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# Determining optimal locations for blood distribution centers

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## Abstract

**Background:** Blood banks have to be thoughtful about supply chain decisions to effectively satisfy the blood product demand of hospitals. These decisions include the number and locations of distribution centers (DC), as this has a strong impact on both transportation cost and the ability to deliver emergency orders in time.

**Study Design and Methods:** We propose a mixed-integer linear programming approach to find optimal DC locations for supplying individual hospitals. The model maximizes the number of hospitals reachable from a DC within a given time-limit, and minimizes transportation cost. The minimal amount of data required is a set of hospital locations. The model can be further attuned to the user's needs by adding various model extensions. The model's use is demonstrated by two case studies, considering the blood banks of the Netherlands and Finland.

**Results:** For both case studies re-locating the DCs would result in a reduction of transportation cost of about 10% without affecting the reliability of delivery. In addition, to save facility exploitation costs, the number of DCs may be reduced in both countries while maintaining the reliability of delivery. The model was also shown to be robust against changes in hospital ordering behavior.

**Discussion:** We demonstrated the general usability and added value of the model by successfully optimizing the blood supply chains of the Netherlands and Finland, which differ substantially. Nonetheless, in both countries potential savings in both transportation and facility exploitation cost could be shown. The model code is open source and freely accessible online.

## KEYWORDS

facility location, linear programming, optimization, supply chain

**Abbreviations:** DC, distribution centers; FRCBS, Finnish Red Cross Blood Service.

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## 1 | INTRODUCTION

Blood transfusions are crucial in many lifesaving hospital treatments. Blood banks are responsible for collecting and testing blood products, which are in many countries obtained from voluntary donations. Hence it is unacceptable to let these products outdate. At all times there should however be enough blood products in stock to fulfill all patient requests. Balancing these two goals can be challenging as demand is highly stochastic.<sup>1</sup>

Because of their perishability, most hospitals only maintain a small inventory of blood products, which has to be supplemented regularly from a blood bank's distribution center (DC). In this study, we distinguish two types of orders that hospitals can place at the blood bank to replenish their stock. These are systematic orders, which are placed and delivered at predetermined times each day or week, and emergency orders, which are placed whenever a product is urgently needed but not present in the hospital's inventory. We assume that there is a maximum time for emergency orders to be delivered, as receiving blood products in time can be of vital importance for the patient.

To be as effective as possible in satisfying hospital demand, blood banks have to be thoughtful about supply chain decisions. An important issue to consider is the number and locations of DCs, which is generally referred to as a facility location problem. In blood facility location research, the most common objective is to minimize costs. These include the cost of transportation,<sup>2–10</sup> the cost of opening, moving or operating a facility,<sup>2–4,6,9–11</sup> and inventory costs such as ordering cost, production cost, outdates, substitutions and stock-outs.<sup>2,3,10,12</sup> The number of DCs is one of the most significant cost parameters,<sup>13</sup> as operating a DC is generally very expensive.

The location of these DCs not only has a strong impact on the transportation costs, but also on the ability to deliver emergency orders to hospitals in time. This combination of cost minimization and the so-called maximal covering location problem has, to our knowledge, been studied only a few times for the blood supply chain.<sup>2,3,6</sup> These studies do, however, not distinguish between different types of orders. Since emergency orders are the only ones requiring fast deliveries, we aim to achieve more meaningful results by only setting time requirements for this type, and including systematic orders only for the estimation of transportation cost. There are also only a few other studies on the topic of blood supply chain design that differentiate between different types of blood products.<sup>6,14,15</sup> Although this distinction is not part of our main approach, we have added this as an optional extension, as discussed in Supplement

B.2. Moreover, the majority of blood facility location studies considers less than 40 candidate locations,<sup>2,4–6,9,10,14–28</sup> one study<sup>8</sup> considers 76 candidates, while two other studies<sup>11,29</sup> aim to find optimal coordinates, whereas we experiment with candidate sets of sizes 15, 111, 300 and 1212. These candidate sets stem from two case studies performed in the Netherlands and Finland, that will be discussed to demonstrate our method.

We propose a mixed-integer linear programming approach to find optimal DC locations. The first objective of this model concerns the “reliability of delivery” (referred to as “reliability”). This reliability indicates the proportion of hospitals that is reachable from a DC within the time limit set for emergency orders, and will be maximized. The second objective concerns the transportation cost, which is minimized.

## 2 | METHODOLOGY

In this section, we will describe the model design and introduce two case studies. The mathematical model formulation can be found in Supplement B.

### 2.1 | Locations and connections

Two types of location sets need to be defined: the demand points (hospitals) and the candidate locations where DCs may be placed. The former is required as data, the latter can be constructed. Supplement A.1 contains a more detailed description of the data required.

To accurately estimate the reliability of delivery, it is important to consider route properties, such as the proximity of a DC to the entrance of a highway. Because these properties are not captured when using Euclidean distances, we use a route planner<sup>30,31</sup> for accurately estimating traveling times and distances between all hospitals and candidate DC locations. The model is therefore provided with a set of candidate locations, as opposed to a continuous range of coordinates.

### 2.2 | The model

#### 2.2.1 | Basic model

We aimed to find DC locations such that, given a set of fixed hospital locations, the total expected transportation cost is as low as possible, and the reliability of delivery is as high as possible. To achieve this the user of the model can choose one of three implementations:

- Minimize the transportation cost and include a constraint stating a minimum percentage of deliveries fulfilling the reliability target;
- Maximize the reliability of delivery and include a constraint stating a maximum value for the transportation cost;
- Both minimize transportation cost and maximize reliability. When choosing this option, the user should select one of both objectives to prioritize. The prioritized objective will then be optimized first, and only within the solution pool that satisfies the optimal objective value found, the second objective will be optimized.

By using constraints, we assure that the number of DCs located by the model equals a pre-defined parameter  $n$ , and that each hospital is served by exactly one DC.

### 2.2.2 | Extension: Blood product orders

A major improvement of the model lies in the inclusion of hospital orders, since hospitals that place more or larger orders impact transports more heavily. When ordering data is available and included, we use the number of transported blood product units to improve the reliability estimate, which we can now measure as the portion of emergency-ordered products that are delivered within the time limit. Moreover, we use the number of transports to each hospital to improve the estimate of transportation cost, by multiplying the cost per delivery by the number of orders placed by each hospital individually.

### 2.2.3 | Extension: Direct and routed transports

Emergency orders will generally be transported straight from a DC to the ordering hospital since the products should be there as quickly as possible. Systematic orders on the other hand can be delivered via routes visiting multiple hospitals, as this reduces the total transportation cost. The inclusion of routing decisions in the facility location model would however add a huge amount of complexity, causing a tremendous increase in computation time and effort.

The efficiency of combining deliveries in routes can be approximated by only using information on the clusters of hospitals that will be combined, without exact information on the routes that will be taken within these clusters. This is illustrated by the effectiveness of the cluster-first route-second approach. This heuristic first

determines clusters of demand points for which deliveries should be combined, and only then finds the shortest route from the source to each cluster, within the cluster, and back to the source. The fact that this is the most common heuristic to solve vehicle routing problems,<sup>32</sup> and that it is widely used in recent publications,<sup>32–34</sup> suggest that forming clusters of hospitals without first knowing the exact optimal routes to take is a valid approach. Also note that Bramel and Simchi-Levi<sup>35</sup> used the facility location problem as a heuristic to solve a vehicle routing problem, which turned out to perform very well compared to state-of-the-art heuristics.

## 2.3 | Case studies

We introduce two case studies for properly demonstrating the model's use in practice. These case studies consider Sanquin Blood Supply Foundation and the Finnish Red Cross Blood Service (FRCBS), which are responsible for the collection, testing, and distribution of blood products in respectively the Netherlands and Finland.

In the Netherlands, the blood product stock of 110 hospitals is supplied by the 7 DCs of Sanquin. If a hospital places an emergency order, Sanquin is expected to deliver the requested product within 1 h. The size of the Netherlands is approximately 33,500 km<sup>2</sup>, with an average of 39.1 km driving distance between all DCs and their allocated hospitals. A yearly total of approximately 400,000 erythrocyte and 50,000 thrombocyte products is supplied.<sup>36</sup>

In Finland, a total of 55 hospital blood banks are supplied by the 4 DCs of the FRCBS, delivering a yearly total of approximately 180,000 erythrocyte and 30,000 thrombocyte products.<sup>37</sup> Only a subset of 11 hospitals representing the largest and most logistically challenging hospitals are included in this study. The geography of Finland is one of the relatively long distances, covering a size of 304,000 km<sup>2</sup>, with an average of 95.9 km driving distance between DCs and their allocated hospitals. For this reason, there is no predetermined time limit for transports. However, we approximated from the real-life data that academic hospitals should receive their orders within 6 h, whereas non-critical transports to all other hospitals are allowed to take up to 24 h. A few more detailed statistics on both countries can be found in Supplement A.2.

### 2.3.1 | Data

For both case studies ordering data was used, being the size and frequency of orders placed by each individual

hospital, to weigh large hospitals more heavily than small ones. For the Netherlands the data covers 2019 and 2020 for the Netherlands, for Finland it covers 2019 and 2021. For the Netherlands both routed and direct transports are considered, whereas for Finland all transports are assumed to be direct deliveries. The data of both countries includes erythrocytes and thrombocytes.<sup>38</sup> In the Dutch data omniasma deliveries<sup>39</sup> are included as well. Transportation times and distances were estimated using the Mapbox API<sup>30</sup> for the Netherlands and using Google Maps<sup>31</sup> for Finland.

### 2.3.2 | Candidate location sets

As the model needs to be provided with candidate locations. For both the Netherlands and Finland, the union of hospitals and current DC locations is used. This set consists of 117 locations for the Netherlands, and of 15 locations for Finland. For both countries, a larger set was created as well, to approximate a so-called “greenfield” set where the model is allowed to choose roughly any point on the map. These sets are visualized in Supplement D, Figure S2. The set consists of 1212 locations for the Netherlands, and of 300 locations for Finland.

### 2.3.3 | Current and optimal locations

For both countries, we first analyzed the current situation. For the Netherlands the maximum transportation time for emergency orders is set to 1 h. For Finland, the maximum time for emergency deliveries to academic hospitals is set to 6 h, and for the other hospitals to 12 h. For the transportation cost we make use of a cost index, which allows for illustrating the impact of different scenarios on transportation cost without sharing any confidential information. For all results discussed in Section 3, this cost index will reflect the ratio between the transportation cost of the scenario considered and the current setting, which has a cost index of 1.

The model's objective was set to minimize transportation cost to find optimal DC locations, whereas using a constraint to ensure that the reliability of delivery will not be impaired. Defining  $n$  as the number of DCs to be located, optimal DC locations were determined for  $n \in \{5,6,7\}$  for the Netherlands, and for  $n \in \{2,3,4\}$  for Finland.

### 2.3.4 | Hardware and software used

All tests were executed using a Lenovo Legion 7-16ACHg6 Laptop (type 82N6), containing an AMD Ryzen 75800H Processor with 8 Cores and 16 Logical

Processors, and 32GB RAM. Note that this is a regular modern PC, and that having access to unreasonably high computing power is not required. The model was programmed in Python (version 3.9).<sup>40</sup> The commercial solver Gurobi (version 9.1)<sup>41</sup> was used to execute the model and generate results. The code is available from [https://github.com/WemelsfelderML/facility\\_location\\_bloodsupply.git](https://github.com/WemelsfelderML/facility_location_bloodsupply.git).

## 3 | RESULTS

In this section, results are discussed for both case studies. We will generally describe the current status of both the Netherlands and Finland with regard to hospital and DC locations, show results of optimizing these locations, and discuss further insights gained from applying the model in these settings.

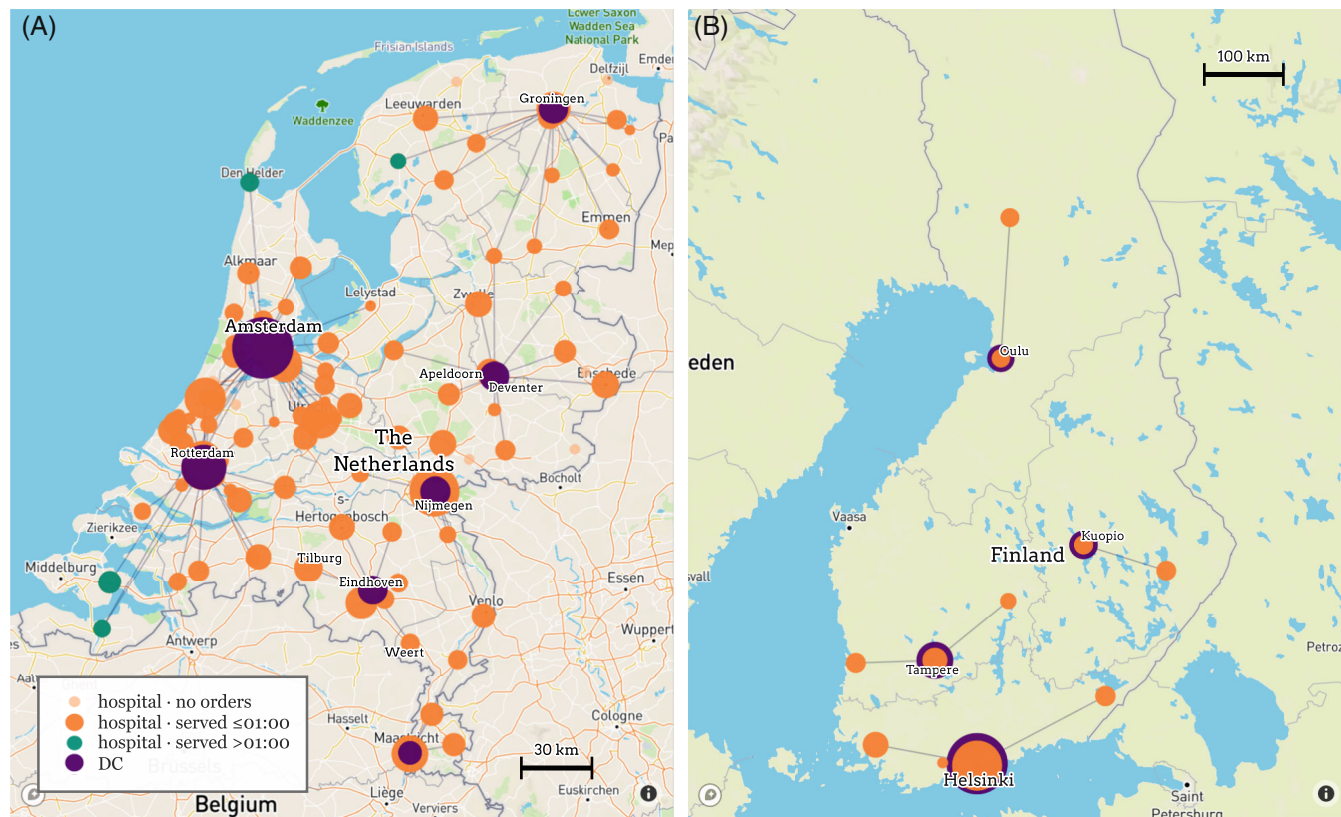
### 3.1 | Current and optimal locations

#### 3.1.1 | The Netherlands

The current DC and hospital locations in the Netherlands are visualized in Figure 1A. The resulting objective value for reliability of delivery is 98.05%. Note that this value does not represent the true reliability of current blood supply, but rather the theoretical result of executing the model with current DC and hospital locations. The value indicates that 1.95% of emergency products is ordered by the four hospitals that are indicated with a green dot in Figure 1A. In the model, all four hospitals are simply regarded as impossible to serve within 1 h. In practice two of these hospitals can however be reached within 1 h if emergency transportation methods are used, allowing the cars to drive faster than usually. With the two other hospitals, Sanquin has made separate agreements regarding their delivery times.

Table 1 contains the results of optimizing for 5, 6, and 7 DCs, showing the transportation cost index, reliability, and cities where a DC is located. We observe that the current reliability of delivery can be maintained for all scenarios, and that the cost index would be lowered to 0.903 by moving one DC from Eindhoven to Tilburg. When reducing the number of DCs to 6 or 5, the transportation cost will go up as a result of the increase in average transportation distances. If these results were to be considered for implementation, the facility exploitation cost of DCs should outbalance this increase in transportation cost.

We also observe that in every scenario a DC is located in Amsterdam, Groningen, and Rotterdam. The same holds for Deventer if  $n \in \{6,7\}$ . However, this DC is



**FIGURE 1** Current locations of distribution centers (DCs) and hospitals in the Netherlands (A) and Finland (B). Dot sizes indicate the number of products that are distributed/requested. The lines indicate to which DC a hospital is allocated. [Color figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

**TABLE 1** Transportation cost index, reliability of delivery and location of distribution centers (DCs) for the current situation and for the optimal DC locations for a given number of DCs in the Netherlands.

	Current locations		Optimized DC locations	
Number of distribution centers	7	7	6	5
Reliability of delivery	98.05%	98.05%	98.05%	98.05%
Transportation cost index	1.0	0.903	0.989	1.118
Cities with a distribution center				
Amsterdam	x	x	x	x
Groningen	x	x	x	x
Rotterdam	x	x	x	x
Deventer	x	x	x	
Apeldoorn				x
Nijmegen	x	x	x	
Maastricht	x	x		
Eindhoven	x			
Tilburg		x		
Weert			x	x

*Note:* For the optimal solutions the transportation cost is minimal while the reliability of delivery (with a maximum delivery time of 1 h) was constrained to be at least as high as the reliability resulting from using the current DC locations (98.05%).

moved to Apeldoorn for  $n = 5$ . In the south-east of the Netherlands, where DCs are currently located in Nijmegen, Eindhoven, and Maastricht, the optimal

locations found are less in accordance with the existing ones. In this area, Weert and Tilburg are proposed by the model as better alternatives for some of the current DCs.

	Current locations	Optimized DC locations		
Number of distribution centers	4	4	3	2
Reliability of delivery	100%	100%	100%	100%
Transportation cost index	1.0	0.887	1.291	1.754
Cities with a distribution center				
Helsinki	x	x	x	x
Kuopio	x	x	x	x
Tampere	x	x		
Oulu	x			
Lappi		x	x	

Note: For the optimal solutions the transportation cost is minimal while the reliability of delivery (with a maximum delivery time of 6 h) was constrained to be as high as the reliability for the current DC locations (100%).

TABLE 2 Transportation cost index, reliability of delivery and location of distribution centers (DCs) for the current situation and for the optimal DC locations for a given number of DCs in Finland.

### 3.1.2 | Finland

The current locations of DCs in Finland are visualized in Figure 1B, showing a reliability of delivery of 100%. Table 2 contains the results of optimizing for 2, 3, and 4 DCs, showing the transportation cost, reliability, and cities where a DC is located.

We observe that it is possible to maintain a reliability of 100% for all considered values of  $n$ , and that the cost index would be reduced to 0.887 by only moving one DC from Oulu to Lappi. When reducing the number of DCs to 3 or 2, the transportation cost will however increase very quickly as a result of the increase in average transportation distances.

## 3.2 | Varying maximum delivery times

As the reliability of delivery is directly dependent on the maximum delivery time, one might wonder what happens if this value is varied. Figure 2 shows the impact of alterations in the maximum delivery time on the number of DCs needed to maintain the same reliability. We observe that for the Netherlands, small changes in the maximum delivery time quite heavily impact the required number of DCs required to keep reliability at its current level. For Finland we observe that in fact more than 1 DC is needed to satisfy 100% reliability of delivery only when the maximum time is shortened.

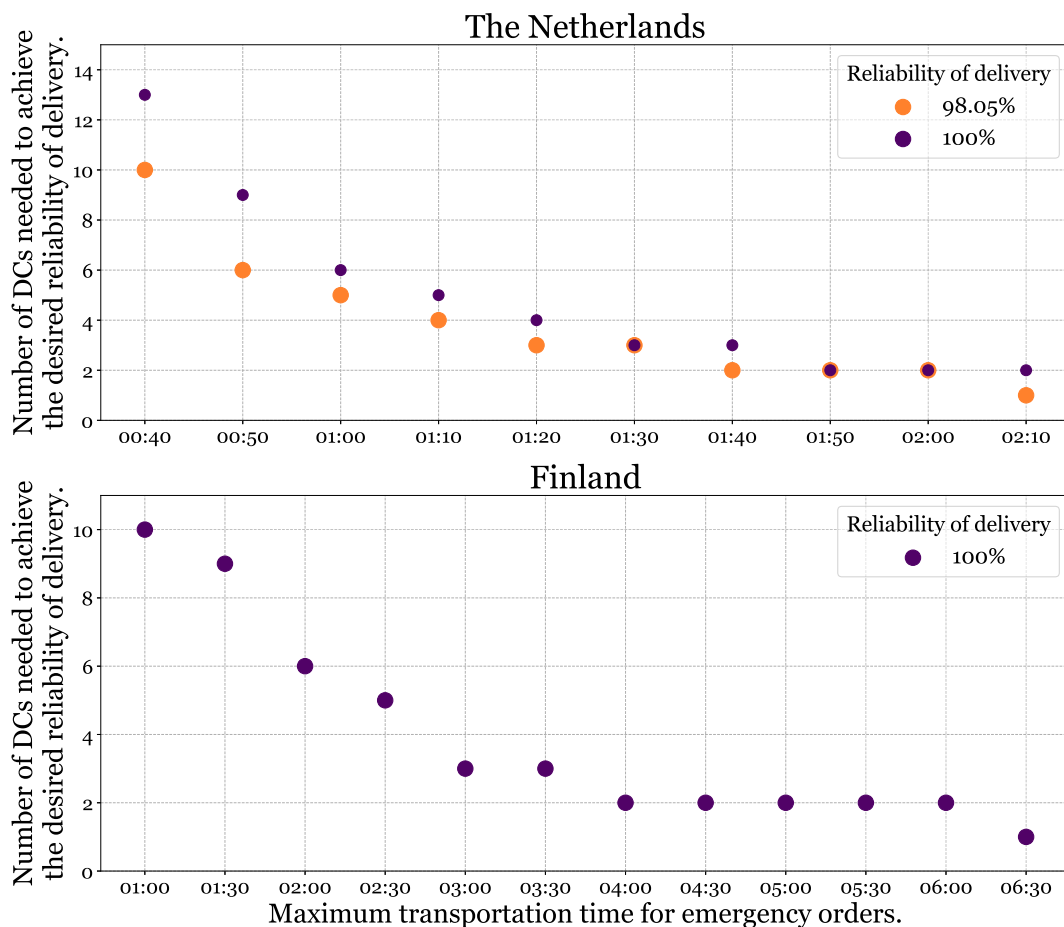
## 3.3 | Computation time

The time needed to solve the model strongly depends on two factors: (1) the size of the candidate location set, and (2) the number of objectives to solve. For the results

presented in Section 3.1, the candidate set used contains all existing facilities, being all current DCs and hospitals. When using the much larger “greenfield” set, for the same analyses this obviously leads to higher computation times. For our case studies, surprisingly, it did not result in better objective values.

The results presented here were obtained by minimizing transportation cost while including the reliability as a constraint. The computation time for such optimizations generally takes less than 5 min for the largest candidate location set, and less than 5 se for the smaller sets (see Table S5 in Supplement C). However, especially for the largest candidate set, we have encountered significantly higher computation times when executing the model with two objective functions instead of one.

For several configurations the optimal objective value was not found within 1 h. However, in all of these cases the last update of lower and upper bounds was already performed while optimizing the prioritized objective. A characteristic example is the location of 6 DCs in the Netherlands, with the “greenfield” candidate set. After 204 s the first objective, minimizing the transportation cost, is solved. Then the optimization shifts to maximizing the reliability of delivery, while maintaining the optimal cost value that was found in the first part. This second optimization starts with a gap of 1.67%, and does not manage to find a smaller gap for the full remaining computation time. Note that the gap is calculated as the difference between the best and worst values that are still considered possible, relative to the best possible value. For both case studies it seemed to be more computationally efficient to optimize only one of both objectives and include the other as a constraint, rather than aiming to optimize it as a secondary objective.



**FIGURE 2** The number of distribution centers required to keep the reliability of delivery at the desired level as a function of the maximum delivery time. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/trf.17147)]

### 3.4 | A more in-depth scenario

When observing Table 1, one might be interested in investigating the  $n = 6$  scenario more in-depth. With respect to the current DC locations, this would mean closing the DCs in Eindhoven and Maastricht, and opening a new one in the area of Weert. This scenario was analyzed by creating a grid of locations covering the area around Weert, as is visualized in Figure 3. We then let the set of candidate location consist of this grid plus all current DCs, minus Eindhoven and Maastricht.

In Figure 3, the large purple dot represents the optimal new location as determined by the model. All hospitals that were within 1 h transportation time from a DC in the original situation still are. The transportation cost has gone up as a result of longer transportation distances on average, but the exploitation cost for one DC is saved.

## 4 | DISCUSSION

In this paper, we propose a facility location model for finding optimal blood DC locations. Only a minimal

amount of information is needed to execute the basic version of the model, requiring only a set of hospital and candidate DC locations. The model can be further attuned to the user's needs by adding model extensions as discussed in Section 2.2.

The use of the model was demonstrated by case studies for the Netherlands and Finland. The blood supply chain designs of both countries differ substantially, demonstrating the general usability of the model. Besides Finland being nine times the size of the Netherlands ( $304,000 \text{ km}^2$  compared to  $33,500 \text{ km}^2$ ), hospitals in the Netherlands are geographically very equally distributed, whereas in Finland both hospitals and their order quantities are concentrated in the south. The supply to hospitals in the northern part of Finland, which require only a relatively small number of orders, are therefore challenging in terms of both distance and delivery time. Then again, the number of DCs per hospital is comparable: 4/5 for Finland and 7/110 for the Netherlands. Despite substantial differences in supply chain structure and properties, the model has shown to generate meaningful results for both settings.

In Supplement B.3 we show that the model is quite robust to changes in ordering behavior. If substantial



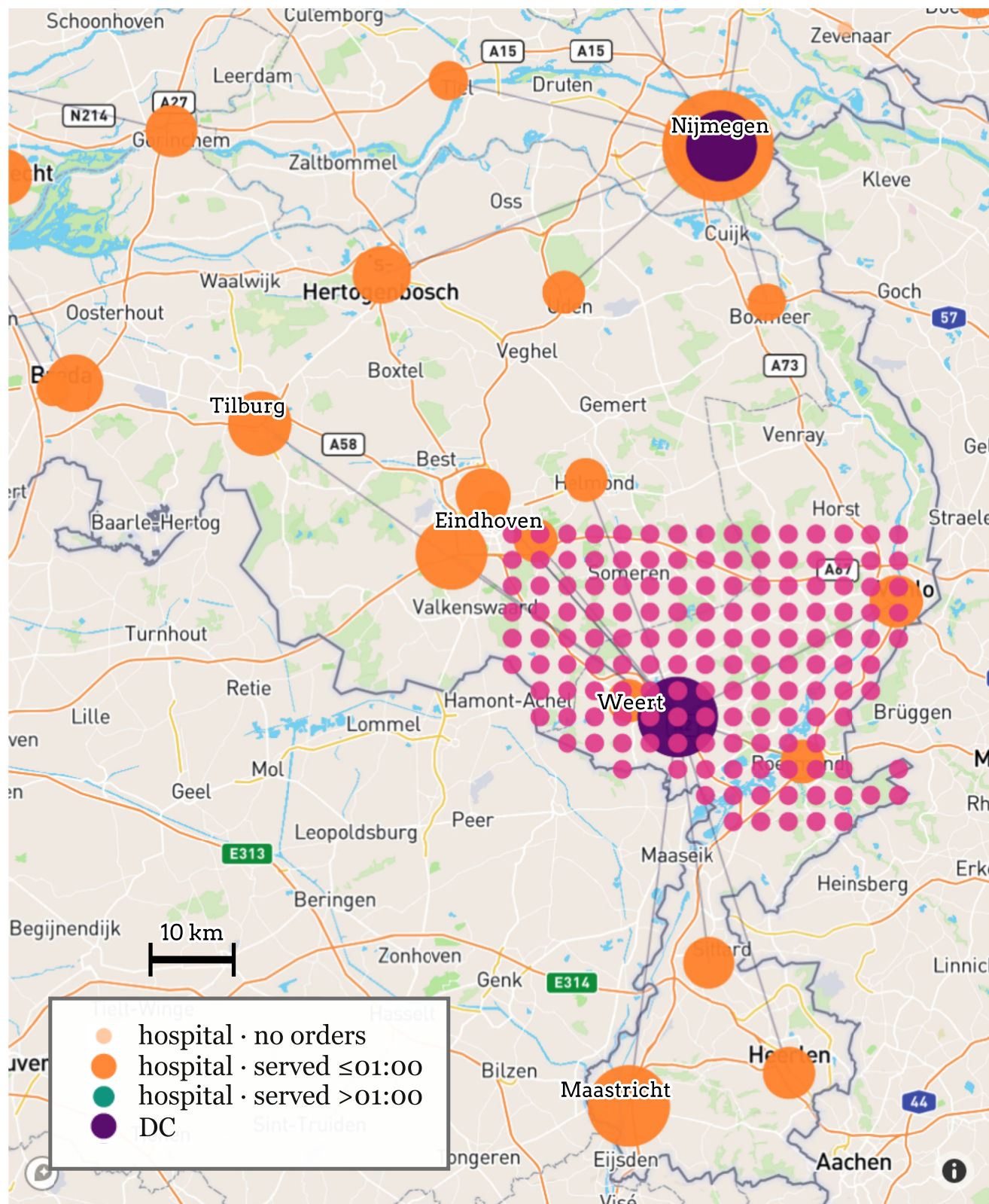


FIGURE 3 Grid to solve the scenario where the current distribution centers (DCs) in Eindhoven and Maastricht are combined to form one new DC in the area of Weert. All candidate locations for the new DC are shown in pink, the optimal location is shown in purple. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/trf.17147)]

changes in ordering patterns are expected one might also consider applying robust optimization methods,<sup>42</sup> which would make the model's solutions inherently robust to uncertainties in ordering behavior.

A further improvement of the model may be achieved by including routing decisions instead of approximating the effects of routing by clustering of hospitals. This might however lead to high computation times and would complicate interpretability of the outcomes obtained. Yet further improvements of the model may be achieved by considering the routes from the blood processing facilities to the DCs, or even the transport from donation centers to the processing facilities.

A model for optimizing the locations of blood DC was developed to prove the efficiency of blood supply. The proposed model is designed as a decision tool to be used to complement many other considerations about candidate DC locations like location-specific implications (e.g., licenses) or compatibility with future plans (e.g., possibilities to expand) that may be relevant to an optimal design of the supply chain. By making the code generic and accessible through a Github repository we hope to contribute to an improvement of the efficiency of the blood supply in other settings as well.

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## CONFLICT OF INTEREST

The authors have disclosed no conflicts of interest.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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