial chaotic stages of a pandemic pose challenges in obtaining a sufficient volume of data, which may potentially lead to prediction errors in our research. Future research endeavors could focus on exploring alternative approaches to address the issue of data scarcity and improve the accuracy of predictions. Another limitation of this study was that the epidemiological aspect of the pandemic was not considered thoroughly. The inclusion of pandemic-specific characteristics, such as periodicity, can further enhance the model's precision by effectively capturing the cyclic nature and unique attributes of the pandemic dynamics. Moreover, other promoting factors, including the execution of quarantine and curfew policies and the invention of vaccines, should also be taken regard to better forecast the change in medical demand. For the optimization part, our primary emphasis has been on meeting hospitalization demands without explicitly considering budgetary constraints for increasing hospital beds number or the maximum capacity of hospitals. Future studies could consider incorporating these limitations into the model to develop a more comprehensive and realistic optimization model, which enables decision-makers to make informed choices based on practical constraints and available resources.

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