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Multiperiod vaccination facility planning

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Abstract

We propose a decision support tool, based on Mixed Integer Programming, to help with the planning of national vaccination campaigns, and test it on data and scenarios obtained from the publicly available information about the Irish COVID-19 vaccination program. We show that a large variety of constraints can be included in the tool, as well as combinations of different objective functions for the different stakeholders. The tests show that the multi-period/multi-vaccine problem can be effectively solved by the given model, while allowing to consider the impact of potential changes in the input data. We also present a number of specific visualizations that help the user understand the plan created by the application.

Keywords: vaccination planning, vaccination scheduling, multi-period planning, public health

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1 Background

The COVID-19 pandemic has not only demonstrated how effective vaccines are in reducing the number of infections, hospitalisations, and deaths [1] but also how critical the logistics involved were in the mass vaccination campaign. Aside from mobilising a large number of people that includes the vaccinees and the workforce of the campaign, there are also a number of factors involved that complicate the operation. First of all, with the extent of demand for COVID-19 vaccines across the globe, supply problems are bound to happen. In the UK, for instance, supply problems were caused by delayed shipments and a need to retest a batch [2]. Ireland has also experienced a shipment delay when Pfizer reduced its deliveries during an upgrade in its production capacity [3]. In short, countries have to sufficiently plan out and ensure that the vaccination programme does not experience disruptions during such eventualities.

Second, some vaccines have storage requirements that pose challenges during vaccine distribution and deployment. Pfizer and BioNTech's Comirnaty vaccine, for instance, have to be initially stored in very cold temperatures of around -80°C to -60°C before the company relaxed the requirements to -25°C to -15°C a year after it was granted emergency use in the US [4]. The Spikevax vaccine of Moderna, on the other hand, required a slightly higher temperature of -20°C. Both vaccines can also only be stored in these very cold temperatures for up to six months [5]. Thus, not only must countries provide for their appropriate storage equipment, the use of the stored vaccines must be planned out as efficiently as possible as well.

Third, given that the vaccine supply is limited from the start up to the middle of the campaign, the WHO Strategic Advisory Group of Experts on Immunisation (SAGE) recommended the prioritisation of target groups that are experiencing greater risks [WHO, 2020]. Thus, populations were also divided according to age cohorts, risks of exposure, and certain vulnerabilities and then sorted based on their urgency to be vaccinated. Ten countries in Europe, for instance, considered healthcare workers as the top priority in the COVID-19 vaccination [6]. England, Germany, Ireland, and Italy also considered individuals aged 75 and older to be in the same level of priority as the healthcare workers while Austria, France, the Netherlands, Poland, and Spain did not [6]. Regardless of which strategy is actually used, prioritising certain groups before others aims to minimise the overall effect of the pandemic and to protect those groups who are more at risk due to their age or the nature of their jobs [7].

Fourth, we have not only seen the fastest vaccines ever developed, but also the greatest number with over 200 candidates in December 2020 [8]. Four different vaccine brands were used in quantity during the Irish vaccination campaign. While it is a monumental feat to have a number of vaccines available for use, the different vaccines have inherent differences. To begin with, they do not require the same number of doses in the initial course. The interval between doses for the double-dose vaccines also varies from 4 to 18 weeks. Not all of the vaccine brands can be administered to all age cohorts, since the benefits and possible side effects vary by age. In Ireland, for instance, the Oxford-AstraZeneca vaccine at some time was not recommended for use to those under 60 years old [9]. Moreover, the prescribed time window between doses was extended for certain age cohorts in the middle of the campaign to increase

the vaccine's efficacy [10][11].As such, a COVID-19 vaccination programme must be sensitive to the time requirements of the subsequent doses and ensure that enough doses will be available to the vaccination centres for those that require them.

Considering that all these factors imply the time-sensitivity of the COVID-19 vaccination, the mass vaccination programme must also be careful to provide the sufficient amount of infrastructure as vaccine supplies roll in. Vaccination sites should not only offer security and infection control regulations for social distancing and ventilation but also ample capacity and accessibility [12]. As existing government infrastructures might not be sufficient, governments might need to tap into private infrastructures, particularly those that were impacted by the COVID-19 restrictions. However, given the economic impact of the pandemic, the costs entailed in using these sites should also be taken into account as well.

1.1 Description of the problem

With the scale and the many factors involved in the COVID-19 vaccination campaign, it is clear that a national campaign needs thorough planning. Location selection is just one component that needs consideration. The other components include the distribution of vaccines, capacity planning, and scheduling of patient cohorts. A planning tool must also be able to deal with the dynamic nature of the problem. It must be able to handle grouping and prioritisation, as well as multiple vaccines and their brand specific difference, including dosing intervals, and the use of single/multiple doses. In this paper, we present a mixed integer programming (MIP) model for a multi-period vaccination planning problem that includes the optimisation of facility location and assignment, modular capacities, and vaccination scheduling. The main objective of the model is to produce a 1-year vaccination programme consistent with the vaccination strategy set out by the government including the prioritisation of cohorts, vaccine brands used, and the dosing interval appropriate to each brand and cohort. More specifically, the model aims to

1. decide whether to use a vaccination centre or not,
2. assign cohorts from a census area to one or multiple vaccination centres in a period,
3. provide treatment capacities to vaccination centres,
4. allocate vaccine equipment to vaccination centres, and
5. allocate vaccine doses to vaccination centres.

Simultaneously, the model also intends to minimise the following costs:

1. the total cost of providing the capacity,
2. the total cost of the vaccine equipment,
3. the total travel cost of the population,
4. the total penalties for late vaccinations of prioritised cohorts, and
5. the total cost of renting the centres.

An input to the model would consist of the

1. census areas (i.e., counties, electoral divisions, etc), which include the age cohort population of these areas and distances between the census areas and vaccination centres;

2. the vaccination centres, which include the distances between the vaccination centres and the national supply point, the maximum capacity of the centre, capacity increments, construction cost, rental cost, whether a centre can be ignored, and the earliest and latest periods a centre can be used;
3. vaccines, which include the required number of doses, vaccine restrictions (i.e., the cohorts that are given the vaccine), dosing interval, transport volume, and national fitting out capacity for a vaccine in a period;
4. age cohorts, which include the lateness cost of giving a vaccine in a period to a cohort;
5. periods, which include the transport capacity for a period, building investment cost in a period, and the national building supply limit per period; and
6. objective function costs, which include the cost weight factor and the objective function cost term.

An input scenario would then comprise of a combination of different values of these components.

We now describe some of the use cases we can solve with the problem defined above (and possibly some extensions). The first use case assumes the input data for a specific scenario, and solves the model to find the best solution for the objective given. Starting with a different input scenario would lead to a different result, which would show the impact of changes in the input data.

The following are other use cases we can consider:

- Given the result of an optimisation run, we may find that a vaccination centre is not used. A natural use case extension would be to disable a nearby vaccination centre to see how the allocation of the unused vaccination centre and other nearby centres are affected.
- Conversely, we may find that some vaccination centres always reach their maximum capacity. The use case extension in this case would be to disable the site capacity limit and see whether there are centres that would be allocated more than their capacity limit.
- Given that vaccine supply is limited, a natural use case for this would be to consider that a certain vaccine cannot be used due to its unavailability.
- A more complete use case would not only consider the ramp-up phase of a vaccination programme, but also consider the wrap-up phase, where capacity is gradually reduced. This could be combined with integrating a booster campaign into an existing vaccination programme.

The contribution of this study is two-fold. First, this study will be particularly beneficial to decision makers in the preparation of mass vaccination programmes during future pandemics. This study provides an understanding of how certain factors, such as the building investment cost, the vaccine doses ordered, the capability of vaccination centres to offer certain vaccines, and the cohort population in a census area, can affect the implementation of vaccination programmes. We tried to simulate as close as possible the real data from Ireland to demonstrate the practicality of the approach. Second, we introduced a multi-period vaccination planning MIP model for an accessible and fair COVID-19 vaccination programme that incorporates the grouping and

prioritisation, multiple vaccines and their dosing intervals, modular capacities, and vaccination programme scheduling.

We also made the following general assumptions:

i. 100% of the population will go to the vaccination centres to get their vaccines.
ii. While fairness of treatment is greatly encouraged, it cannot be fully achieved. Groups are not treated in the same manner due to the differences in their urgency to be vaccinated. The 2-dose course of majority of the vaccine brands also adds another layer of complexity, where the second dose of a higher-priority group takes precedence over the first dose of a lower-priority group. However, people within the same cohorts are treated fairly.
iii. All the vaccines available for a period are used up.
iv. Both first and second doses are administered at the same vaccination centre.
v. The second dose, if there is, is assumed to be given during the prescribed waiting time.

The remainder of this paper is organised as follows. In the next subsection, we explore the literature related to vaccination planning and each of its components. In Section 2, we present the MIP model used in this study. In Sections 3 and 4, we present the problem instance used and the results of the experiments respectively. We discuss the insights derived from the results in Section 5. Lastly, we close the paper with our conclusions and future directions in Section 6.

1.2 Related work

1.2.1 Vaccination planning

Vaccination planning is a broad term that connotes a number of aspects in vaccination. However, there seems to be two undercurrents in the literature that refer to two of the four components of the vaccine supply chain: *allocation* and *distribution* [13]. The literature is not clear and consistent in the use of both terms so we refer to their definition according to Duijzer et al in [13], which says that *allocation* determines how available doses will be divided among the population, and who among the population is to be vaccinated and prioritised. It also includes re-allocation of vaccines to certain regions once a surge occurs. *Distribution*, on the other hand, refers to the logistical concerns of transporting the vaccines from the manufacturer to the end user.

There are a number of studies that used the term vaccination planning when referring to allocation strategies. In [14][15], the term refers to finding the optimal vaccination strategy to minimise the cost and reproduction of the disease. Calafiore et al [16] also has a similar definition of the term when they devised a framework for a two-dose COVID-19 vaccination campaign under uncertain supplies, which maximises the vaccination coverage, while taking the number of doses received into consideration.

On the other hand, the definition of Tang et al [17] of vaccination planning implies location selection and capacity planning. They defined an optimal plan as that which determines the number of optimal vaccination sites to open, the number of stations to open at each site, the assignment of vaccine recipients to the opened sites, and the replenishment quantity of each site. Montenegro-dos Santos et al [18] seem to have a similar notion in their multi-modal vaccination problem for vaccination planning, but

also included minimising the total timespan of vaccinating the priority groups and the total cost of vaccination resources including the facilities, staff, and etc. In this paper, the same notions for vaccination planning are used in that it not only includes location selection, but also capacity planning and scheduling.

1.2.2 Location problems

Location selection has been a well-studied topic in healthcare for the optimal location of both medical services and materials [19]. Given a set of demand nodes and a set of potential locations, the problem commonly referred to as facility location problem (FLP) can be described as the problem of finding the optimal set of locations that can serve the demands in their immediate vicinity. It has many variants in the literature but optimality generally depends on the cost of running the locations, the cost of opening/closing the locations, the distance between demand nodes and locations, or a combination of these and more.

Location problems are also best described in terms of space and time. Static FLPs deal with issues that concern space while dynamic FLPs deal with those that concern time. There are two broad categories of static FLPs: covering-based and median-based. Covering-based problems require demand nodes to be within a certain coverage distance from the facilities that serve them. Three well-known types are set covering, maximal covering, and p-centre. Set covering minimises the cost of establishing the facilities. It was used for the optimal placements of emergency ambulance services [20] and mobile vaccination centres [21]. Maximal covering maximises the total demand that facilities can cover and was used in COVID-19 vaccination facility location [22], vaccine distribution [23], warehouse location [24] and capacity planning [25]. Lastly, p-centre minimises the maximum distance travelled by a customer to a facility and was also used in the COVID-19 warehouse location [24]. Median-based problems, on the other hand, find facilities to minimise the weighted average distance between demand nodes and facilities. The two well-known problems that fall under this category are p-median and fixed-charge. The difference between them is that fixed-charge also minimises the total cost of establishing the facilities [26]. It was used for optimising the location of mobile COVID-19 vaccination clinics [27] while the p-median problem was used for the optimal location of clinics [28] and COVID-19 vaccination facilities [29] and for delivering near-expired COVID-19 vaccines to vaccination facilities [30].

Cluster analysis also appears to be an approach used in facility location since demand nodes are assigned and are essentially grouped to their nearest facility. In fact, the concept of clustering as a way to approach location problems dates back to the late 1950s and early 1960s [31]. This becomes more intuitive when dealing with large-scale instances, as pointed out by Panteli et al [28] in their multiple p-median problem model based on biclustering. Emu et al [32] used k-medoids clustering in determining the optimal number and location of COVID-19 vaccine distribution centres. They then use a constraint satisfaction programming model to optimise the distribution of the vaccines in a given cluster. Akwafuo et al [33] similarly optimised the number and location of COVID-19 vaccine distribution centres as well as the amount of vaccines that are stored in each centre but used a modified k-means++ instead. Their algorithm

also allows the planners to input two initial centre locations, instead of a purely random set of points.

Multi-period FLPs is a type of dynamic FLP that usually considers several discrete-time horizons and deal with fluctuations and uncertainty in terms of demands and capacity that occur in each of them [26]. Since pandemics last for longer periods, the multi-period aspect has been considered in past studies. Ekici et al [34], for instance, developed a multi-period model for providing food during an influenza pandemic, where the opening and closing of distribution networks over time were based on the demand. This was also considered during the COVID-19 pandemic. Liu et al [35] used a multi-period model to identify the optimal location and capacity strategies of testing facilities within the planning horizon. Tavana et al [36] likewise proposed a multi-period model for an equitable vaccine distribution in developing countries that determines the location of distribution centres, the amount of vaccines that need to be transferred, and the amount that should be stored in every period. Tang et al [17] also considered it in their bi-objective model for the vaccination planning problem, where it determines the facilities that need to operate, assigns the recipients to facilities, and decides the vaccine quantity for each facility. Wang et al [37] also considered the multi-period aspect in their drone-based robust vaccination location and scheduling model that optimises the facilities to open throughout the time horizon, the number of drones to deploy and the number of vaccines to administer at each period. Maliki et al [38] also developed a multi-period facility location model but using mobile facilities. They considered demand fluctuations and facility disruptions at each period and optimised locations and assignments while balancing the total costs and CO_2 emissions. Lastly, Karakaya et al [39] also used multiple periods in their robust model for vaccination scheduling, where the amount and type of vaccines are determined in every period, depending on the capacity and demand of the facilities, as well as the rollout policy and coverage rules.

1.2.3 Modular capacities

Dynamic facility location problems often also include capacity planning as changes to the demands throughout the planning horizon also propel any adjustments to facility resources, most particularly its capacity. Some proposed adjustments include closing facilities and opening new ones [40], partial closing and reopening of facilities [41], relocating facilities [42], expanding and reducing capacities [43], and relocating capacities [44]. Jena et al [45] introduced a general dynamic FLP with generalised modular capacities that allow modular capacity changes subject to a cost matrix that contains the cost associated with a change from one capacity level to another. Correia & Melo [46] also introduced a variant of the multi-period FLP, where the capacity of the facility is also expressed in modular units that are installed and is either increased or reduced throughout the horizon. A fixed cost is also associated with opening, adding and removing modular units to the capacity of a facility. This has been applied to the COVID-19 pandemic as well. Liu et al [35] included dynamic capacity planning in their model for COVID-19 testing facility location, where the capacity increments are decided in every period and a construction cost is associated with each unit of capacity added to a facility in a period. In Tang et al's [17] COVID-19 vaccination

planning model, the number of vaccination stations launched at a vaccination site is determined based on the number of recipients assigned to the facility in a period and a cost is also associated with each station added at the site in every period.

1.2.4 Vaccination scheduling

The term vaccination scheduling, like vaccination planning, seems to also have two connotations in the literature, which largely depend on the discipline within which the study was undertaken. The first originated from medical studies that aimed to analyse the effects of phasing age-structure vaccination strategies and the vaccine coverage achieved in each using SEIR models, particularly those on measles vaccination [47][48], age-specific vaccination scheduling during the H1N1 pandemic in 2009 [49], and a general vaccination campaign for any disease [50]. In the COVID-19 pandemic, Meerza et al [51] also has a similar usage of the term to determine an optimal control strategy using a modified SEIR model. Their objective is to find the minimum number of infected individuals while providing the optimal vaccine doses to reduce the susceptible population.

The second came from earlier studies in operations research that used the term for paediatric immunisation scheduling but were mainly concerned with the logistical aspects of the problem and as such closely resemble a project scheduling problem. Engineer et al [52] studied the catch-up scheduling problem that constructs a timetable for missed doses within the age range required for the vaccine and dose, as well as the required interval between doses. The model maximises the number of completed vaccination courses and the total number of scheduled doses while minimising the total delay of administering the doses based on the recommended age. Pan et al [53] has a similar definition in their problem, which determines the earliest time for a child to get a certain vaccine, the dosage of that vaccine, and the minimum interval between vaccinations. They also considered balancing out the number of daily vaccinations to subsequently balance out the staff.

In the COVID-19 pandemic, Wang et al [37] also has a similar definition for the scheduling component of their robust drone-based location and scheduling model. When the vaccine supply is known, their model determines the number of vaccine doses at each demand site in a given period. Its objective is to maximise the vaccination profit, which consists of successful vaccinations with minimum delays, unsatisfied schedules, and wastage, while minimising the total cost, which includes facility costs, drone deployment costs, vaccination costs, and other inventory costs. Fabbri et al [54] similarly used the term for determining the calendar for stock availability and forecast, vaccine types for each target cohort, and sub-district demands while assuring that vaccination sites are within the desired coverage. The objective of their model is to serve all the demand at the shortest time possible. Although Karakaya et al [39] used the term national vaccination calendar, their model also sets the start time and durations for each priority cohort while considering the multiple doses, dosing intervals, and the uncertainty of supply. They also extended the model by including a reactive scheduling component, where schedules can be updated based on policy changes, such as changes in the dosing interval, with minimal disruptions. Like Wang et al, Zhang et al [55] also incorporated the location selection in their vaccination scheduling problem, which

not only includes the vaccination site selection and scheduling, but also appointment acceptance and appointment assignment. Its objective is to minimise the fixed cost of vaccination sites, the travel distance of recipients, the appointment rejection cost, and the vaccination penalty cost. In this paper, we refer to the vaccination scheduling problem that deals with the arrangement of priority cohorts in the time horizon.

1.2.5 Multiple vaccines

While several studies on COVID-19 vaccine supply chain [56][57][58] and vaccine allocation and distribution [59][36][60] have considered multiple vaccine brands, dosing intervals, and/or multiple doses in their model, this is not as common for studies on COVID-19 vaccination facility location alone. Most of the early studies only considered multiple doses and they only dealt with optimising the scheduling of the vaccination campaign. For instance, Shumsky et al [61] explored how the overall duration of a vaccination campaign can be optimised while prioritising second doses over the first doses and penalising the delay in the administration of second doses. While the multiple dose regimen was considered, they only adhered to the double-dose vaccines and did not include the single-dose vaccine. Calafiore et al [16] similarly left out the single-dose vaccine in their stochastic optimisation model for the COVID-19 vaccination scheduling and considered as fully vaccinated only those individuals who received two doses of vaccine. They however included a minimum and maximum number of weeks for the dosing interval. Fabbri et al [54] also left out the single-dose vaccine in their vaccine scheduling model but included mixed vaccination wherein patients get a different vaccine in the second dose from that given in the first dose. Wang et al [37] also only took the multiple doses into account in their drone-based robust location and scheduling model. They used a two-stage robust optimisation framework to address the uncertainty of supply, where the model allows for the rescheduling of vaccinations after the vaccine supply is known. Moreover, a wastage penalty is imposed if the delivered vaccines are not eventually used and a penalty cost is also imposed after a vaccine is not administered as scheduled. Karakaya et al [39], on the other hand, considered multiple vaccine brands and their corresponding dosing intervals in their 2-stage robust model for vaccination scheduling. The model sets the vaccination schedule and duration for each priority group while minimising the total deviations between the planned and optimal schedules depending on the supply scenario that actually transpire.

1.2.6 Grouping and prioritisation

The grouping and prioritisation established by governments is also another aspect that requires consideration in a location and scheduling model. The assignment to a facility would also depend on the kind of vaccine that is allowed to be administered on the priority group and on whether the centre has the capability to administer the vaccine. In their vaccine distribution model, Tavana et al [36] considered the grouping enforced when allocating vaccines to each state in any given period. However, they did not include the prioritisation in the model. On the other hand, Karakaya et al [39] considered the prioritisation of groups in that a coverage percentage for the first dose of a preceding group has to be reached first before the vaccination of the next group

can be started. The coverage percentage of a priority group also needs to be achieved in the same period that vaccination has started for that group.

2 Method

We use Mixed Integer Linear Programming (MIP) [62] to approach the combinatorial optimisation problem described in the previous section. In this section, we present the model by introducing the concepts and input data on which the model relies, and then describing its variables, constraints and objectives.

2.1 Concepts and data

Upper case characters denote sets, lower case characters denote indices over that set. All symbols used in the description are summarised in Table 11.

2.1.1 Time

There are P periods of the vaccination programme to be considered. Lower period indices denote earlier stages of the programme, we also use the symbol $\prec$ to describe the total order on the periods. In the early stages, supply of vaccine, and materials to build vaccination centres are limited.

2.1.2 Population

There are I census areas to be considered in the problem. The population is partitioned into K cohorts, ordered by the urgency of vaccinating this part of the population. The cohorts may be age related, or grouped by the impact the vaccination has on the overall population. In the COVID-19 case, the most urgent cohort were healthcare workers, followed by "at-risk" persons with a medical higher risk of unvaccinated infection, followed by age cohorts. Lower cohort indices indicate more urgent patient groups. Values n_{ik} give the population of cohort k in census area i.

We are planning to see the more urgent patients in early periods of the programme, but we cannot guarantee that all patients in some cohort k are seen in a certain period. We use a cost value l_{kvp} to define the cost of vaccinating a patient of cohort k in period p with vaccine v. This allows us to express preferences for certain vaccines for some cohorts, as well as deal with the delay between first and second doses to provide partial protection after receiving the first dose of the vaccine. The costs should be monotonically increasing: Within one cohort, waiting longer for a first dose should have a higher cost, and for the same period, more urgent cohorts should have a higher cost than less urgent ones.

2.1.3 Centres

There are J possible sites for vaccination centres. If a site is opened in period p with a certain capacity, then the centre will stay open in subsequent periods. If the centre j is opened at some point, a single rental cost of ρ_j must be paid to cover the complete planning period. The selected capacity of a centre j in period p is a decision variable,

but the initial capacity must be in multiples of a given increment q with a cost of b_p. The capacity of a centre can be increased (but not decreased) in later periods in fixed increments of size q at cost b_p. Each potential site has a maximum capacity c_j. We assume that the cost of adding capacity decreases with time, as skills and materials accumulate. In an interactive version of the model we can force the centre to be ignored ι_j, and we can exclude time periods before the earliest start σ_j or after the latest use of the centre τ_j.

There is a national supply limit of h_p for building capacity in each period.[1]

2.1.4 Distances

The distance between census area i and vaccination centre j is denoted by d_{ij}. The distance between vaccination centre j and the national supply point is denoted by d_j.

2.1.5 Vaccines

There are V possible vaccines that can be used in the programme. There is limited supply nationally, at least in the early stages of the programme. s_{vp} gives the available national supply of vaccine v in period p. There may be some restrictions as to which vaccine should be used by which cohort. The Boolean constant r_{vk} states if vaccine v can be used for cohort k. The decision as to how many doses of vaccine to allocate to each centre is a decision variable.

Some vaccines require special equipment (e.g. low-temperature freezers) to store it in a vaccination centre. Only a centre having this equipment can supply that vaccine to patients. The cost of the equipment decreases over time, given by values f_{vp} describing the cost of fitting out one vaccination centre for vaccine v in period p. The overall supply of this equipment in each period is limited nationally to e_{vp}.

Multiple doses

There are some vaccines that are administered in multiple doses, i.e. the patient gets two vaccinations several weeks apart to achieve the full vaccination effect. We assume that patients are given the same vaccine for all doses, administered in the same vaccination centre, and spread by the recommended delay between doses.

At the level of user input data, we can describe this by introducing two attributes for a vaccine, the number of doses to apply (γ_v), and the time between consecutive doses. But for our model we use a slightly more complex description, which leads to much simpler constraints in the model.

As the second vaccination date is determined by the time and location of the first event, we do not need to introduce additional variables to describe the second vaccination event, but can reuse the variables describing the first event. On the other hand, as the time between doses depends on the vaccine type, we have to rely on variables w_{ikvjp} to differentiate the number of patients that get the different vaccines in each location and time period.

[1] If we also want to model the shut-down of the vaccination programme, we may want to consider closing a location after some time, without being able to reopen the location again.

We use constants α_{vl} to describe the delay between the first and second doses of a vaccine v. The constant defines which fraction (real, 0-1) of patients getting vaccine v will receive the second dose l periods after the first dose. These values can be easily computed from the period length and the required delay between doses, as we will show with a few examples.

As a first example, assume that the required delay between doses is eight weeks, and our period length is four weeks. A patient receiving the first dose in period p will receive the second dose eight weeks later. Regardless of the exact time of the first vaccination in period p, the second event will always be two periods later, in period $p+2$. In this situation, α_{v2} will be one, and all other α_{vl} will be zero.

As a second example, consider a delay of six weeks between doses, and again a period length of four weeks. A patient receiving a first dose on the first day of period p will receive the second dose six week later, in the middle of the following period $p+1$. A patient receiving a first dose on the last day of period p will receive the second dose in period $p+2$. If we assume a uniform distribution of vaccinations during the period, it is easy to see that half of the total (those vaccinated in the first half of period p) will receive their second dose in period $p+1$, while the other half will receive the second dose in period $p+2$. In that case $\alpha_{v1} = 0.5$ and $\alpha_{v2} = 0.5$.

If the delay is shorter than the period length, then some fraction of the patients will receive their second dose in the same period as their first dose. Consider a delay of three weeks, and a period length of four weeks. Patients being vaccinated in the first week of the period will receive their second dose in the same period, while all others will get their second dose in the following period. Thus $\alpha_{v0} = 0.25$ and $\alpha_{v1} = 0.75$ in this case.

If a vaccine only requires a single dose, then α_{vl} will be zero for all l. If the vaccine requires two doses, then the different fractions must add up to one, $\sum_{l=0}^{\lambda} \alpha_{vl} = 1$, so that every patient receives two doses. The integer constant λ gives the longest delay, in periods, required for any of the vaccines considered.

Note that we do not aim for absolute precision in this model of the delay, we ignore for example the potential unit mismatch between period length (in months or quarters) and the specified delay (in days or weeks). We also do not consider that the daily vaccination rate may vary throughout the period, due to variations caused by the day of the week, or buildup of capacity during the period. We also ignore variations in the actual length of a period (for months or quarters), and additional delays caused by patient preferences, if a choice of appointments is given. Finally, our model is based on the assumption that the patient receives the same vaccine for both doses. If we allow a mixed vaccination programme, then we may have also to consider different waiting times between doses depending on the vaccines used for the first and second dose. This seems to be too complex to model in an initial approach to the problem.

2.2 Variables

u_j a Boolean 0/1 variable indicating whether vaccination centre j is used for some period(s) in the allocation or not.

x_{ikjp} non-negative real (alternative integer) stating how many persons from census area i and cohort k are getting their first vaccine dose in centre j in period p.

y_{jp} integer variable stating that the capacity of centre j is increased in period p with a capacity of $y_{jp} * q$

z_{jvp} Boolean (0/1) variable to state that centre j is equipped to handle vaccine v from period p onwards.

v_{jvp} non-negative real stating the number of doses of vaccine v applied in centre j during period p. This includes both first and second doses of that vaccine. As we use fractions to sum up this total, these variables need to be continuous.

w_{ikvjp} non-negative real (alternative) integer stating how many persons from census area i and cohort k are getting their first vaccine dose of vaccine v in centre j during period p.

2.3 Constraints

The total building capacity is limited in each period by the national supply (national capacity constraint).

$$\forall_{p \in P}: \quad \sum_{j \in J} y_{jp} * q \leq h_p \tag{1}$$

The cumulative capacity provided in each centre over all periods must be below the capacity of the location. The centre must be open to allocate any patients to it. If the centre is not open, then no patients can be assigned.

$$\forall_{j \in J}: \quad \sum_{p \in P} y_{jp} * q \leq c_j u_j \tag{2}$$

We can only provide centres with equipment for handling some vaccine up to the national capacity (equipment constraint).

$$\forall_{p \in P} \forall_{v \in V}: \quad \sum_{j \in J} z_{jvp} \leq e_{vp} \tag{3}$$

We can only invest in equipment for vaccine v at location j once, we may not install the equipment at all.

$$\forall_{j \in J} \forall_{v \in V}: \quad \sum_{p \in P} z_{jvp} \leq 1 \tag{4}$$

The total number of people vaccinated in each centre in each period must be below the capacity of the centre. Here we have to consider patients either getting their first or their second dose, as both events use up capacity in the centre. The number of people getting their first dose is given by x_{ikjp}, while for the second dose we have to compute the number from the vaccinations in earlier periods and the fraction of patients using a specific vaccine v with a delay of α_{vl}. As a notational convenience, we ignore all w entries for which the period $p - l$ is not defined.

Note that the right-hand side is the total capacity built up in centre j throughout all earlier time periods up to including p.

$$\forall_{j\in j}\forall_{p\in P}: \quad \sum_{i\in I}\sum_{k\in K}(x_{ikjp}+\sum_{v\in V}\sum_{l=0}^{\lambda}w_{ikvjp-l}\alpha_{vl}) \leq \sum_{p'\leq p} y_{jp'} * q \tag{5}$$

The total number of doses of each vaccine v applied in all centres j during a period p must be below the national supply.

$$\forall_{v\in V}\forall_{p\in P}: \quad \sum_{j\in J} v_{jvp} \leq s_{vp} \tag{6}$$

A centre can only provide a vaccine if it has been equipped to do so, e.g. the required equipment has been installed before.

$$\forall_{j\in J}\forall_{p\in P}\forall_{v\in V}: \quad v_{jvp} > 0 \Rightarrow \sum_{p'\leq p} z_{jvp'} \geq 1 \tag{7}$$

All people must get a first dose of a vaccine. Here we only count the first dose being applied, other constraints handle the requirement that some vaccines may require a second dose.

$$\forall_{i\in I}\forall_{k\in K}: \quad \sum_{j\in J}\sum_{p\in P} x_{ikjp} = n_{ik} \tag{8}$$

The total number of doses of a specific vaccine v applied to a centre j in a period p matches the people getting that vaccine in the centre. Here we again have to count both people getting their first, as well as their second dose, of vaccine v. We again ignore terms for which the period $p-l$ is not defined.

$$\forall_{j\in J}\forall_{v\in V}\forall_{p\in P}: \quad \sum_{i\in I}\sum_{k\in K}(w_{ikvjp}+\sum_{l=0}^{\lambda} w_{ikvjp-l}\alpha_{vl}) = v_{jvp} \tag{9}$$

Each member of any cohort must be assigned one of the available vaccines for that cohort.

$$\forall_{i\in I}\forall_{k\in K}\forall_{j\in J}\forall_{p\in P}: \quad \sum_{v\in V} w_{ikvjp} = x_{ikjp} \tag{10}$$

If a vaccine cannot be used for a cohort, then the number of people assigned to it should be zero

$$\forall_{i\in I}\forall_{k\in K}\forall_{j\in J}\forall_{p\in P}\forall_{v\in V}: \quad r_{vk} = 0 \Rightarrow w_{ikvjp} = 0 \tag{11}$$

In our model we assume that the full vaccination programme must be completed at the end of the last time period. We should not have any patients still waiting for their second dose of the vaccine. This means that we cannot apply the first dose too

late, so that some w variables in the final periods must be zero. We use the notation $\lambda_v := \max\{0 \leq l \leq \lambda \; s.t. \; \alpha_{vl} > 0\}$ to define the longest delay between first and second dose encountered for vaccine v. Then for any period where the longest delay would exceed the planning horizon for some vaccine, the number of patients receiving a first dose of that vaccine must be zero.

$$\forall_{i\in I}\forall_{k\in K}\forall_{v\in V}\forall_{j\in J}\forall_{\{p\in P \text{ s.t. } p+\lambda_v>|P|\}} : \quad w_{ikvjp} = 0 \tag{12}$$

2.3.1 Travel distance

A guiding principle should be that people should not have to travel a long distance to get their vaccination, the centres should be set up so that this is possible.

People from a census area must be assigned to one of the m nearest potential vaccination centre sites. This deals with an issue that some census areas may be far away from any potential vaccination site, but the number of centres to be opened must be high enough for this to be feasible. This may lead to delays in vaccinating some cohorts until enough centres have been opened.

This leads to constraints of the form

$$\forall_{i\in I}\forall_{k\in K}\forall_{v\in V}\forall_{j\notin \text{nearest}(i,m)}\forall_{p\in P} : \quad w_{ikvjp} = 0$$

where the function `nearest` returns the set of the m nearest vaccination centres to census area i.

2.3.2 Restricting the use of vaccination centres

In an interactive use of the model, we allow the user to force ignoring some vaccination centre.

$$\forall_{i\in I}\forall_{k\in K}\forall_{v\in V}\forall_{j\in J}\forall_{p\in P} : \quad \iota_j \Rightarrow w[i][k][v][j][p] = 0$$

We can also restrict the earliest and latest use of any vaccination centre in an interactive version of the model. The values σ_j and τ_j describe the earliest respectively latest period that a centre can be used.

$$\forall_{i\in I}\forall_{k\in K}\forall_{v\in V}\forall_{j\in J}\forall_{p\in P} : \quad (p \prec \sigma_j \vee \tau_j \prec p) \Rightarrow w[i][k][v][j][p] = 0$$

2.4 Objective

The total objective is the (weighted) sum of different cost terms. The cost of providing capacity for the centres is given by

$$g_1 = \sum_{p\in P}\sum_{j\in J} y_{jp} b_p \beta_j \tag{13}$$

The cost of providing capacity in a centre depends on the period when the work is done (earlier periods are more expensive), and on the location (some locations are more difficult to modify, or to reach).

The cost of equipment for all centres is

$$g_2 = \sum_{p \in P} \sum_{v \in V} \sum_{j \in J} z_{jvp} * f_{vp} \tag{14}$$

There is the travel cost of the population from their homes to the assigned vaccination centres

$$g_3 = \sum_{i \in I} \sum_{k \in K} \sum_{v \in V} \sum_{j \in J} \sum_{p \in P} w_{ikvjp} * d_{ij} * \gamma_v \tag{15}$$

We need to consider that, for multi-dose vaccines, the patients have to travel multiple times to the (same) vaccination centre, and the cost needs to take that into account.

There are penalties if patients of cohort k are seen in a later period p. The penalty depends on the vaccine used, we therefore use the w variables to compute this cost.

$$g_4 = \sum_{i \in I} \sum_{k \in K} \sum_{v \in V} \sum_{j \in J} \sum_{p \in P} w_{ikvjp} * l_{kvp} \tag{16}$$

The total rental fee is determined by which vaccination centres are open or closed, and the rental cost ρ_j for each centre.

$$g_5 = \sum_{j \in J} \rho_j u_j \tag{17}$$

The total cost is

$$\min \text{obj} = a_1 g_1 + a_2 g_2 + a_3 g_3 + a_4 g_4 + a_5 g_5 \tag{18}$$

with appropriate weight factors a_i.

We may want to have additional cost terms for unused capacity and unused vaccines. If we provide capacity that is not used in a later period, then we pay a penalty proportional to the unused capacity. We assume that any vaccine delivered, but not used, in a given period is lost. We have to pay a penalty for that unused vaccine.

3 Problem instance

We next present a case study based on Ireland's COVID-19 vaccination setting to illustrate the practicality of the proposed model in the real world. We used, when possible, all publicly available data that are accessible on the Central Statistics Office (CSO) website (https://www.cso.ie) and Ireland's Open Data Portal (https://data.gov.ie).

Note however that it is not the intention of this study to recreate the exact real-world setting. Rather, we only intend to recreate a sufficiently similar setting to be able to make projections using the tool.

3.1 Census areas

Two levels of granularity were considered for the census areas: 1) electoral divisions (ED) and 2) small areas (SA). Electoral divisions are the smallest legally defined administrative areas in the Republic of Ireland while small areas are further subdivisions of electoral divisions and the lowest level of geographical areas created for compilation of statistics [63]. There are 3,409 electoral divisions while there are 18,641 small areas.

3.1.1 Vaccination centres

In the Irish setting, vaccination centres are existing government infrastructures, such as city halls and primary care centres, and private infrastructures that were repurposed for the campaign, such as hotels, stadiums, game clubs, and racetracks. There are 36 vaccination centres used in the case study although there are 38 vaccination centres that were initially used [64]. See Figure 1 for the location of these centres on the map. The national supply point was set at Citywest industrial park in southwest Dublin [65]. The maximum capacity and costs incurred in the operation of these centres were taken from the Health Protection Surveillance Centre (HPSC) document on COVID-19 vaccination [66].

Shapefiles for the census areas were obtained from the Open Data Portal. Centroids were already given for the ED shapefiles while centroids have to be computed for the SA shapefiles. Shortest distances between census area centroids and vaccination centres were requested from the Graphhopper Routing API using the car profile. For census areas in islands, such as Clare Island and the Aran Islands located off the west coast, the initial point in the path was repositioned to an inland point in the mainland.

3.1.2 Age cohorts

Although the National COVID-19 Vaccination Programme [67] stated a different set of groups, the age cohorts in the dataset on the COVID-19 vaccination figures released by OSI (Ordnance Survey Ireland) were in decades. In order for us to be able to make a contextual evaluation of the model, we used the cohorts in the National COVID-19 Vaccination Programme and the OSI age decades while maintaining the sequencing set forth by the Department of Health. The following are the cohorts in order of priority:

- Age 80+
- Healthcare workers (HCW)
- Persons with prior medical conditions
- Age 70-79
- Age 60-69
- Age 50-59
- Age 40-49
- Age 30-39
- Age 20-29
- Age 10-19
- Age 0-9

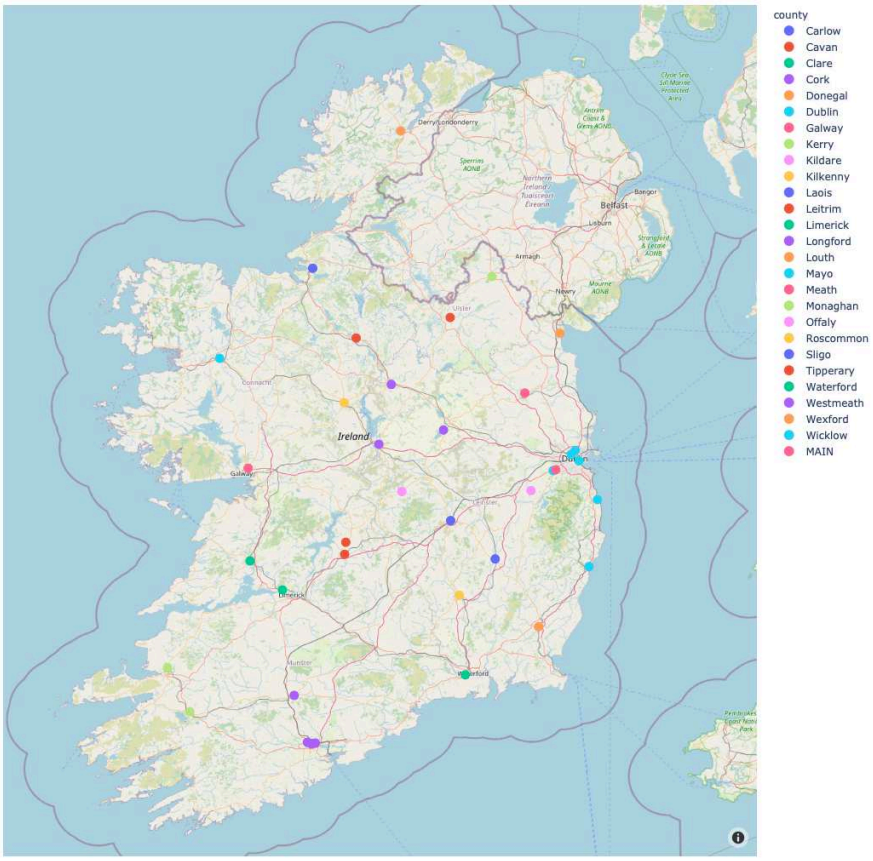


Fig. 1 Vaccination centres in Ireland. Colours are based on county.

The HCW population was estimated to be 3% of the working cohorts. Assuming the workforce is aged 20-69 years, healthcare workers are then extracted from the populations of the corresponding decades. The population with prior medical conditions was also estimated to be 5% of the entire population, which was similarly extracted from all the age cohorts.

Figure 2 shows the cohort percentage of total using the population from the small areas data. The population data for the electoral divisions is comparable albeit slightly different. Figures 3a and 3b present the choropleth maps showing the total population for ED and SA.

3.1.3 Periods

The planning horizon is 1 year from January 2021 up to December 2021 and each period is 1 month. Figure 4 shows the simulated national building supply limit per period while Figure 5 shows the simulated building investment cost per period.

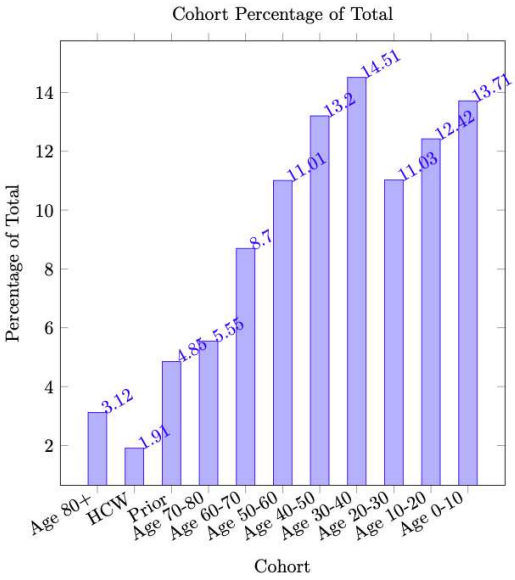
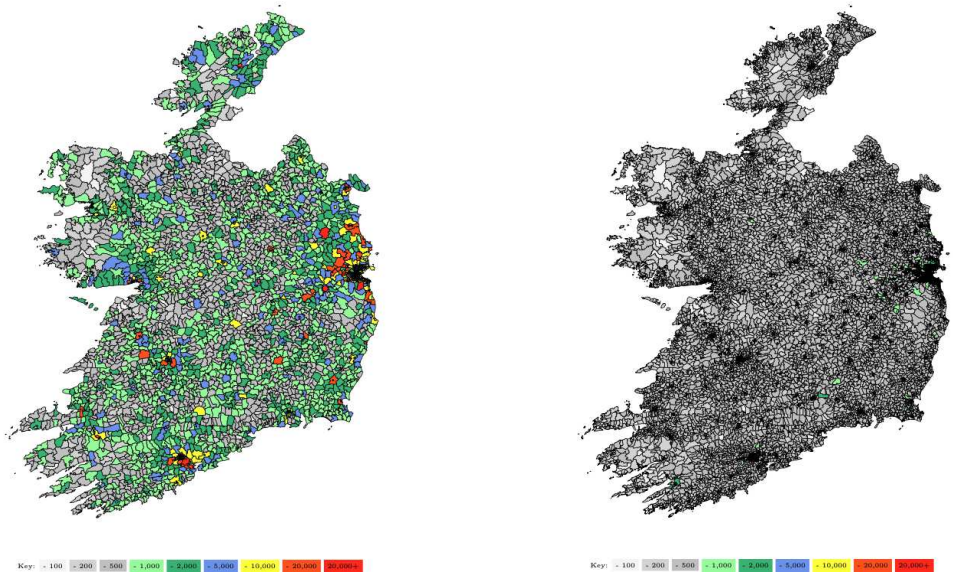


Fig. 2 Cohort percentage of total



(a) Electoral divisions (b) Small areas

Fig. 3 Population of census areas

3.1.4 Vaccines

There are four authorised COVID-19 vaccines in Ireland: 1) Comirnaty (Pfizer/BioNTech), 2) Spikevax (formerly Moderna), 3) Vaxzevria (formerly AstraZeneca), and 4)

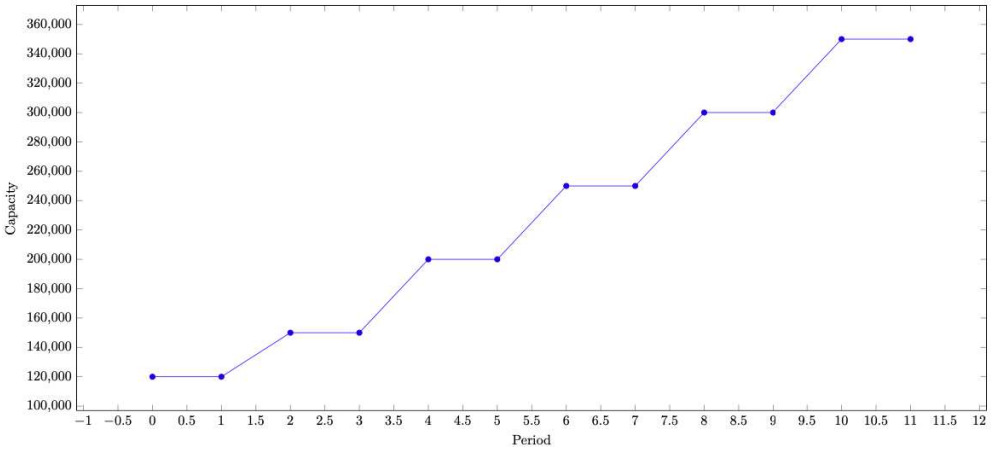


Fig. 4 National Limit on Capacity Building per Period

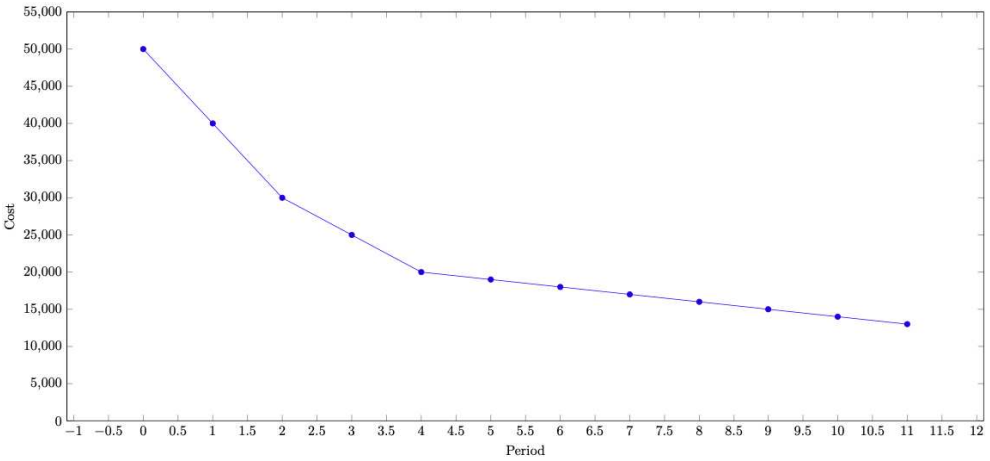


Fig. 5 Investment Cost per Unit Q over Time

Jcovden (Janssen) [66]. The first three require two doses in the primary course while Jcovden only requires one. The national supply limit for each vaccine was estimated based on data obtained from the COVID-19 Data Hub (https://covid-19.geohive.ie) on February 2021 while the transport volume was estimated from various sources, including the WHO Vaccine Management Handbook [68]. Figure 6 shows the simulated total vaccine supply while Figure 7 shows the vaccine supply per period. Tables 1 and 2 show the vaccine fitting out capacity and cost respectively.

The second dose of Vaxzevria was used to be given 12 weeks after the first dose but was reduced to 8 weeks in the middle of the campaign. On the other hand, the gap between doses for Comirnaty and Spikevax used to be 4 weeks in the beginning but

Vaccine	Jan21	Feb21	Mar21	Apr21	May21	Jun21	Jul21	Aug21	Sep21	Oct21	Nov21	Dec21
Comirnaty	3013	3013	3013	3013	3013	3013	1955	1955	1955	1955	1955	1955
Vaxzevria	1955	1955	1955	1955	1955	1955	836	836	836	627	627	627
Spikevax	1955	1955	1955	1955	1955	1955	836	836	836	627	627	627
Jcovden	1955	1955	1955	1955	1955	1955	836	836	836	627	627	627

Table 1 Vaccine fitting out capacity

Vaccine	Jan21	Feb21	Mar21	Apr21	May21	Jun21	Jul21	Aug21	Sep21	Oct21	Nov21	Dec21
Comirnaty	4	7	6	12	15	18	20	22	23	24	26	27
Vaxzevria	1	1	2	2	3	3	4	4	4	5	5	5
Spikevax	100	100	100	100	100	100	100	100	100	100	100	100
Jcovden	100	100	100	100	100	100	100	100	100	100	100	100

Table 2 Vaccine outfitting cost

was extended to 8 weeks in the middle of the campaign. The second dose may also be given for a minimum interval of 3 weeks if the individual requires urgent protection [69]. However, to show the flexibility of the model, we assumed the following gaps for the double-dose vaccine brands: 8 weeks for Comirnaty, 6 weeks for Vaxzevria, and 3 weeks for Spikevax. Table 3 shows the second dose waiting fractions. Based on various news articles, Table 4 shows the age restrictions of these vaccines.

Vaccine	D0	D1	D2	D3
Comirnaty	0.00	0.00	1.00	0.00
Vaxzevria	0.00	0.50	0.50	0.00
Spikevax	0.25	0.75	0.00	0.00
Jcovden	0.00	0.00	0.00	0.00

Table 3 Second-dose waiting fractions

The lateness cost of the vaccines takes the time to achieve full protection into account. This means that a single-dose vaccine administered at the same time as a double-dose vaccine is preferable, as the full protection is achieved earlier. The waiting time for the second dose is considered by adding a value of 10 per month of waiting time. The cost values for each vaccine are strictly increasing with time, and with priority of the cohort. This ensures that the system always picks the most urgent patient to be vaccinated as early as possible. The actual values chosen do not have a unit, and cannot be directly compared to the other cost values. Table 5 shows the cost values for the double-dose vaccines with a gap of 8 weeks.

3.2 Clustering

As mentioned in Section 2.3, cohorts from a census area must be assigned to one of the m nearest potential vaccination centre sites. As there would clearly be a number of centres that have the same nearest sites, it is quite intuitive to cluster the centres based on their m nearest potential sites. Doing so would significantly reduce the number of census areas to work with in terms of vaccination centre assignment. Figures 8a and 8b show the clustering when $m = 2$ for EDs and SAs respectively. The centres are coloured based on their nearest centre.

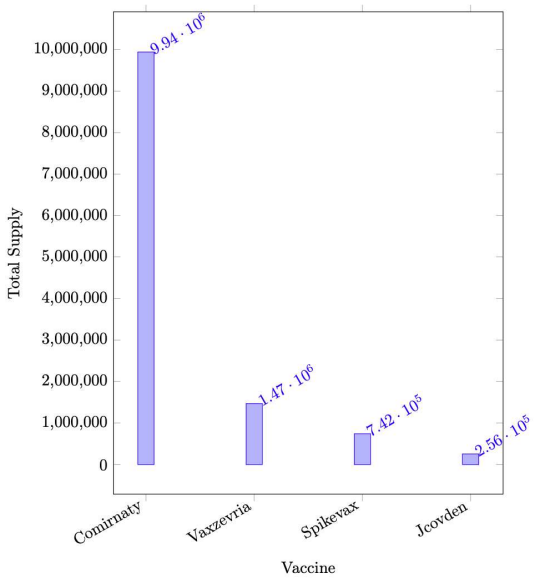


Fig. 6 Total vaccine supply

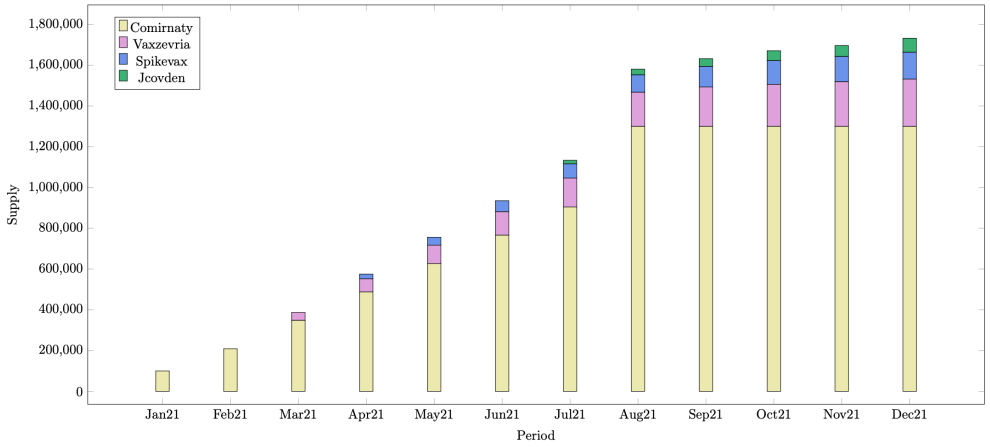


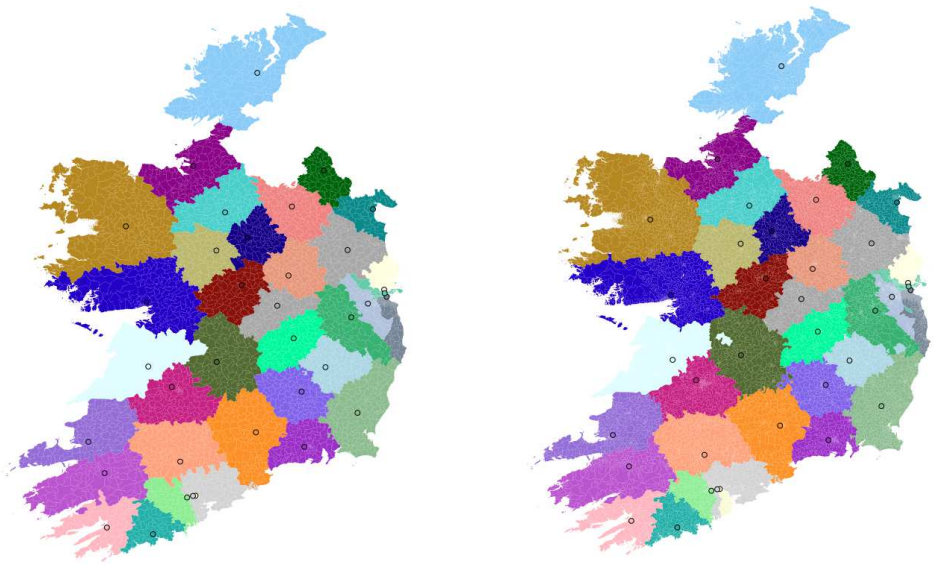
Fig. 7 Vaccine supply by period

Vaccine	Age 80+	HCW	Prior	70-79	60-69	50-59	40-49	30-39	20-29	10-19	0-9
Comirnaty	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Vaxzevria	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗
Spikevax	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗
Jcovden	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗

Table 4 Age restrictions of vaccine brands

Cohort	Jan21	Feb21	Mar21	Apr21	May21	Jun21	Jul21	Aug21	Sep21	Oct21	Nov21	Dec21
Age 80+	6,000	8,000	10,000	12,000	14,000	16,000	18,000	20,000	22,000	24,000	26,000	28,000
HCW	3,000	4,000	5,000	6,000	7,000	8,000	9,000	10,000	11,000	12,000	13,000	14,000
Prior	1,500	2,000	2,500	3,000	3,500	4,000	4,500	5,000	5,500	6,000	6,500	7,000
Age 70-79	600	800	1,000	1,200	1,400	1,600	1,800	2,000	2,200	2,400	2,600	2,800
Age 60-69	300	400	500	600	700	800	900	1,000	1,100	1,200	1,300	1,400
Age 50-59	150	200	250	300	350	400	450	500	550	600	650	700
Age 40-49	60	80	100	120	140	160	180	200	220	240	260	280
Age 30-39	30	40	50	60	70	80	90	100	110	120	130	140
Age 20-29	15	20	25	30	35	40	45	50	55	60	65	70
Age 10-19	6	8	10	12	14	16	18	20	22	24	26	28
Age 0-9	3	4	5	6	7	8	9	10	11	12	13	14

Table 5 Cost values for the Comirnaty vaccine



(a) Electoral divisions (b) Small areas

Fig. 8 Clustering of census areas for $m = 2$

4 Results

The model was implemented as a Java 17 desktop application using the version 22.1.0 of IBM's CPLEX solver. All experiments were performed on a Windows 11 desktop computer with one Intel(R) Xeon(R) W-2275 CPU at 3.30GHz containing 14 cores, and 128 GB memory.

4.1 Scenarios

As mentioned in Section 2.4, there are five minimisation objectives: 1) the cost of providing capacity for the centres, 2) the cost of equipment for all centres, 3) the travel

cost (distance) of the population from their centres to the assigned vaccination centres, 4) the total penalties for vaccinating cohorts in a later period, and 5) the total rental cost of all vaccination centres. Each objective function can be applied an appropriate weight factor to drive solutions towards those that favour certain objectives. One constraint, particularly that which limits the national building capacity, can be disabled as well. As mentioned in Subsection 2.1.3, each vaccination centre can also be ignored in a solution. To simulate the removal of a vaccine brand, the stock of a vaccine brand can also be set to 0 in the application. The following five possible scenarios were tested:

- Scenario 1: Baseline
- Scenario 2: No national building capacity limit
- Scenario 3: Exclude Cork City Hall
- Scenario 4: No Vaxzevria
- Scenario 5: No maximum site capacity

The following aspects were then observed in each scenario:

1. Usage of vaccine supply and capacity
2. Usage of vaccine brands,
3. Vaccination coverage of cohorts,
4. Overall vaccination coverage, and
5. Usage of vaccination centres.

When applicable, the solutions produced by the model were also evaluated based on the following key performance indicators (KPI) that are based on the objective functions(see Table 6):

KPI	Notation
Average capacity cost per person	$\bar{g_1}$
Average equipment cost per person	$\bar{g_2}$
Average travel distance per person	$\bar{g_3}$
Average lateness cost per person	$\bar{g_4}$
Average rental cost per person	$\bar{g_5}$

Table 6 Key performance indicators

To get the average cost per person, each of the objective functions was divided by the total population $\sum_{i \in I} \sum_{k \in K} n_{ik}$ (see Subsection 2.1).

The following shows the results using the SAs. The results using the EDs are comparable with very minor differences.

4.1.1 Scenario 1: Baseline

In the Baseline scenario, all the objectives are given equal weights, i.e., a weight factor of 1.

Usage of vaccine supply and capacity

Figure 9 shows the relationship between the capacity, vaccine supply, and doses used. Both the centre capacity, and doses used peak at period 7 while the first doses peak

at period 8. The first doses and consequent doses used begin to go down afterwards. The second doses peak at period 10 and then begin to descend afterwards as well. After period 7, the capacity plateaue, which means that there are no longer any new capacities that are added to the centres. On the other hand, there are still arriving vaccine supplies until the end of the horizon.

It can also be observed that at periods 3 and 4, there is lesser available capacity than the vaccine supply. This can also be observed at periods 7 onwards. However, it is expected in this case as it is already midway through the campaign.

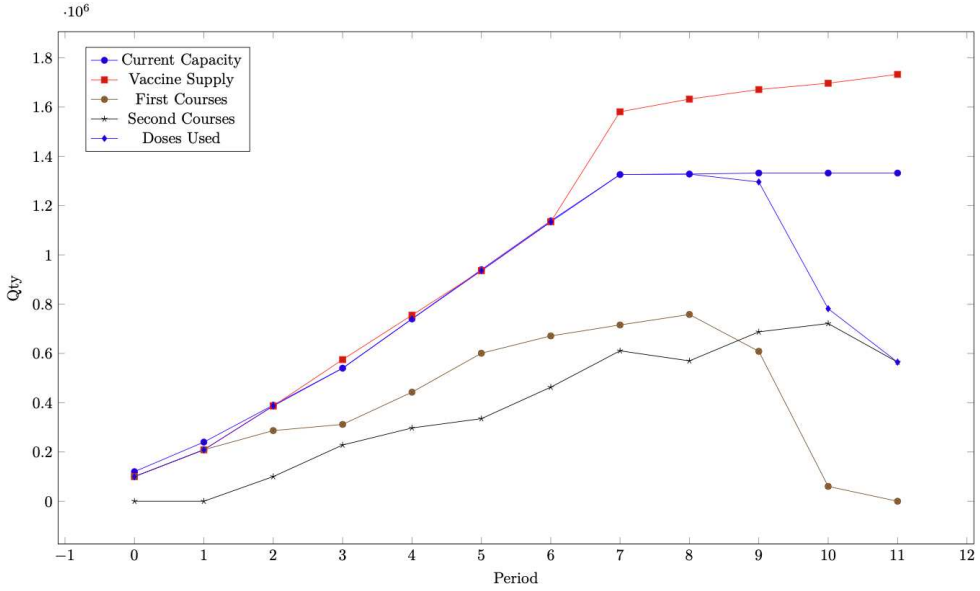


Fig. 9 Current supply and allocation

Usage of vaccine brands

Given the restrictions of certain brands to be administered to certain cohorts and the cohort population of census areas, there are differences in terms of how the different brands were allocated to vaccination centres. Figure 10 shows the number of patients that are given a particular vaccine brand. Since the Comirnaty vaccine can be administered to all age cohorts and has the biggest supply as well, it is also expected that all vaccination centres are administering this vaccine.

Figure 11 shows the amount of vaccine supply and the amount that is used for each of the vaccine brands. It can be observed that supplies of Spikevax and Vaxzevria are not completely used at periods 3 and 4 and this is consistent with what we also observed in Figure 9 above. Usage also begins to drop by period 6 for the Spikevax and Vaxzevria vaccines, period 9 for the Comirnaty vaccine, and period 10 for the Jcovden vaccine.

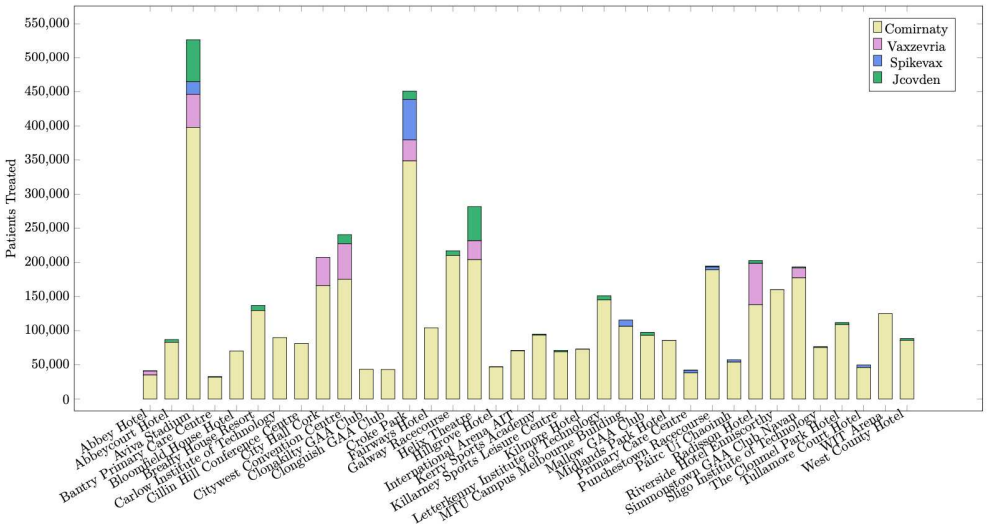


Fig. 10 Vaccines given in centres

Vaccination coverage of cohorts

Figure 12 shows the number of doses applied to each age cohort. This certainly depends on the cohort population of census areas that were assigned to the vaccination centre. While the said figure shows the doses applied per vaccination centre, Figure 13, on the other hand, shows the number of first and second doses are used for the cohorts per period. As expected, the oldest cohorts are vaccinated first followed by the HCW, those with prior medical conditions, and then the rest of the age cohorts in descending order. It can be noticed that it takes around 6 months to fully vaccinate a cohort.

Overall vaccination coverage

To appreciate how vaccination coverage is achieved across the country, see Figure 14. A discernible percentage of full vaccination can be observed starting at period 3, which can be observed all throughout the country. Notice that Dublin (at the eastern side), which is also the most populated area, is the last to get a full vaccination coverage. It achieves the lowest coverage at around 80% at period 11 while the rest of the country gets 90% to 100% vaccination coverage.

Usage of vaccination centres

Figure 15 shows the percentage of built capacity in centres that are actually used. While there are 4 out of 36 or 11% of the centres that reach more than 99% of its built capacity used, majority of the centres or 88% have a $< 90\%$ percentage in terms of usage. The lowest usage percentage is 74.29%.

Figure 16a shows the built capacity and usage of the Aviva Stadium, one of the centres that reached $> 99\%$ usage of its built capacity while Figure 16b shows Páirc Uí Chaoimh, which has a high maximum capacity that was not maximised by the model.

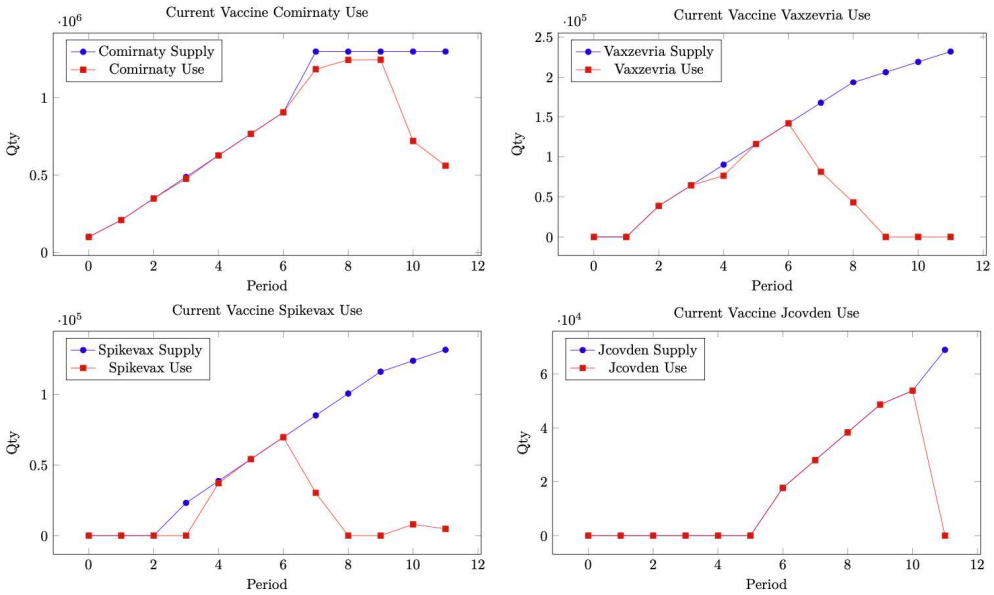


Fig. 11 Available vs used vaccines

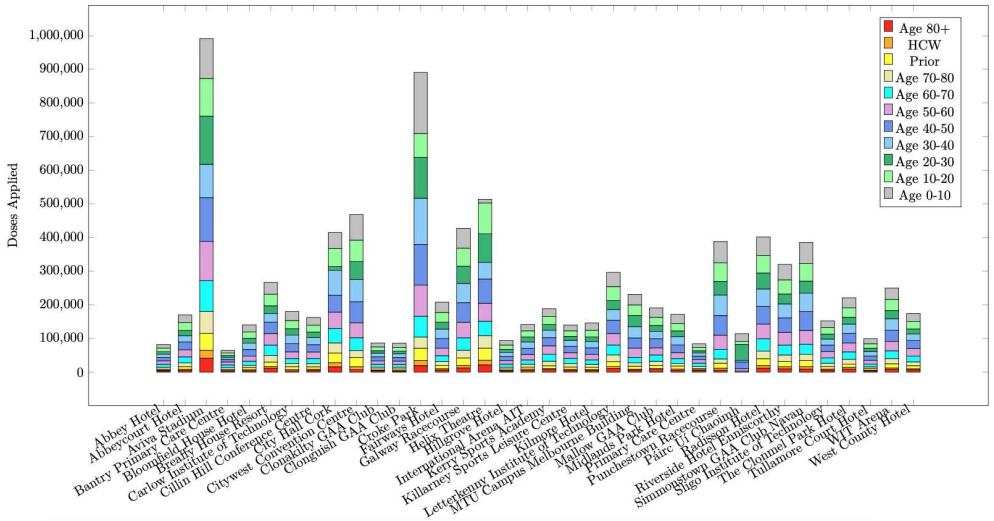


Fig. 12 Doses per cohort per centre

It has a low capacity allocation and subsequently low albeit commensurate usage as well.

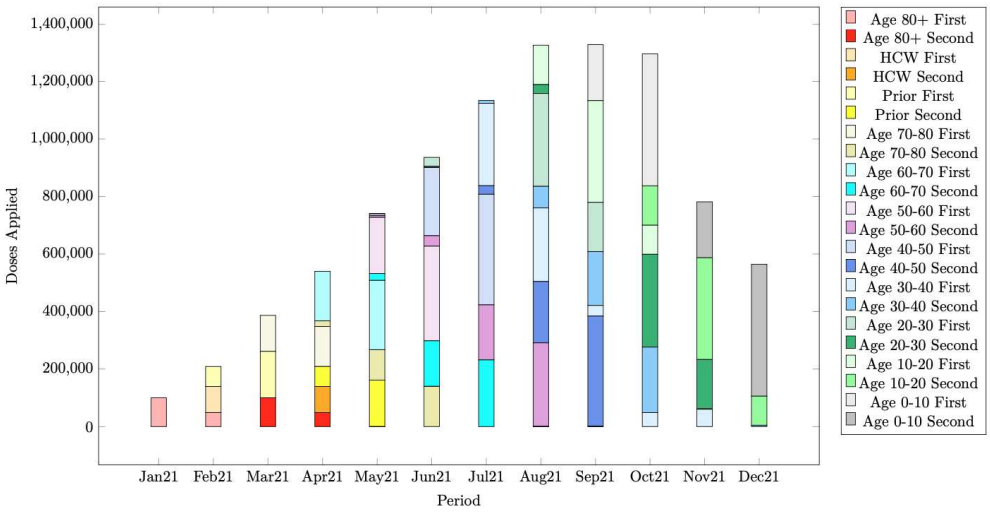


Fig. 13 Doses per cohort per period

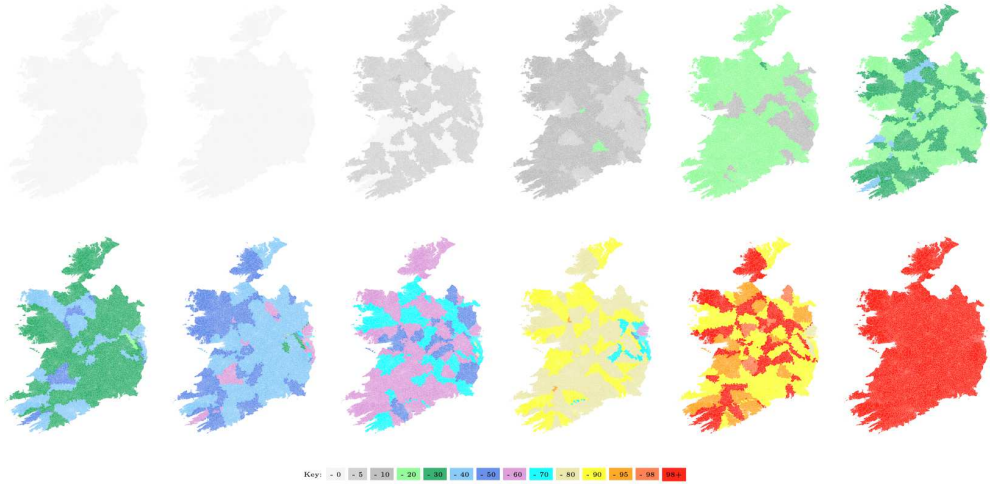


Fig. 14 Fully vaccinated percentage per period (from left to right)

Figure 17 shows the number of centres that are opened against the number of centres that are actually used throughout the planning horizon. Notice that as vaccination peak at period 8 for most cohorts (see Figure 13), usage of the vaccination centres begin to decline afterwards.

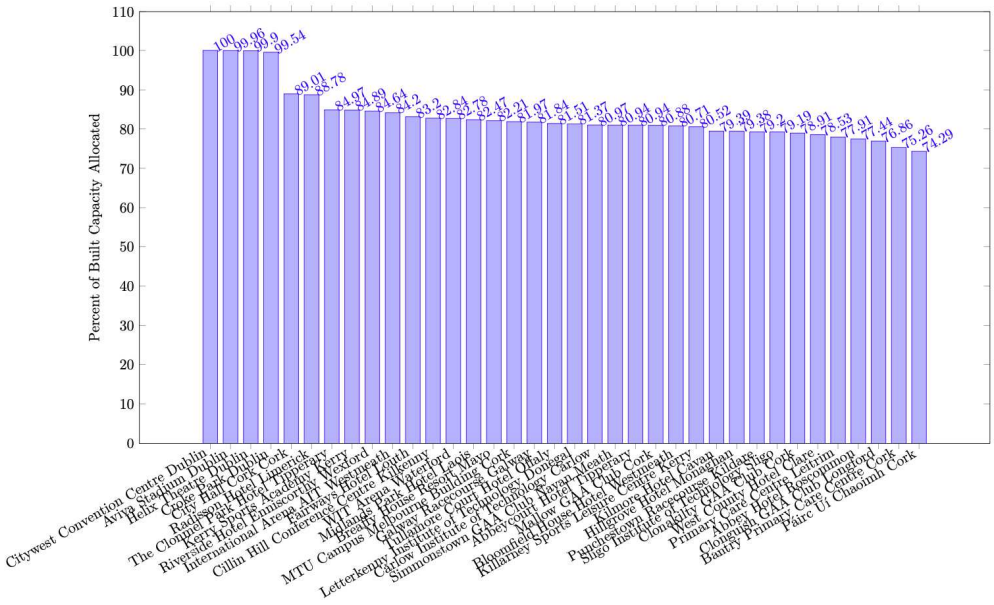
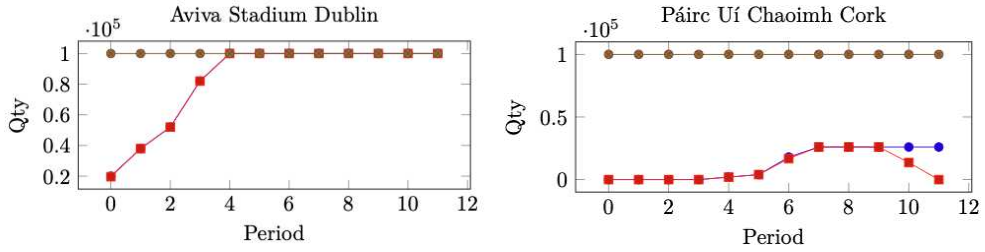


Fig. 15 Usage of built capacity



(a) Aviva stadium

(b) Páirc Uí Chaoimh

Fig. 16 Highest and lowest centre capacity and allocation

4.1.2 Scenario 2: No national building capacity limit

In this scenario, we want to observe the effects of removing the national building capacity limit to the usage of vaccine supply and capacity as well as to the usage of vaccine brands. As it can be observed in Figure 9 Scenario 1 (see 4.1.1), there are lesser available capacity at periods 3 and 4 than the vaccine supply. This can be attributed to the national building capacity limit not measuring up to the vaccine supply. We thus disabled the national building capacity constraint (1) (see Section 2.3).

Usage of vaccine supply and capacity

In the comparison of the current supply and capacity between Scenario 1 and Scenario 2, the capacity, vaccine supply, and doses used are now quite in sync with each other

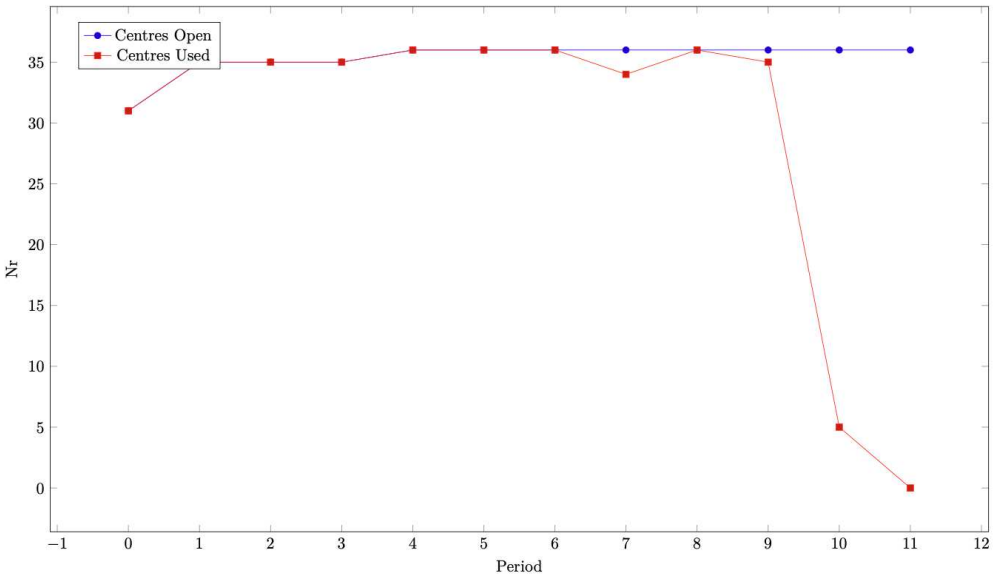


Fig. 17 Opened vs used centres

in Scenario 2 as compared to that of the Baseline scenario (see Figure 9). There is however a difference in terms of how the first doses are used in Scenario 2, where there is a smoother climb at periods 3 and 4 as compared to the Baseline scenario.

Moreover, the capacity cost per person is 6.11 in Scenario 2, which is lower than 6.16, the capacity cost per person in the Baseline scenario.

Usage of vaccine brands

In the comparison between the available and the used vaccines in Scenario 1 and Scenario 2, all vaccines are completely used before period 6 for the double-dose vaccines, particularly Spikevax and Vaxzevria, in Scenario 2. As is seen, this is contrary to the Baseline scenario where both vaccines are not completely used at periods 3 and 4.

Usage of vaccination centres

In Figure 18, we have seen an overall increase in utilization of built capacity as compared to Figure 15. However, a side effect of this is a decrease by 6% from 74.29% in the utilization of Páirc Uí Chaoimh.

4.1.3 Scenario 3: Exclude Cork City Hall

In the previous scenarios, we have seen that Páirc Uí Chaoimh is quite underutilised. This might be due in part to the number of seemingly redundant vaccination centres in Cork. Based on its proximity to Cork City Hall (see Figure 19), it seems that Cork City Hall is the more preferred vaccination centre. In this scenario, we intend to observe the effects of removing the Cork City Hall from the vaccination centres

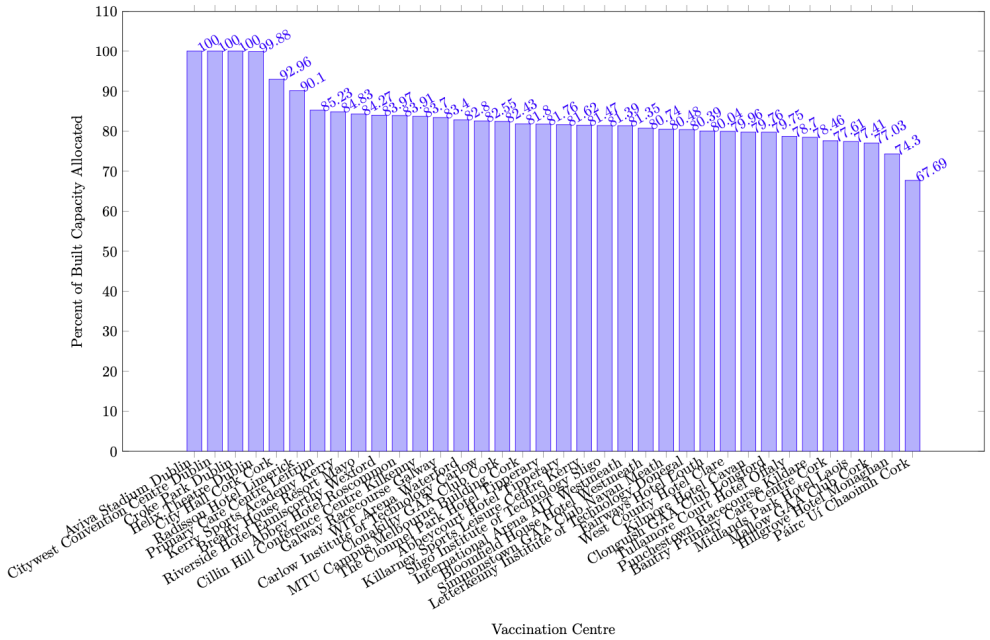


Fig. 18 Usage of built capacity

and see whether this will improve the utilisation of Páirc Uí Chaoimh, which is just 2 kilometres away. At the same time, we also want to observe how the travel distance is affected for those around Cork. To do so, we simply set the ι_j of Cork City Hall to 0 so the centre will be ignored in the solution. We will no longer show results for aspects where there are no apparent differences as compared to the baseline scenario.

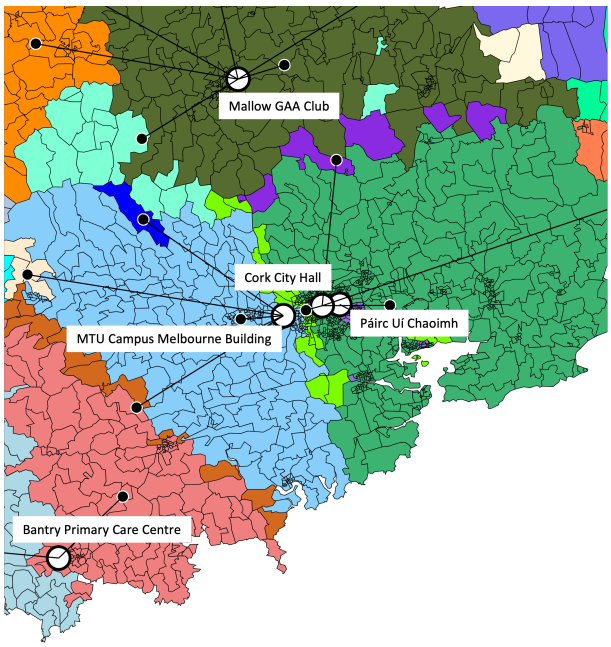


Fig. 19 Cork vaccination centres. Colours are based on the cluster assignment of the census areas.

Usage of vaccination centres

As can be seen in Figure 20, the utilization of Páirc Uí Chaoimh increases, as expected, to 80.98% from 69.7% in the baseline scenario. The usage of the other vaccination centres in Cork also similarly increases. This can be seen in Table 7. The usage and allocation of capacity throughout the horizon of these vaccination centres can be seen in Figure 21.

Cork vaccination centre	Scenario 1	Scenario 3
Bantry Primary Care Centre	73.55%	76.7%
Clonakilty GAA Club	79.87%	83.94%
Mallow GAA Club	80.66%	85.31%
MTU Campus Melbourne Building	80.67%	81.7%
Páirc Uí Chaoimh	69.7%	80.98%

Table 7 Comparison of the usage of vaccination centres in Cork between Scenarios 1 and 3

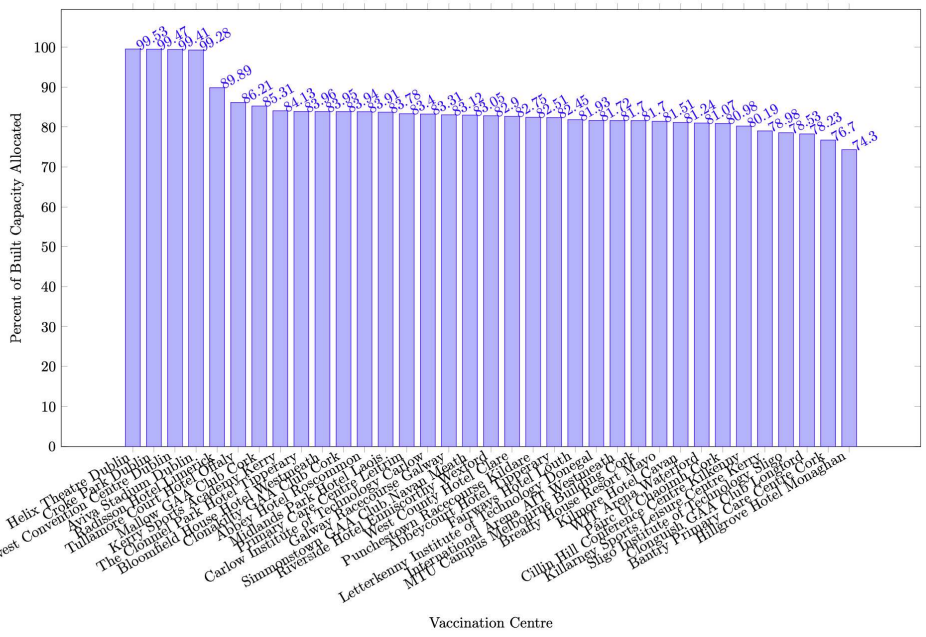


Fig. 20 Usage of built capacity

Travel distance

A look at the maximum distance travelled by those assigned to vaccination centres in Scenarios 1 and 3 showed us that there are almost no changes around the Cork area. There might be a bit of excess travel for those around Cork City but this is still fairly manageable and lesser as compared to those who are along the boundaries of the areas around the centres.

This can also be seen in the average distance travelled per person, where it is 32.71km in the baseline scenario and 32.87km in this scenario.

4.1.4 Scenario 4: No Vaxzevria

Another scenario that we experimented with is the removal of the Vaxzevria vaccine brand from the campaign. This has in fact happened in the middle of the campaign for some countries. In this scenario, however, we assumed that Vaxzevria was taken out or has not been considered at all during the planning period. We want to observe how this would affect the usage of the vaccine supply and capacity and the usage of other vaccine brands.

Usage of vaccine supply and capacity

Needless to say, removing Vaxzevria certainly affects the vaccine supply in this scenario as compared to the Baseline scenario (see Figure 22). The first doses also peak earlier at period 7 as compared to period 8 in the Baseline scenario. The second doses similarly peak earlier at period 9 as compared to period 10 in the Baseline scenario.

The capacity, on the other hand, is able to keep up with a lower vaccine supply at period 3 until 7. However, the capacity cost per person in this scenario is greater than the baseline scenario at 6.40.

Usage of vaccine brands

In Figure 23, notice that the other vaccine brands have to compensate for the removal of Vaxzevria. Comirnaty and Jcovden are fully utilised until the usage dropps after period 9 for Comirnaty and after period 10 for Jcovden. Spikevax, on the other hand, is also similarly fully utilised before period 7 but experiences a drop afterwards until usage picks up again at period 10. This can be attributed to the fact that Spikevax is not allowed for the Age 20-30 cohort, a number of which are already being vaccinated at period 9.

As such, the removal of Vaxzevria also affects how vaccine brands are distributed among vaccination centres in Figure 24. Either Spikevax completely replaces Vaxzevria or the supplies for Comirnaty and Jcovden are increased to compensate for its removal.

This can also be shown in the equipment cost per person, where it is 0.02713 in Scenario 2 while it is 0.03129 in the Baseline scenario.

Nonetheless, this still affects how vaccination progresses in terms of how promptly the cohorts are vaccinated. The average lateness cost per person is 333.57 in the baseline scenario while it is 340.37 in this scenario. This without a doubt shows that the removal of a vaccine brand slows down the vaccination to some degree.

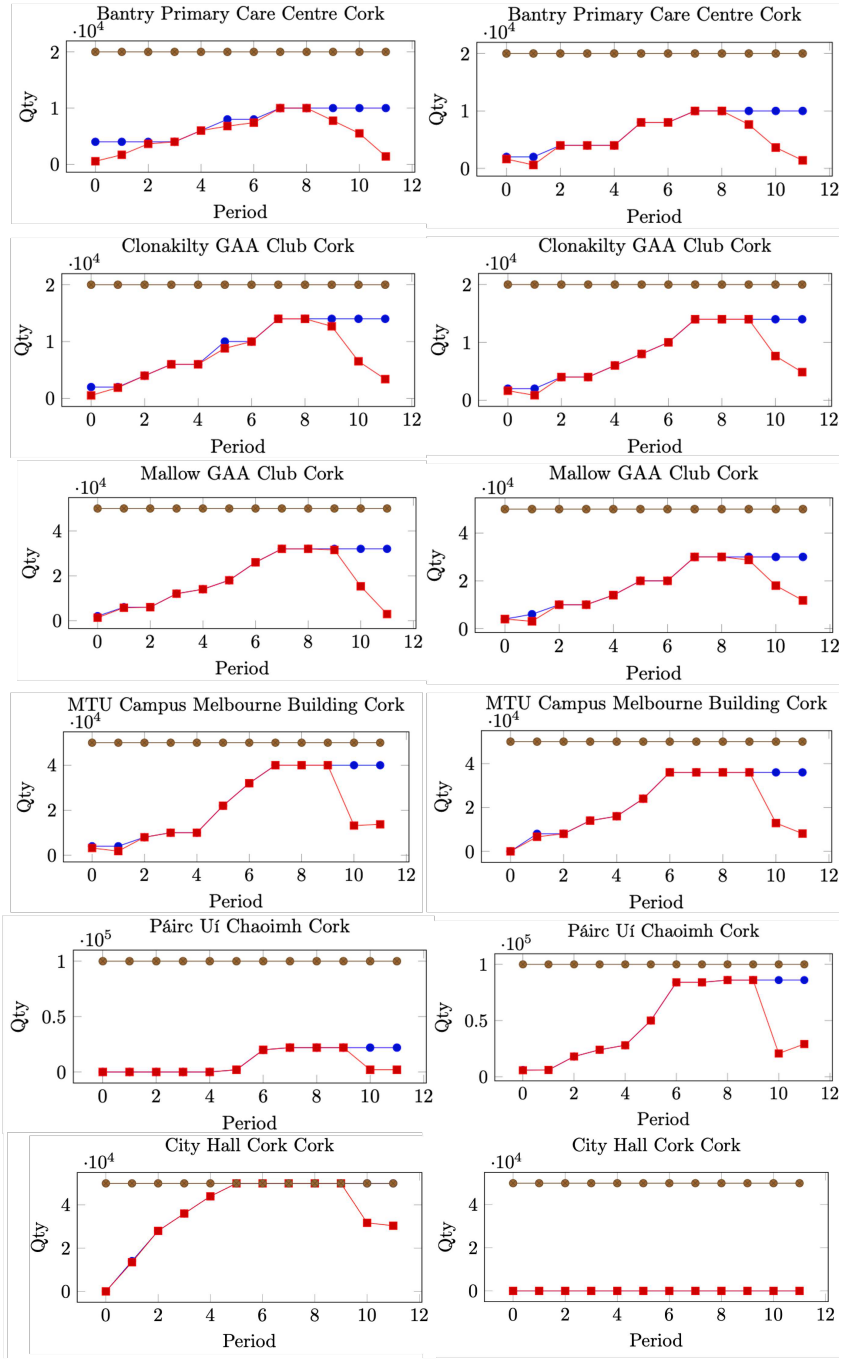


Fig. 21 Comparison of allocation and capacity of vaccination centres in Cork between Scenarios 1 and 3

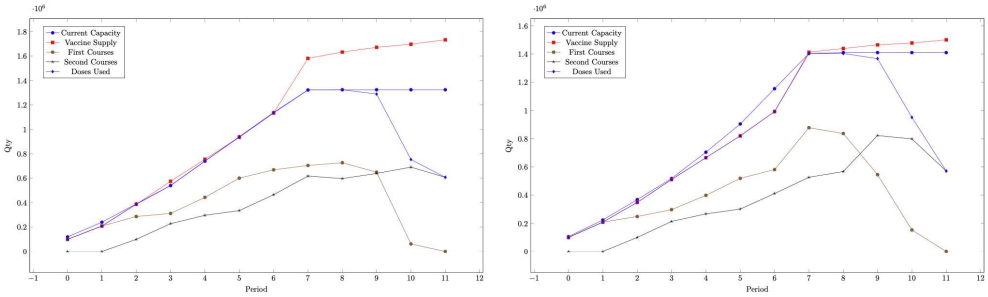


Fig. 22 Comparison of current supply and allocation between Scenarios 1 and 4

4.1.5 Scenario 5: No maximum site capacity

A final scenario that we want to show is the results of removing the maximum capacity limit imposed on each vaccination centre. This was prompted by an observation that vaccination centres in Dublin, such as the Aviva stadium (see 16a), have been completely utilised. This is true for the Radisson Hotel in Limerick as well. Thus, instead of increasing the maximum capacity limit only for the vaccination centres in Dublin, we instead remove this limit for all vaccination centres. We then want to observe the effect of this on the usage of vaccination centres and the vaccination coverage of cohorts.

Usage of vaccination centres

True enough, the three vaccination centres in Dublin, which are the Aviva Stadium, the Citywest Convention Centre, and Croke Park, exceed the maximum capacity limit that were initially set (see Figure 25). Similarly, the Radisson Hotel in Limerick and the Cork City Hall also exceed the maximum capacity limit that were initially set. This means that the limit initially set for these vaccination centres is not enough to meet the demands of the census areas assigned to them. Surprisingly, the capacity cost per person is only slightly higher than the baseline scenario at 6.20.

Vaccination coverage of cohorts

The removal of the maximum site capacity limit has an effect on the vaccination coverage of cohorts as well. A close look at Figure 26 would show that there is a slight speedup in terms of vaccinating cohorts with a higher priority. For instance, the Age 30-40 cohort finishes at period 11 as compared to period 12 in the Baseline scenario. There are also fewer individuals from the Age 10-20 cohort who still get vaccinated at period 12 in this scenario as compared to Scenario 1.

This can be seen quantitatively in the average lateness cost per person as well. In the baseline scenario, the average lateness cost is 333.57 while it is 333.27 in this scenario.

In summary, the KPIs for all the scenarios described above are in Table 8.

Scenario	$\bar{g_1}$	$\bar{g_2}$	$\bar{g_3}$	$\bar{g_4}$	$\bar{g_5}$
1: Baseline	6.16601	0.03129	32.71	333.57	1.60
2: No national capacity limit	6.11353	0.03205	32.68	332.39	1.60
3: No Cork City Hall	6.17147	0.03149	32.87	333.57	1.60
4: No Vaxzevria	6.40573	0.02713	32.86	340.37	1.60
5: No maximum site capacity	6.20212	0.03117	32.07	333.27	1.60

Table 8 Key performance indicators of all scenarios

4.2 Execution time

Let us make now some observations in relation to the execution time. As CPLEX allows the user to specify the number of threads, we first tried to determine the appropriate number of threads. For this we chose one scenario (Baseline) and tried the different combinations of clustering level and number of threads. The results are summarised in Table 9. Based on the values shown, we decided on a cluster limit of two for our experiments, as it provides the best compromise between computational complexity and accuracy. In the scenarios studied, it is exceedingly rare that a census area is not served by either one of the two nearest vaccination centres. When considering that choice of cluster limits, the results suggest that using 2 threads leads to the best performance overall. However, the choice of the number of threads is machine dependent, i.e., a different number of threads could be more appropriate for other machines with a different CPU and cache structure.

Cluster Limit	1	2	3	4	8	16	25
1	218.06	303.96	163.82	158.46	311.66	55.60	304.98
2	288.42	124.13	207.54	238.24	201.97	216.56	255.69
3	611.70	1009.83	754.11	693.32	1017.92	988.60	1254.12

Table 9 Execution for the Baseline scenario varying both the number of threads and the level of clustering.

Leaving the number of threads fixed, we then tried all the scenarios (see Table 10). In these experiments, we have set the optimality gap to 0.05% and we are using a timeout of 1200 seconds. We can see that in all cases reported in Table 10, an optimal solution (subject to the optimality gap) is reported in much less time than the set timeout.

Scenario Choice	Time (sec)
Baseline	121.263
NoNationalCapacityLimit	194.695
NoCorkCityHall	205.865
NoVaxzevria	91.934

Table 10 Execution for different scenarios for different the level of clustering.

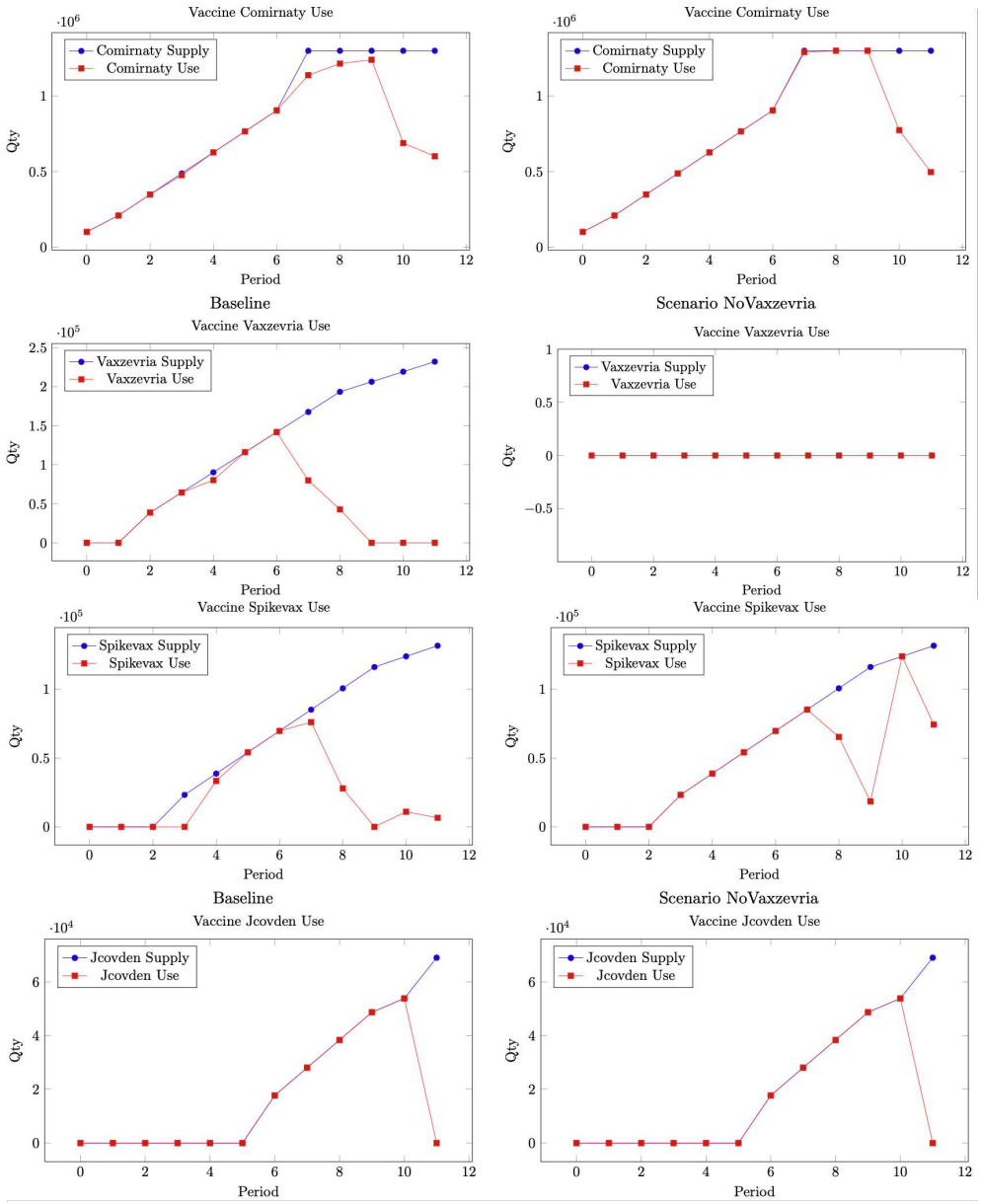


Fig. 23 Comparison of available vs used vaccines between Scenarios 1 and 4

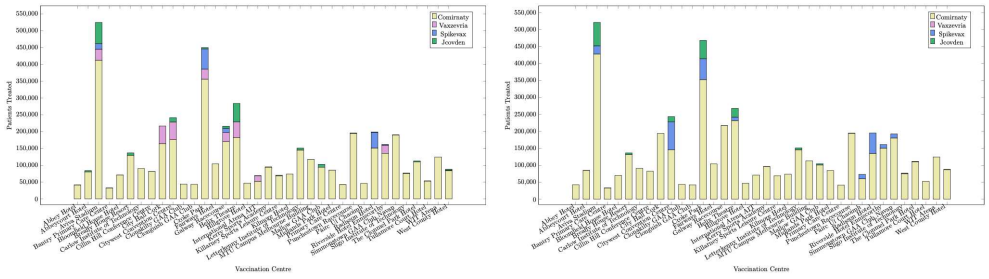


Fig. 24 Comparison of vaccines given in centres between Scenarios 1 and 4

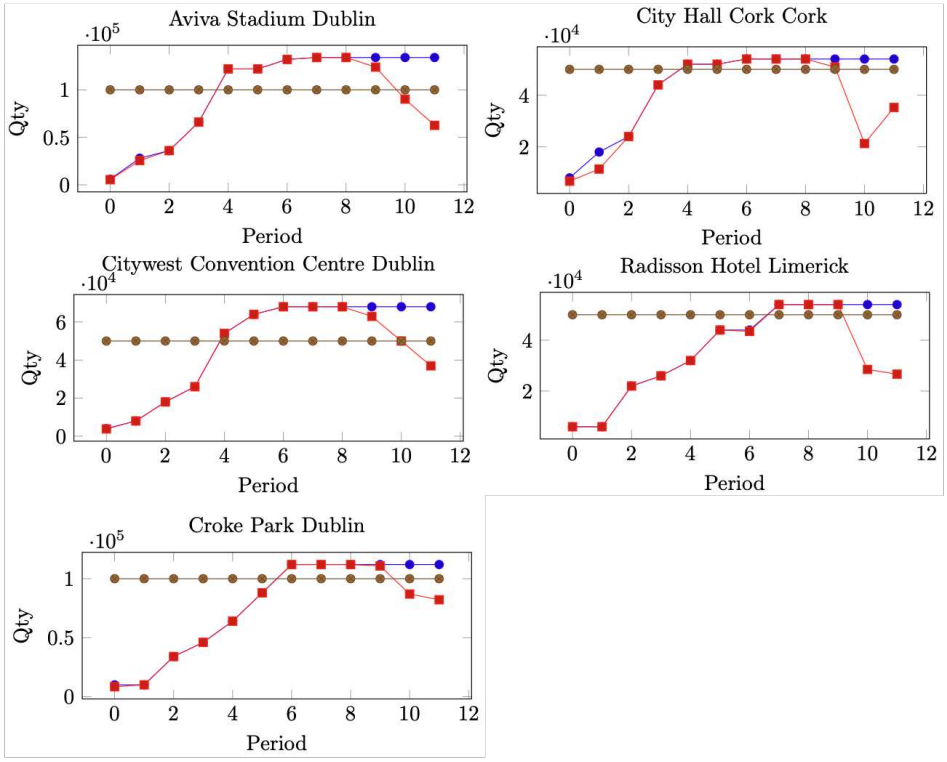


Fig. 25 Centre capacity and allocation that exceeded the site limit

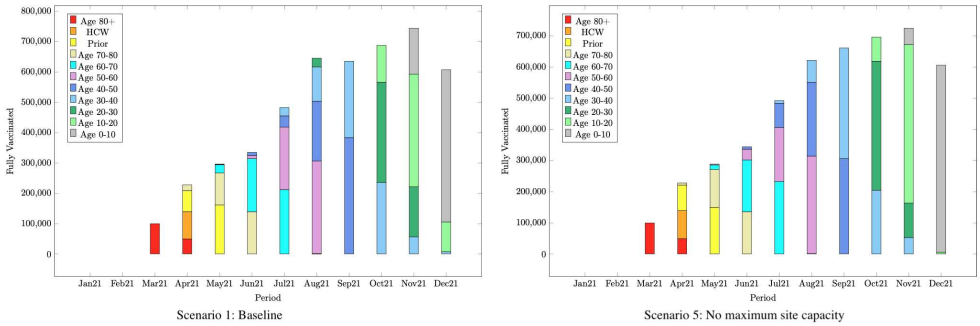


Fig. 26 Comparison of available vs used vaccines between Scenarios 1 and 5

5 Discussion

Our analysis of the results led us to the following insights:

- While it might be good to control building costs by setting a limit on the building capacity at the national level, it might also curtail the progress that the vaccination campaign makes. This was seen in the Baseline scenario (see Subsection 4.1.1), where there is a national building capacity limit, as compared to Scenario 2 (see Subsection 4.1.2), where this limit is removed. Thus, controlling the building costs is best imposed not as a constraint but in some other manner, such as an objective function.
- While it is also natural to impose a maximum capacity for each vaccination centre, it might also be best to see how the allocation and usage will proceed if there is no maximum capacity imposed. As can be seen in Scenario 5 (see Subsection 4.1.5), all three vaccination centres in Dublin have allocations that exceeded their maximum capacity. Such a simulated scenario should prompt decision makers to extend the maximum capacity of these vaccination centres or possibly put up another vaccination centre in Dublin.
- Removing Vaxzevria during the planning period does not necessarily affect the completion of the vaccination campaign although it still slows down the vaccination. However, it would have been better to also show the effects if such a removal happens in the middle of the campaign.
- Both the capacity built and the vaccine supply drive the vaccination forward. The results clearly show that both are limiting factors of the vaccination campaign. Limiting either will surely affect how the vaccination proceeds. Thus, decision makers need to guarantee that both the vaccine supply and capacity are up to the demands in each period of the campaign.

6 Conclusions

Aside from the scenarios whose results are shown above, an infinite number of scenarios can also be tested. More importantly, we believe that a model and a tool that makes use of the model will both be valuable for the decision makers at the planning stage of the vaccination campaign. Using a tool such as the one used in this study will allow the decision makers to simulate possible scenarios that might come up before the campaign and make informed decisions based on the results.

Given that decisions made during the COVID-19 vaccination campaign were also made dynamically, a model that also takes this dynamic nature into consideration would be an additional benefit. For instance, some of the scenarios described above happened in the middle of the campaign in reality, such as the removal of a certain vaccine brand, the shutdown of a vaccination centre, the change of the maximum capacity of a vaccination centre, and the change of the dosing interval of any of the vaccine brands. A tool that allows decision makers to simulate such scenarios systematically in the middle of the campaign would also be a great benefit as it would allow them to adjust their decisions accordingly based on the results.

Lastly, given that the data used in the study was not the exact real-world setting, there is no way to be able to evaluate the results of the tool against what has transpired during the actual vaccination campaign. This is not a limitation of the tool but a limitation of the data used. Nonetheless, it clearly shows that planning a national vaccination campaign using the tool is effective.

A Symbols

Variable/parameter		Description
A	a_i	cost weight factor
B	b_p	building investment cost of providing one capacity unit of size q in period p
C	c_j	maximum capacity of site j per period
D	d_{ij}	distance between population and vaccination centres, d_j distance between national supply point and vaccination centre
E	e_{vp}	national fitting out capacity for vaccine v in period p
F	f_{vp}	cost of fitting out one vaccination centre for delivery of vaccine v
G	g_i	objective function cost term
H	h_p	national building supply limit per period p
I		census areas set I, index i
J		vaccination centres set J, index j
K		population cohort set K, index k
L	l_{kvp}	lateness cost of vaccinating member of cohort k in period p with vaccine v; this allows to express different costs for vaccines with different delays between first and second doses
N	n_{ik}	size of cohort k in census area i
O	o_{ij}	people from centre i should not be assigned to centre j
P		periods of programme set P, index p
Q	q	capacity increment
R	r_{vk}	0/1 vaccine restriction, can vaccine v be given to cohort k
S	s_{vp}	national supply limit for vaccine v in period p
T	t_v	transport volume demand for one unit of vaccine v
U	u_p	transport capacity for period p, in volume*km
V		vaccine types set V, index v
	variable v_{jvp}	also, number of doses of vaccine v applied in centre j during period p
W	variable w_{ikvjp}	the number of people of census area i in cohort k that receive their first does of vaccine v in centre j during period p
X	variable x_{ikjp}	number of people from location i in cohort k assigned to centre j in period p
Y	variable y_{jp}	capacity investment in centre j for period p
Z	variable z_{jvp}	equipment investment for vaccine v at centre j in period p
α	α_{vl}	real fraction (0-1) of patients using vaccine v getting their second dose l periods after their first. l ranges from 0 to λ, the maximum delay (in periods) encountered
β	β_j	construction cost factor for vaccination centre j, reflecting that building capacity in different places varies in cost.
γ	γ_v	the number of required doses for vaccine v (we currently only consider one or two)
ι	ι_j	is a Boolean flag to indicate if vaccination centre j is forced to be ignored in the solution
λ		the maximum delay in periods between first and second doses of any of the vaccines used
ρ	ρ_j	is the rental cost of vaccination centre j for the complete planning period. This does not consider if the centre is only used for some of the months of the overall programme.
σ		the period σ_j is the earliest period that centre j can be used
τ		the period τ_j is the latest period that centre j can be used

Table 11 Symbols

B Declarations

B.1 Ethics approval and consent to participate

Not applicable.

B.2 Consent for publication

Not applicable.

B.3 Availability of data and materials

The availability of the experimental data and simulation results used in this study is contingent upon the results of the review process.

B.4 Competing interests

The authors have no competing interests.

B.5 Funding

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B.6 Authors' contributions

GT collected and formulated the initial experimental data, prepared the initial visualisation of results, and drafted the manuscript. HS participated in defining the problem scope and the resulting MILP model, and worked on the final visualisation of results. LQ and GT participated in the design, implementation and evaluation of the model. BO came up with the problem and oversaw the process that led to this submission.

B.7 Acknowledgements

None.

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