Chapter 2
Literature Review

In this chapter, a literature review of the existing research papers on the HHC problem has been provided. This aims to establish the appropriate place for the HHC delivery problem under consideration. First, in Section 2.1, a brief evolutionary history of the HHC literature is presented based on the complexity of considered objectives and constraints. Section 2.2 elaborates on the employed solution methodologies with regard to their capabilities in solving single/multi-period HHC delivery problems. Then, a summary of works published in the broader field of logistics and transportation is used to inspire new ideas for the HHC problem. Finally, Section 2.4 highlights the research gap identified from the literature, with Section 2.5 providing the conclusion for the chapter.

2.1. Home healthcare delivery problem

The HHC routing and scheduling is a multi-faceted and widely discussed problem in the literature. With finding the most appropriate routes and schedules being one of the most essential goals in the literature, the home healthcare routing and scheduling problem (HHCRSP) is often described as an extension of the Vehicle routing problem (VRP). However, as early as 1974, Fernandez et al. (1974) introduced a nascent version of the healthcare delivery problem as a simple allocation problem. The work focused on the daily workings of the community nurses in the United Kingdom and took the task of finding the proper allocation of healthcare staff to the regions under an estimated travel time. In subsequent years, Begur et al. (1997) introduced the more well-known version of the HHC problem. Like VRP, the paper considers the minimization of total travel time as the goal while introducing several key aspects of the HHC problem, such as multiple depots, time windows, and workload balancing. Following this, the first mathematical model for the problem was developed by De Angelis (1998) with the objective of maximizing the number of admitted patients. Ikegami and Uno (2007) were the first to incorporate continuity of care and caregiver's time window to the home help staff scheduling problem and tried to improve efficiency by minimizing the number of hired help. Under the possibility that requests made exceed the available capacity of the service provider, Cinar et al. (2019) modelled the HHC problem as an Orienteering problem where a player tries to gain as many points as possible within the given time. The model simultaneously utilizes the concept of a rolling horizon to pick the unmet request of a current period into the next.

It can be clearly seen that the variety observed in early literature, in the selection of objectives and the setup, is still present in the current works. Several new aspects of home healthcare setup are consistently being introduced to the literature to account for the wide variety and complexity of different healthcare delivery setup and their unique requirements. Bertels & Fahle (2006) were the first to introduce multiple objective formulations to the HHC literature. In addition to the travel time, the developed mathematical model also considered the total working time and the soft time window violation as an additional objective. Similarly, Akjiratikarl et al. (2007) introduced the concept of partial fulfillment of demand while minimizing the number of unassigned activities along with the total traveling distance in the context of home care worker scheduling. New and exciting aspects of home healthcare delivery setup (like incorporating overtime and patient/caregiver preferences) are increasingly being added to the literature. Cissé et al. (2017) categorized the HHC problem based on the use of different objectives, multiple combinations of real-world constraints, choice of decision-making period, and the suitability of problem-solving methods.

An emerging trend of incorporating additional decisions with the HHC routing and scheduling problems can also be observed in the literature. With increasing computational capability, researchers have tried to include additional decisions other than assignment, routing, and scheduling (Cakırgil et al., 2020). Mısır et al. (2015) incorporate duty rostering, deciding which staff will cover which shift on what day. In the case of staff employed on a contractual basis, the decision of hiring/firing is considered by Nasir & Dang (2018) in conjunction with the basis HHC model. Similarly, Hiermann et al. (2015) integrated the transportation decision with the HHC model to find a suitable mode of transport among walking, car, and public transport. Additionally, transportation consideration was also used to incorporate time-dependent travel time for public transport by Rest & Hirsch (2016). Environment sustainability (Fathollahi-Fard et al., 2018) and disaster management (Trautsamwieser et al., 2011) are also at the forefront of the current research on the HHC delivery problem. However, the presented literature review only focuses on the core HHC delivery problem with its complexity relating to the objective function, constraints, and solution methodology. Hence, the remaining discussion on the complexities involved in HHC routing and scheduling has been presented from the perspective of model objectives, constraints, and solution approaches.

Table 2.1: Classification of research papers based on the selection of objectives.

Serial Number	Author(s) and Year of Publication	Objective functions													
		Total cost	Travel distance	Travel time	Waiting time	Staff overtime	Patient preferences	Number of nurses/shifts	Soft constraint violation	Workload balance	Number of tasks	Service quality	Prize collection	Outsourced patient	Completion time
1	Anoshkina & Meisel (2019)	✓				✓				✓		✓			
2	Frifita & Masmoudi (2015)			✓											
3	Hanafi, et al. (2019)										✓		✓		
4	Quintanilla, et al. (2019)	✓		✓											
5	Erdem & Koç (2019)			✓											
6	Cakırgil, et al. (2020)	✓												✓	✓
7	Nasir & Dang (2018)		✓		✓			✓		✓				✓	
8	Ros-McDonnell, et al. (2019)	✓													
9	Trautsamwieser, et al. (2011)			✓		✓	✓		✓						
10	Fikar & Hirsch (2016)	✓		✓	✓										
11	Rest & Hirsch (2016)			✓	✓	✓		✓				✓			
12	Xiao, et al. (2018)	✓									✓				

Table 2.1: Contd.

Serial Number	Author(s) and Year of Publication	Objective functions													
		Total cost	Travel distance	Travel time	Waiting time	Staff overtime	Patient preferences	Number of nurses/shifts	Soft constraint violation	Workload balance	Number of tasks	Service quality	Prize collection	Outsourced patient	Completion time
13	Issabakhsh, et al. (2018)	✓							✓						
14	Pereiraa, et al. (2020)														✓
15	Fathollahi-Fard, et al. (2018)	✓	✓												
16	Moussavi, et al. (2019)			✓											
17	Zhan & Wan (2018)	✓	✓		✓	✓									
18	Cinar, et al. (2019)			✓									✓		✓
19	Lin & Yu (2017)							✓					✓		
20	Duque, et al. (2015)		✓									✓			
21	Demirbilek, et al. (2019)							✓			✓				
22	Kandakoglu, et al. (2020)		✓			✓		✓		✓					
23	Gomes & Ramos (2019)			✓						✓					
24	**Current study**	✓	✓		✓	✓	✓		✓	✓	✓		✓		

2.1.1. Objective functions

As established by Fikar & Hirsch (2017), there is a clear preference in HHC literature for some objectives over others. Minimization of operational cost (Eveborn et al., 2006), travel time (Bredstrom & Ronnqvist, 2008), and travel distance (Akjiratikarl et al., 2007) were found to be dominating over the more obscure objective of maximizing utilization of available resources by either maximizing assigned task (Dohn et al., 2009) or minimizing the staff requirement (Allaoua et al., 2013). A similar conclusion can be reached by analyzing the recent works summarized in **Table 2.1**. While optimizing the operational cost is still a major focus for the researchers (Ros-McDonnell et al., 2019), the incorporation of additional objectives using multi-objective formulation (Trautsamwieser et al., 2011) to reflect various hidden costs like the resignation of a competent staff because of unbalanced workload (Kandakoglu et al., 2020) or cost of an unsatisfied patient by reduced service quality (Rest & Hirsch, 2016) is becoming more common in the literature. Similarly, in the case of multiple visits for a single patient in a single day, Pereiraa et al. (2020) introduce the minimization of make-span, the total time from the start of the first visit to completion of the last visit of the day, as a novel objective to the HHC literature.

As stated previously, maximizing resource utilization was not given significant consideration in the early HHC literature. However, with the emergence of a new problem class of orienteering problem (OP) where an agent tries to collect as many points as possible scattered across the given area under the restriction on the total allowed travel distance (Gunawan et al., 2016), “prize-collection” is being used as an umbrella term for maximization of the number of patients treated in a day. Cinar et al. (2019) present a mathematical model for scheduling and routing a single nurse with a prize attached to each viable patient (based on priority). In the case of multiple nurses, the objective function will be modelled as a Team Orienteering Problem (TOP), where multiple agents try to collect points on a common map. Due to the given time restriction, it might not be possible to visit all nodes in TOP. Hence, multiple patient selection/rejection strategies have already been developed to guide the model in a preferred direction in the context of TOP for HHC routing. While Cinar et al. (2019) use the priority to increase the odds of selection in the current period for patients rejected in the last period, Grenouilleau et al. (2019) used an 'essential patient' parameter to force the model to pick specific patients over others.

As the HHC delivery problem is a variation of the vehicle routing problem with time windows (VRPTW), optimizing the travel aspect of the HHC delivery model is also an understandable choice for the multi-objective formulation. Travel distance, travel time, and travel cost are frequently used in single-objective and multi-objective HHC problems (Chaieb et al., 2020; Liu et al., 2014). While some studies (Kandakoglu et al., 2020) have taken the travel cost as a separate objective, Braekers et al. (2016) include it within the operational cost. Similarly, the hiring cost in Yuan et al. (2015) and Shi et al. (2019) and the cost of the idle time for the hired staff in Mısır et al. (2015) are also optimized as a part of the daily operational cost. Further, the violation of implemented soft constraints has also been treated as a cost (Malagodi et al., 2021) by plenty of studies and added to the operational cost to be minimized. While Grenouilleau et al. (2019) implement the penalty for unscheduled visits as a part of the operating cost, Mosquera et al. (2019) allow the visits to be scheduled without fulfilling all the mentioned preferences and calculate the penalty in relation to unfulfilled preferences. Similarly, while Xiao et al. (2018)

also include the penalty for unscheduled visits as an additional cost, Gomes and Ramos (2019) calculate the penalty for rescheduling a visit in a dynamic setup as the additional cost. In contrast, Mathlouthi et al. (2018) present the operational profit as a unique objective in literature where operational cost is subtracted from the total gain to get the net profit. The study uses the penalty method to adhere to the overtime and compulsory break requirements for the caregiver. Alternatively, optimizing overtime has also been considered a component of a caregiver's workload (Rest & Hirsch, 2016). As reviewed by Cissé et al. (2017), most of the studies optimize the workload balance among staff by minimizing the maximum workload assigned to the caregivers (Cappanera et al., 2018; Mutingi & Mbohwa, 2014). However, Trautsamwieser and Hirsch (2011) and Nickel et al. (2012) only balance the overtime assigned to the staff under the assumption that regular workload is a part of the fixed shift. In a similar manner, while most of the studies penalize the violation of the time window in both directions, Mankowska et al. (2014) only penalize the visits scheduled after the given time as a measure of tardiness and also implement an additional objective function to cap the tardiness beyond a limit by minimizing the maximum tardiness. Alternatively, Anoshkina and Meisel (2019) and Cakırgil et al. (2020) improve the attractiveness of the visit schedule by explicitly minimizing the job completion time as a separate objective.

Further improvements to the day-to-day operational efficiency are also proposed by either reducing the total employed staff (Kandakoglu et al., 2020) or by minimizing the total working time for the hired employees (Nasir & Dang, 2018) when the wages are related to the total working hours (Moosavi et al., 2022). Additionally, Trautsamwieser and Hirsch, (2011), Rest and Hirsch, (2016), and Li et al. (2021) consider the qualification level of the employees and derive an objective function that improves the utilization of the hired resource by minimizing the qualification difference between job and caregiver. Li et al. (2021) also introduce the minimization of out-patient waiting time as a novel objective under an integrated outpatient and home healthcare setup. Finally, Fathollahi-Fard et al. (2018) introduce the environmental sustainability aspect to the HHC problem class. The study minimizes the total CO_2 emission during daily operations by incorporating an additional penalty cost into the total travel cost.

2.1.2. Constraints

In case of constraints, a clear preference for time window, work time regulation, and skill requirement can be observed as shown in **Table 2.2**. With a single time-window being the most widely incorporated constraint in HHC modelling, Cissé et al. (2017) point out that no paper has considered the case of multiple preferable time slots for a single patient. The paper also points out that in the early modelling of the HHC problem, the task-to-staff assignment was primarily done based on skill requirements and staff's capability only. Nevertheless, patient preferences regarding HHC staff (e.g., gender and language) have been considered for some time now (Eveborn et al., 2006). Some attention has also been given to the nurse's preference. A few criteria, such as pet ownership (nurse's allergies) and the smoking habits of patients, have been considered as preference criteria for nurses (Erdem & Koç, 2019). Further, in addition to considering 'maximum individual workload' and 'maximum allowed overtime' for individual staff, 'workload balance' among the staff and 'proper break assignment' has also been taken into account to further improve the quality of staff's work life (Xiao et al., 2018). Fikar & Hirsch (2016) have also tried to take job satisfaction for HHC staff into account by only allowing one downgrade (assigning a job below the nurse's skill level) for any assignment. This trend of giving similar importance to all parties involved in the decision-making is certainly a welcomed one.

To adequately schedule multiple visits for a particular patient, several temporal constraints are considered in the literature. While precedence (Issabakhsh et al., 2018) and disjunction (Yuan et al., 2015) are the most common considerations, Rasmussen et al. (2012) present five different temporal dependencies for the HHC routing and scheduling problem. In contrast, a single visit requiring multiple healthcare staff is commonly modeled using synchronization, where multiple staff are scheduled to arrive at the same location at the same time (Bredstrom & Ronnqvist, 2008). Apart from this, various team formation strategies have also been used to fulfill multi-staff requirements. Quintanilla et al. (2019) utilize historical understanding to form a fixed team prior to the start of the decision-making period. Similarly, Anoshkina & Meisel (2019) use mixed-integer programming and information regarding available staff to come up with teams that will most likely be able to tackle a wide variety of tasks.

Some of the requirements considered in the existing literature are essential and readily implemented in the daily delivery of home healthcare. However, the papers also include some necessary but uncommon features that undoubtedly improve the core functioning of HHC delivery. One notable improvement is vehicle assignment for picking up and dropping off caregivers based on their assigned duties. It is clear that further avenues for improving existing HHC delivery can be found in the adjacent field of logistics and transport. Therefore, the following section presents a brief review of logistics and transport problems, specifically focused on the movement of personnel.

Table 2.2: Classification of research papers based on the selection of constraints.

Serial Number	Author(s) and Year of Publication	Constraints																	
		Time window	Skill level	Skill requirement	Working time regulation	Breaks	Essential visits	Patient preferences	Caregiver's shift	Visit synchronization	Disjunction	Procedure precedence	Heterogeneous staff	Vehicle assignment	Multi depot	Nurse's preference	Team formation	Geographical area	Contact restrictions
1	Anoshkina & Meisel (2019)			✓													✓		
2	Frifita & Masmoudi (2015)	✓		✓						✓	✓	✓	✓						
3	Hanafi, et al. (2019)				✓							✓							
4	Quintanilla, et al. (2019)													✓					
5	Erdem & Koç (2019)	✓		✓				✓				✓		✓	✓	✓			
6	Cakırgil, et al. (2020)		✓	✓													✓		
7	Nasir & Dang (2018)	✓		✓	✓	✓			✓										
8	Ros-McDonnell, et al. (2019)			✓										✓					
9	Trautsamwieser, et al. (2011)	✓		✓	✓	✓			✓										
10	Fikar & Hirsch (2016)	✓		✓	✓	✓			✓					✓					
11	Rest & Hirsch (2016)	✓	✓		✓	✓		✓	✓										
12	Xiao, et al. (2018)	✓		✓	✓	✓			✓	✓									

Table 2.2: Contd.

Serial Number	Author(s) and Year of Publication	Constraints																	
		Time window	Skill level	Skill requirement	Working time regulation	Breaks	Essential visits	Patient preferences	Caregiver’ s shift	Visit synchronization	Disjunction	Procedure precedence	Heterogeneous staff	Vehicle assignment	Multi depot	Nurse’ s preference	Team formation	Geographical area	Contact restrictions
13	Issabakhsh, et al. (2018)				✓							✓			✓				
14	Pereiraa, et al. (2020)			✓								✓							
15	Fathollahi-Fard, et al. (2018)	✓			✓														
16	Moussavi, et al. (2019)				✓														
17	Zhan & Wan (2018)																		
18	Cinar, et al. (2019)	✓			✓														
19	Lin & Yu (2017)	✓			✓		✓												
20	Duque, et al. (2015)	✓	✓		✓			✓											
21	Demirbilek, et al. (2019)																	✓	
22	Kandakoglu, et al. (2020)	✓			✓	✓			✓									✓	
23	Gomes & Ramos (2019)	✓			✓	✓													
24	**Current Study**	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		✓		✓		✓

2.2. Literature on logistics and transportation

While existing literature considers the various aspects of the HHC delivery problem, further improvement or refinement can be suggested by studying the broader field of logistics and transportation operations. Patient convenience, arriving as a result of consistency in care schedule, is one such aspect. In cases where multiple visits are to be scheduled in a single day, a small- and fixed-time window cannot be used to ensure temporal consistency (Goeke et al., 2019). Similarly, person-oriented consistency, where the same driver regularly visits the same customers (Luo et al., 2015), can help reduce the service time and improve the service experience in the case of HHC. By relating the service time with the experience of caregivers (number of visits by a caregiver) to a specific patient-procedure combination, the HHC problem can be treated as the problem presented in Van Peteghem and Vanhoucke (2014), where multiple modes for job execution is considered. Similarly, multi-modal transportation options should also be widely incorporated to find a better travel arrangement for caregivers. Hiermann et al. (2019) consider multiple modes of transport, such as bikes, scooters, and vans, for solving a heterogeneous vehicle routing problem (VRP). In the HHC setup, where caregivers are expected to travel by public transportation system, the conclusion presented by Artigues et al. (2013) can be pretty valuable. They considered various public transportation modes (walking, car, bus, and subway) for the daily commuter and found that frequent switching between the modes leads to a shorter travel time.

Additionally, an HHC setup can be imagined where a dedicated in-house fleet is used to carry the caregivers from one location to the other. Such a setup will be similar to the two-echelon VRP problem presented in Grangier et al. (2016), where joint optimization of two route levels (fleet and caregivers) is required. A truck-drone goods delivery system, an example of a two-echelon VRP, as presented in Murray and Chu (2015), can be used for further inspiration. A sensible restriction on the maximum route distance for the second-tier vehicle (caregiver), where a caregiver is supposed to walk between multiple patients in the same locality, is similar to the drone's travel capability on a fixed battery (Coelho et al., 2017). Similarly, as presented by Murray and Chu (2015), a collaborative truck-drone system can be used to model the drop-off and pickup of the caregiver by different vehicles from the dedicated in-house fleet. Further, horizontal collaborative planning, where multiple service providers pool their resources and jointly perform the logistics operations to improve efficiency (Padilla Tinoco et al., 2017), can also be tested for both the caregiver and the fleet level in an HHC setup. With the current climate situation where the environmental effects of the logistics operations cannot be ignored, the viability of electric vehicles with limited battery capacity (driving range) should also be studied (Eskandarpour et al., 2019). With a gas-powered vehicle, Demir et al. (2014) conclude that a significant reduction in CO_2 emission can be observed by allowing a slight increase in travel time. In the HHC setup, where synchronization among caregivers leads to some unavoidable waiting, the goal of CO_2 minimization can easily be achieved by reducing vehicle speeds. In relation to disaster management, additional decisions for selecting the location of the hubs (Rezaei-Malek et al., 2016) and the most reliable routes (Wang et al., 2014) should also be studied for disaster-prone areas. It should also be noted that the regular medical requirements of the population cannot be ignored entirely during a disaster. Bulhões et al. (2018) present a service level constraint for the VRP, where the minimum level of deliveries is ensured for two distinct sets of customers. Similar implementations can also be employed for HHC deliveries during a disaster. In a specific case of a disease outbreak, methods used by Dolicanin et al. (2018) to route the unmanned combat aerial vehicles in order to avoid the threat areas can be incorporated to plan a safer route for the caregivers. Lastly, the simplicity of implementing a solution can also be explicitly considered in the mathematical model itself. While technically optimal, a counter-intuitive and complex solution may face reluctance from the dispatcher and the driver during implementation. A route with fewer turns and clustered service nodes intuitively represents an efficient logistics operation (Rossit et al., 2019).

2.3. Solution methodologies

In the context of solution methodologies, while off-the-shelf commercial solvers have been quite helpful in solving small-scale HHC models (Bräysy et al., 2009), decomposition methods (Anoshkina & Meisel, 2019) and metaheuristic (Mathlouthi et al., 2021) have been adopted more frequently than any other algorithm for solving large scale problems. The use of branch-and-price and Dantzig-Wolfe decomposition (Dohn et al., 2009) to separate master-problem and subproblem has proven a fruitful strategy. In addition to these decomposition techniques, set partitioning has also been used as a viable method for solving large-scale problems (Grenouilleau et al., 2019). During the first stage, patients are assigned to different staff according to their requirements and compatibility to form several sets, and then a modified model is used to find scheduling and routing decisions for these sets. Further location-based districting models (Cissé et al., 2017) have also been used to divide the large problem into smaller manageable problems. Clusters (districts) of healthcare staff and patients are created based on their proximity, and a unified model (assignment-routing-scheduling) can be applied to these autonomous districts without considering other clusters.

Metaheuristics are also being successfully used in solving large-scale HHC problems. Akjiratikarl et al. (2007) use particle swarm optimization. In addition to solving the HHC model, heuristics and metaheuristics are also used in improving the quality of solutions obtained by decomposition methods (Bertels & Fahle, 2006). Some hyper-heuristics have also been developed to choose the best method based on the problem dynamically (Mısır et al., 2015). However, due to the lack of standardized benchmark HHC instances in literature, no metaheuristic can be clearly shown to be dominating others.

As discussed earlier, plenty of works have considered multiple objectives while formulating the HHC delivery problem. However, many do not use any dedicated method to obtain the Pareto optimal set (or a set of non-dominated solutions). By using the weighted sum approach, a multi-objective mathematical model is ultimately converted to a more convenient single-objective model. Fikar and Hirsch (2017) point out that the weighted sum approach is frequently used without accurate knowledge of the relative weightage for the objectives or even when the objectives do not have the same units. Similarly, Cissé et al. (2017) criticize the weighted sum method for not being capable of finding the entire Pareto front. In contrast, one of the major advantages of the weighted sum method is that it is easy to implement and works well if the relative utility for the considered objectives can be known. The analytical hierarchy process can be used to find the relative utility of the objectives for the decision-maker. With only the rank of importance for the objective known, Duque et al. (2015) utilize the lexicographic approach. In case the relative utility cannot be calculated, algorithms to find the Pareto optimal front should be used. Braekers et al. (2016) propose a bi-objective HHC problem and use a ε-constraint method to enumerate the Pareto front.

Similarly, Cakırgil et al. (2020) also utilize ε-constraint method to solve the small-scale bi-objective HHC problems but advocate for approximate heuristics like multi-objective variable neighborhood search for the larger problem instances. Finally, Fathollahi-Fard et al. (2018) explore the bi-objective HHC problem with population-based metaheuristics and propose modifications to the simulated annealing and salp swarm algorithm to tackle the problem. The study uses four performance metrics to evaluate the quality of the Pareto front and on the basis of that, establishes the superiority of metaheuristics over the heuristics. It is clear that very few studies have utilized the true capability of population-based metaheuristics for multi-objective setup and primarily relied on the weighted sum method to reduce the proposed models to a single or bi-objective model. A richer implementation of multi-objective metaheuristics can be observed in the adjacent field of healthcare inventory transportation. As an example of a multi-objective problem where more than two competitive objectives are considered, Niakan and Rahimi (2018) propose a healthcare inventory routing problem with a total of six objectives. Considered objectives are eventually sorted into three groups, and Torabi and Hassini's algorithm is used to find the Pareto approximates set (Torabi & Hassini, 2008). Similarly, Asghari and Al-e-hashem (2020) use the same algorithm alongside a self-learning, non-dominated sorting genetic algorithm to solve a green delivery-pickup problem for home hemodialysis machines. Like Fathollahi-Fard et al. (2018), the paper also uses performance metrics to evaluate the quality of the obtained Pareto front. Finally, Nikzamir and Baradaran (2020) implement and compare three different metaheuristics for a healthcare waste disposal problem where ten objectives are grouped into two groups. The performance of the Multi-Objective Water Flow-like Algorithm (MOWFA), Multi-

Objective Imperialist Competitive Algorithm (MOICA), and Multi-Objective Simulated Annealing (MOSA) are tested based on the quality of the obtained Pareto set. In addition to the performance metrics used in Fathollahi-Fard et al. (2018), the study introduces the computational time and error ratio as new quality indicators for the Pareto set. Both studies also employ the Taguchi method to calibrate the parameters of the proposed algorithms. The technique utilizes a carefully constructed orthogonal matrix of the appropriate size to reduce the required number of trials from a full factorial analysis. Finally, to improve the performance of a metaheuristic for a large-scale many-objective optimization problem, Wang and Tan (2019) advocate for an information feedback model while generating a new solution for the next iteration. They conducted an extensive analysis by implementing six variations of the information feedback model for ten different algorithms with varying levels of success. In the specific case of NSGA-III, two versions of the information feedback model were shown to be very competitive in solving the large-scale many-objective test problem (Gu & Wang, 2020). Similarly, Yi et al. (2020) studied the effect of different crossover operators on the performance of NSGA-III for large-scale optimization problems and concluded the superiority of uniform crossover operator for the six large-scale problems.

2.4. Gaps identified in the literature

From the discussion above, it can be seen that the existing studies have considered several practical aspects for modelling HHC routing and scheduling problems and proposed several exact and heuristic approaches to solve the problem. However, we have identified gaps in the existing literature that need to be addressed in order to develop a model that can adequately meet the general requirements of the Indian home healthcare industry.

i. Constraints limiting the unnecessary contact between any two pairs of individuals have not been presented in the literature. Some works do minimize the number of different caregivers needed to meet all the requirements of a patient. However, the interaction between two caregivers, in the case of team-ups, has been left entirely unexplored.

ii. The effects and complexities of multiple or inconvenient time windows have not been studied in the literature. Existing literature mainly focuses on a single preferable time window as the patient's primary requirement regarding the visit schedule. This is either unnecessary or a hindrance in the case of scheduling multiple visits to a patient, where visits need a minimum time gap, a frequent requirement.

iii. Existing research does offer the capability of scheduling multiple procedure requests for a patient. However, the Literature lacks the mathematical formulation that can handle more complicated requirements, such as procedures with multiple visit requirements, where each visit might also need multiple staff in order to be carried out effectively.

iv. Similarly, some works for the existing literature do try to optimize for the patient convenience by minimizing the makespan. However, this implementation does not account for the minimum time gap needed to be scheduled between two interdependent visits and can lead to unnecessarily scattered visits within the time gap.

v. Finally, existing literature commonly presents modifications to the existing heuristic and metaheuristic algorithms to improve their efficiency and compares them with commercially available mathematical model solvers. While commercial solvers are continuously being adapted for the evolving hardware, such as GPU and multi-core computing, no such attention has been given to the existing heuristics and metaheuristics.

2.5. Conclusions

In this chapter, literature relating to the single-period home healthcare delivery problem is considered, and a critical review of the same, based on the considered objective, constraints, and solution approaches, is presented. The exercise has resulted in the identification of several gaps in the existing literature. When considering the broader field of transportation and logistics, the literature on the home healthcare delivery problem falls short in several aspects. The existing literature in the field of single-period HHC delivery problems mainly considers the single preferable time slot as the ubiquitous scheduling preference for the patients. Multiple time slots and inconvenient time windows have not yet been implemented in the literature. Application of the same has led this research in the direction of defining and quantifying the patient inconvenience that arises due to improper scheduling. Literature is also lacking in the works that limit unnecessary person-to-person interaction, which can be helpful during a viral outbreak. Another major criticism of existing literature on HHC delivery is that the presented models are highly specific and cannot be easily adapted for a slightly different home healthcare delivery setup without an expert's intervention. Finally, commercially available solvers, heuristics, and metaheuristics are commonly used to solve the proposed mathematical models. While the former is continuously optimized for the evolving computing hardware and architecture, no such rigor has been awarded to the heuristics and metaheuristics. Hence, we study the home healthcare delivery problem in the subsequent chapters to fill these literature gaps. A generalized monolithic multi-objective home healthcare delivery model is presented with efficient ‘hardware-first’ solution approaches capable of providing assignment, routing, and scheduling decisions for practical problem instances.