Chapter 11 Operations Research Applications in Home Healthcare

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Abstract The home health care industry is an important component of health care systems that have the potential to lower the system-wide costs of delivering care, and free capacity in overcrowded acute care settings such as hospitals. Demand is doubling, but resources are scarce. A nursing shortage and near-zero profit margins hinder the ability of home care agencies to meet the increasing patient demand. The effective utilization of resources is vital to the continued availability of home care services. There is tremendous opportunity for the operations research community to address the challenges faced by home care agencies to improve their ability to meet as much patient demand as possible. This chapter describes tactical and operational planning problems arising in home health care, and discusses alternative configurations of home health supply chains. Formulations for home health nurse districting, home health nurse routing and scheduling, and home health supply chain problems are presented, and the relevant literature is reviewed. Recent developments in remote monitoring technologies that could change the home health care landscape are discussed, and future research directions are proposed.

11.1 Introduction

The home health care industry is an important component of health care systems that has the potential to lower the system-wide costs of delivering care, and free capacity in overcrowded acute care settings such as hospitals. In home care,

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R. Hall (ed.), Handbook of Healthcare System Scheduling,

specialized services such as IV medications and wound care are provided to patients in their homes by licensed clinical personnel. The number of visits and specific care that each patient receives is determined by the ordering physician. Short-term services may be provided following a hospitalization, or long-term assistance with disease management may be provided for chronic conditions. The groups of patients most often receiving home care are the elderly, disabled, and chronically ill (CMS [2008\)](#page-20-0).

The National Association for Home Care and Hospice estimates that there were approximately 17,700 providers of home care nationwide in 2005 with projected total annual expenditures of \$53.4 billion (NAHC [2007\)](#page-21-0). In 2007, over 200,000 nurses were employed in home care, and 7.6 million patients received home care services (NAHC [2007](#page-21-0)). The demand for home care is expected to double by 2030 as the trend towards shifting the delivery of care to less acute settings continues (Super [2002\)](#page-21-0). Factors driving this shift include an aging population, chronic disease epidemic, rising health care costs, and technological advances that enable home-based disease management (Steven et al. [2010\)](#page-21-0):

- By 2040, the number of people aged 65 and older will quadruple (US [2004](#page-21-0)),
- 50% of all American adults have at least one chronic disease (CDC [2009](#page-20-0)),
- Care is cheaper in the home at \$132/day versus \$1889/day in the hospital (NAHC [2007](#page-21-0); AHRQ [2007\)](#page-19-0),
- The market for home-based health technologies is expected to double from \$3 billion in 2009 to \$7.7 billion in 2012 (King [2010\)](#page-20-0).

The resources required to accommodate this shift of delivery of care to the home setting include home health nurses, automobiles, medical supplies and equipment, agency office space, and administrative personnel. Yet, a 20% gap between the supply and demand of skilled nursing services is expected by 2030 (Buerhaus et al. [2000](#page-20-0)). Additionally, high operating costs and low reimbursement lead to near-zero profit margins for many home care agencies, and are often negative for those operating in rural areas (NAHC [2006](#page-21-0)). With such scarce resources, their effective utilization is vital to the continued availability of home care services.

There is tremendous opportunity for the operations research community to address the challenges faced by home care agencies. The resource allocation and materials management problems encountered in home health care resemble those arising in health care facilities such as hospitals, but are complicated by geographically distributed patients and resources. Additionally, routing nurses to visit patients in their homes requires solving problems similar to those encountered in the freight transportation industry, but is complicated by critical patient service considerations. While the scientific community has actively addressed such problems in hospitals and freight transportation, the studies in the literature specific to home health care are relatively few. Existing research has focused on two primary problems: the tactical problem of assigning home health nurses to geographic service districts, and the operational problem of routing and scheduling home health nurses. Recently, the home health supply chain has also begun to receive attention.

The objectives of this chapter are to describe operations research applications in the home health industry, offer formulations for specific problems encountered, survey the relevant literature, and inspire the scientific community to actively address future topics in dire need of attention. The remainder of this chapter is organized as follows. In Sect. 11.2, select planning problems encountered in home health care are described, and formulations for those problems are presented. For each problem presented, [Sect. 11.3](#page-10-0) reviews the relevant literature. In [Sect. 11.4](#page-14-0), recent developments that could change the home health care landscape are discussed. Finally, in [Sect. 11.6](#page-17-0), future research directions are proposed.

11.2 Problems and Formulations

In this section, three classes of problems arising in home health care applications are described, and their formulations are presented. First, the operational problem of routing and scheduling home health nurses is discussed in Sect. 11.2.1. Then in [Sect. 11.2.2](#page-4-0), the tactical planning problem of developing home health nurse service districts is described. Finally, in [Sect. 11.2.3](#page-7-0), an overview of home health supply chain problems is given.

11.2.1 Home Health Nurse Routing and Scheduling

Home health care workers in the United States drive 5 billion miles each year to visit patients—double the number of miles traveled by United Parcel Service (UPS) drivers annually (NAHC [2009](#page-21-0); UPS [2009](#page-21-0)). The logistics challenges associated with deploying nurses to deliver health care to patient homes are complicated by medical constraints and patient service considerations. The research community has actively addressed routing problems arising in the freight transportation industry, and nurse scheduling problems arising in health care facilities such as hospitals and clinics. However, the studies addressing routing and scheduling applications in the home health care industry are strikingly few (Akjiratikarl et al. [2007;](#page-19-0) Begur et al. [1997](#page-19-0); Bertels and Fahle [2006](#page-19-0); Eveborn et al. [2006;](#page-20-0) Rich [1999](#page-21-0); Steeg [2008;](#page-21-0) Bennett and Erera [2011](#page-19-0)).

Home health nurse routing and scheduling (HHNRS) problems are defined for a set of patients that need to be visited in their homes according to a prescribed weekly frequency for a prescribed number of consecutive weeks during a planning horizon. The weekly visits for each patient must be performed by clinical personnel that meet patient-specific requirements (e.g., appropriate skill level, language, patient preference). Additionally, the weekly visits must occur according to patient-specific day and time requirements, with visit days selected from a set of allowable visit day combinations, and visit times selected from a set of allowable appointment times or appointment windows. An allowable visit day combination for a two visit per week patient could be ${Monday, Wednesday}$ or ${Tuesday}$, Thursday, and allowable appointment times could be $8:00, 8:30, 9:00$, etc., if the patient requires a morning visit. Day and time requirements may be specified by the doctor providing the prescription for home care, if the service to be delivered is time-critical. An example is IV medication that must be administered at 24-h intervals throughout a 10-day period. Day and time requirements may instead be specified by the patient, if they are only available to receive in-home nurse visits on certain days and times.

A set of nurses perform patient visits, where each nurse is available for a fixed workday length on select days throughout the planning horizon. Nurses may be differentiated according to characteristics such as skill level (e.g., Registered Nurse, Nurse Practitioner) and language spoken. A solution to a home health nurse routing and scheduling problem assigns a nurse, visit day, and appointment time to each patient visit throughout the planning horizon. Each nurse begins each day at their own home, visits their assigned patients at the times specified, and returns to their own home. The solution is feasible if the route of each nurse conforms to workday length constraints and patient requirements are met. A primary objective is minimizing total nurse travel time, because of the related (and most important) objective of maximizing the number of visits performed per nurse.

When the assignments of patient visits to nurses and days are treated as exogenous decisions, the resulting problems can be modeled as multiple traveling salesman problems with soft or hard time window side constraints (m-TSPTW). Including nurse assignment decisions require modeling the problem as a multidepot vehicle routing problem with time windows (MD-VRPTW) with additional side constraints that match patient requirements and/or preferences with nurse characteristics. Further expanding the scope of decisions to include the assignment of patient visits to days results in a periodic routing problem variant (PMD-VRPTW).

In addition to minimizing total nurse travel time, other important objectives in home health nurse routing and scheduling problems include maximizing nurse and visit time consistency. Nurse consistency, referred to in the health literature as continuity of care, has positive implications for care outcomes. Studies have shown a correlation between continuity of care, increased patient satisfaction, and decreased hospitalizations and emergency room visits (Cabana and Jee [2004\)](#page-20-0). Consistency in visit time has also been indicated as a predictor of patient satisfaction in conversations with various home health agency personnel. When nurse and visit time consistency objectives are considered, the resulting PMD-VRPTW models must also include linking variables and constraints that require each patient to be visited by the same nurse (or set of nurses) on the same days at the same times each week. In the routing literature, such problems that enforce driver and/or time consistency have recently been referred to as consistent vehicle routing problems (Groer et al. [2009](#page-20-0)). Because periodic and multi-depot components are

Problem characteristics	m -TSPTW	MD-VRPTW+	PMD-VRPTW+	CPMD-VRPTW+
Visit time assignments	\mathbf{x}	X	х	X
Time consistency				X
Visit day assignments			х	x
Visit day consistency				х
Nurse assignments		x	х	х
Nurse consistency				х

Table 11.1 Models for HHNRS problems and the decisions each considers

also considered when CVRP models are used for HHNRS problems, such models are referred here as CPMD-VRPTW.

Models for HHNRS problems and the decisions each considers are summarized in Table 11.1 . In the table, "+" is used to denote models that include additional side constraints to match patient requirements and preferences with nurse characteristics. An ''x'' is used to denote decisions each model treats endogenously. It should also be noted that discussion of HHNRS problems thus far has focused on static problem variants, where patient requests are assumed to be known with certainty. In realistic applications, the set of patients to be visited varies throughout the planning horizon as patients are discharged and new patients are admitted. Visit requests corresponding to future patient admissions are not known. Thus, dynamic variants of each model in Table 11.1 result.

11.2.2 Home Health Nurse Districting

A tactical planning problem in home health care that partially determines the quality of solutions that can be obtained for home health nurse routing and scheduling problems is the home health nurse districting problem (HHND). In the HHND problem, the geographic service area of a home health care agency is divided into districts to be served by teams of nurses. The geographic location of a patient determines the nurse to which they are assigned. The capacity of each nurse team is limited, and their productivity is influenced by the size of the region in which their assigned patient requests are distributed. A large region equates to longer travel times, requiring more total time to visit the same number of patients than in a small region. Nurse consistency measures can also be influenced by district size and staffing. If demand is not properly balanced across districts, nurses may be asked to temporarily cover demand in districts to which they are not assigned.

Home health nurse districting problems are defined for a connected service region that includes a set of $\mathcal{N} = \{1, ..., n\}$ subunits, e.g., zip codes, where each subunit *i* has an area v_i and demand p_i , measured by the number of patient visits required to subunit i per day. A set of k nurses are available each day to serve

patient demand within the service region, and each nurse has a target workload b. Workload can be measured in a variety of ways, for example, by the number of hours each nurse is available to work, or by the number of patient visits each nurse performs. Nurses work in teams of size $f_i \in \mathbb{Z}^+$, where the number of nurses may vary by team; thus, the target workload of team j is bf_i . The problem is to develop a set of contiguous districts, one for each team of nurses, such that each subunit is assigned to exactly one district, and the workload of each district is near the target $\beta_i = bf_i$. Possible objectives include minimizing nurse travel and workload imbalance across districts.

Two formulations appropriate for HHND problems, depending on the specific application, are location-allocation and set partitioning. Location-allocation models require that a fixed set of district centers, or finite number of potential district centers, is known. Decisions include selecting which district centers to open (if necessary), and assigning each subunit to exactly one district center, subject to additional constraints. This formulation may be useful in applications where the district center serves as a depot, at which all nurse routes within the district begin and end. Set partitioning models do not require a fixed set of district centers. Instead, the set of potential districts includes every possible combination of subunits that meet district feasibility conditions. Then, a subset of districts are selected such that each subunit is included in exactly one district. The two primary formulations are discussed in detail below.

Location-Allocation Formulation of HHND

The location-allocation formulation developed in Hess et al. [\(1965](#page-20-0)) for the political districting problem is adapted here for the HHND problem. Suppose there are *m* district centers and *n* subunits. Let C_{ii} represent the cost of assigning subunit i to district center j. Let p_i be the daily demand of subunit i, and let β_i be the target workload of district *j*. Let x_{ij} be a binary decision variable indicating whether subunit i is included in district j . Then, the location-allocation formulation of HHND is as follows:

Minimize
$$
\sum_{i=1}^{n} \sum_{j=1}^{m} C_{ij} x_{ij}
$$
, (11.1)

Subject to
$$
\sum_{i=1}^{n} p_i x_{ij} = \beta_j
$$
 for $j = 1, ..., m$, (11.2)

$$
\sum_{j=1}^{m} x_{ij} = 1 \quad \text{for } i = 1, ..., n,
$$
 (11.3)

$$
x_{ij} \in \{0, 1\} \quad \text{for } i = 1, \dots, n, j = 1, \dots, m. \tag{11.4}
$$

Objective function (11.1) minimizes the total cost of assigning subunits to districts, constraints (11.2) (11.2) (11.2) require that the total demand assigned to each district is equal to the target workload, and constraints [\(11.3\)](#page-5-0) together with binary decision variables require that each subunit is assigned to exactly one district. Because it is unlikely that the cumulative demand of subunits assigned to each district j will equate to β_i , constraints ([11.2\)](#page-5-0) may be replaced with upper bound inequality constraints, i.e., $\leq (1 + \alpha)\beta_j$, if some maximum allowable workload should not be exceeded. Alternatively, if balancing workload across districts is desired, a set of lower and upper bound inequality constraints may be used, with limits $(1 \pm \alpha)\beta_i$.

The objective function in the location-allocation formulation of HHND may be linear or nonlinear, depending on methods used to evaluate the cost of assigning a subunit to a district. Suppose t_{ij} represents the travel time from the centroid of subunit *i* to district *j*, approximating C_{ij} as t_{ij} results in a linear objective function equal to the sum of the travel times between all subunits and their assigned district centers. While compact and contiguous districts would be preferred in optimal solutions, the sum of out and back travel times does not mimic the true application. In practice, if subunit i is assigned to district center j , a nurse leaves his/her home, visits a sequence of patients in i and other subunits assigned to j , and returns home. Thus, approximating C_{ij} as expected daily routing costs is a more realistic modeling approach, but requires a nonlinear objective function.

The capacity constraints in the location-allocation formulation of HHND may also be linear or nonlinear, depending on methods used to measure workload. If workloads are considered balanced when each nurse performs an equal number of daily visits, then approximating β_i as described in Eq. 11.5 results in linear capacity constraints:

$$
\beta_j = f_j \left(\frac{\sum_{i=1}^n p_i}{\sum_{j=1}^m f_j} \right). \tag{11.5}
$$

If the expected length of a patient visit varies between subunits, and workload is measured by the total amount of time spent performing patient visits, capacity constraints are again linear. Let γ_i be the average length, in hours, of visits to patients in subunit *i*. Then, constraints (11.2) can be replaced with:

$$
\sum_{i=1}^{n} \gamma_i p_i x_{ij} = f_j \left(\frac{\sum_{i=1}^{n} \gamma_i p_i}{\sum_{j=1}^{m} f_j} \right).
$$
 (11.6)

Just as the objective function in the location-allocation formulation of HHND becomes nonlinear when expected daily routing costs are considered, nonlinear capacity constraints result when expected daily routing costs are included in workload estimation. Despite computational difficulty, this modeling approach may be desired for home health agencies whose geographic service areas include both rural and metropolitan areas. The total time required to perform patient visits

and travel between them is longer in large, sparsely populated districts, than in small, densely populated districts.

An alternate formulation that allows for evaluating complex district cost and feasibility outside the core optimization problem is presented next.

Set Partitioning Formulation of HHND

The set partitioning formulation of HHND allows for evaluating complex nonlinear district cost and feasibility conditions outside of the core optimization problem. Let J denote the set of all feasible districts, i.e., those that are contiguous and meet workload balance constraints. Let ρ_{ii} be equal to 1 if district j includes subunit *i* and 0 otherwise. Let C_i be the cost of district *j*, and let y_i be a binary decision variable denoting whether district j is selected in a solution to the set partitioning problem. Let m be the number of districts to be selected. Then, the set partitioning formulation for HHND is as follows:

Minimize
$$
\sum_{j \in J} C_j y_j
$$
, (11.7)

Subject to
$$
\sum_{j \in J} \rho_{ij} y_j = 1
$$
 for $i = 1, ..., n$, (11.8)

$$
\sum_{j\in J} y_j = m,\tag{11.9}
$$

$$
y_j \in \{0, 1\} \quad \text{for } j \in J. \tag{11.10}
$$

Objective function (11.7) minimizes the total cost of the selected districts. Constraints (11.8) together with binary decision variables require that each subunit is included in exactly one selected district. Constraint (11.9) ensures that the desired number of districts are selected. Methods for evaluating district cost and feasibility discussed in ''Set Partitioning Formulation of HHND'' can be used to externally create feasible districts and determine C_i .

11.2.3 Home Health Supply Chain

A 2008 survey of 1381 health care supply chain professionals conducted by the Association for Health care Resource and Materials Management (AHRMM) and the Center for Innovation in Health care Logistics at the University of Arkansas (CIHL) revealed that the average health care provider responding to the survey spends 31% of their total annual operating budget on supply chain functions (Nachtmann and Pohl [2009\)](#page-20-0). In a 2009 survey of 1600 nurses and nurse executives conducted by Owens and Minor, half of the respondents reported spending too

much time on supply duties (Ferenc [2010\)](#page-20-0). It is not clear that home health care professionals and nurses are represented in responses to the above mentioned surveys. However, information being collected from home health care agencies regarding their supply chain practices in an ongoing CIHL project suggests that home health nurses are often assigned responsibility for portions of home health care supply chain processes as well (Bennett and Mason [2011\)](#page-19-0).

The home health supply chain is distinct from hospital supply chains because care is delivered, and thus supplies are required, in geographically distributed patient homes. Patients receiving home health care are visited by a nurse one to three times per week throughout the duration of their episode of care - often a 60 day period. During each patient visit, a nurse assesses the supplies needed during the next visit to the patient, and those needed by the patient for self-use, considering the inventory of supplies the patient has available. If it is determined that a particular supply needs to be replenished, or a new supply needs to be ordered, the nurse initiates the order management process specified by the home health agency where he/she is employed. Once the order is received by the supplier, the supply distribution process agreed upon by the supplier and home health agency is executed.

Bennett and Mason [\(2011](#page-19-0)) have identified two frequently employed order management processes and two frequently employed channels of distribution in the health supply chain. The associated information and product flows in the home health supply chain are depicted in Fig. 11.1 using dashed and solid lines, respectively. Information received from the patient helps determine orders placed by the nurse. Depending on the policy of the home health agency, the nurse may place orders directly with the supplier, or with a supply manager at the home health agency that consolidates and relays orders to the supplier. Depending on the agreement between the home health agency and the supplier, supplies are either direct shipped to the patient, or shipped first to the home health agency for storage and subsequent nurse pickup and delivery to the patient.

When the home health agency serves as the intermediary in the supply distribution channel, nurse involvement may be required in certain supply chain functions. Examples of daily nurse routes when an agency employs a distribution channel in which they are an intermediary when they are not are depicted in Fig. [11.2](#page-9-0) . In this simple example, the agency (A) employs two nurses, N1 and N2, and there are four patients, P1 through P4. Nurse 1 must visit P4 before visiting P3, and Nurse 2 must visit P1 before visiting P2. When supplies are stored in an inventory room at the home health agency main office, nurses begin their daily routes by traveling first to the agency before visiting patients. When supplies are shipped

Fig. 11.2 Example of nurse routes based on supply storage and delivery policies. a Supplies stored at agency, b supplies not stored at agency

directly from the supplier to the patient, the nurse is not required to visit the agency at the beginning of each day. Letting t_{ij} represent the time required to travel from location i to location j , the difference in travel time required by the process depicted in (a) and that in (b) is:

$$
t_{N1,A} + t_{A,P4} + t_{N2,A} + t_{A,P1} - t_{N1,P4} - t_{N2,P1}.
$$
 (11.11)

Assuming a complete symmetric network with travel times satisfying the triangle-inequality (a common assumption in logistics planning problems), the quantity in Eq. 11.11 is non negative. Thus, nurses spend more time traveling when supplies are stored at the agency than when they are not. The nurses may also be required to spend time picking up supplies needed for each of their patient visits, if supplies are kept in an inventory storeroom by type and no other nonclinical personnel are assigned the responsibility of picking up patient-specific supply orders.

Due to these ''hidden'' costs that exist in home health supply chains, models to estimate the costs associated with alternative home health care supply chain configurations are needed. Letting TC denote the total annual supply chain cost for a home health agency, a general model is defined in Eq. 11.12 that includes the following components:

- C_n : annual cost of nurse involvement in non-clinical supply chain duties,
- C_d : annual direct cost of supplies,
- C_h : annual holding cost of supplies,
- C_t : annual cost of delivering supplies to patients,
- C_a : annual administrative cost of supporting supply chain functions,
- C_p : annual penalty cost associated with stockouts,

$$
TC = C_{n} + C_{d} + C_{h} + C_{t} + C_{a} + C_{p}.
$$
 (11.12)

In this model, C_n represents charges incurred when nurses spend time on supply chain responsibilities that they would otherwise have available for providing patient care. The per unit of time cost coefficient could thus include an hourly pay rate and/or a penalty cost associated with decreased nurse availability. Holding cost includes the cost of space for storing supplies and the opportunity cost of capital invested in inventory. Transport cost, C_t , may be modeled as a per order delivery cost, or as per mile reimbursement cost. Administrative costs can include, for example, the cost of technology and information systems used in the execution of supply chain functions, and the salaries paid to non-clinical personnel with supply chain responsibilities. Finally, penalty costs associated with not having supplies available for the patient when needed may include the cost of decreased patient satisfaction or negative care outcomes.

11.3 Prior Research

In this section, prior research corresponding to each of the problems presented in [Sect. 11.2](#page-2-0) is reviewed.

11.3.1 Home Health Nurse Routing and Scheduling

In much of the prior home health nurse routing and scheduling research, visit day combination decisions for patients are not considered. Exogenous visit day combination assignments imply, for each day, a fixed set of patients that need to be seen by one or more nurses, each of whom has a fixed limit on the number of hours they can work. Thus, the problems frequently addressed in the literature most closely resemble m-VRPTWs with side constraints. The problems are not periodic because visit day assignment decisions need not be made, and they are not dynamic because all patients are known in advance. Researchers instead focus on various side constraints, such as skill level requirements and patient preferences for a particular nurse. Also, in the surveyed research, nurses are assumed to be stationed at a central depot, instead of their own home locations. The approaches used and the types of decisions considered in papers that model HHNRS problems as m-VRPTWs with side constraints are summarized in Table [11.2.](#page-11-0) These papers are reviewed in more detail in Bennett and Erera ([2011\)](#page-19-0).

More recently, the scientific community has addressed the complicating dynamic and periodic aspects of HHNRS problems. For example, Steeg [\(2008](#page-21-0)) considers the nurse assignment, visit day combination assignment, and visit time assignment decisions. A constraint programing and large neighborhood search method is used to determine these decisions for a set of known patient requests. A tabu search algorithm is used to dynamically update routes to include newly arriving patient requests. However, consistency of provider and visit time throughout the duration of a patient's episode of care are not considered.

Bennett and Erera ([2011\)](#page-19-0) model the HHNRS problem as a dynamic periodic routing problem variant with fixed appointment times, where each patient visit must be assigned a precise appointment time from a fixed menu of allowable times, e.g., {8:00, 8:15, 8:30,…}. Visit day combination and appointment time

Ref.	Objective	Decisions considered	Solution approach
Begur et al. (1997)	Minimize distance traveled	Assign nurses and visit times to patient visits; managerial considerations addressed manually	Clarke-wright savings heuristic with nearest neighbor TSP reoptimization and manual route improvement via GIS tool
Akjiratikarl et al. (2007)	Minimize distance traveled	Assign nurses and adjust exogenously specified appointment times within allowable windows	Particle swarm optimization with local route improvement
Eveborn et al. (2006)	Maximize number of patient visits and minimize distance traveled	Assign nurses based on patient preferences and skill level requirements and assign appointment times within allowable windows	Set partitioning with matching algorithm and interactive tool
Bertels and Fahle (2006)	Minimize sum of distance traveled plus penalty cost	Assign nurses based on skill levels, shift length constraints, and patient and provider preferences, and assign appointment times within allowable windows	Hybrid tabu search, simulated annealing, and constraint programming heuristic

Table 11.2 HHNRS problems modeled as m-VRPTWs in the literature

decisions are made for each patient during the planning interval in which they arrive. To achieve visit day and time consistency, these decisions are not allowed to be changed to accommodate new requests for visits in future planning intervals. A single-nurse variant is the focus of the paper; thus, nurse assignment decisions are not treated endogenously, but perfect nurse consistency is implied. The authors develop a myopic rolling horizon planning approach that explicitly considers the capacity of the nurse's schedule (remaining time available) when making scheduling decisions for known requests, with the objective of preserving capacity for inserting future visit requests. The approach is compared to a rolling horizon planning procedure that considers only the traditional distance-based insertion criteria when scheduling known requests. Computational experiments demonstrate that the capacity-based approach is able to accommodate 4% more patient visits per day, while requiring 8.7% additional minutes of travel per visit, on average.

11.3.2 Home Health Nurse Districting

Districting problems have appeared in the literature in a variety of applications, for example: police officer territories (D'Amico et al. [2002\)](#page-20-0), sales territories (Hess and Samuels [1971;](#page-20-0) Zoltners and Sinha [1983](#page-21-0)), school districts (Caro et al. [2004\)](#page-20-0), vehicle delivery districts (Haugland et al. [2007\)](#page-20-0), and political districts (Bozkaya et al. [2003;](#page-20-0) Garfinkel and Nemhauser [1970](#page-20-0); Hess et al. [1965](#page-20-0); Hojati [1996](#page-20-0); Mehrotra et al. [1998](#page-20-0); Ricca and Simeone [2008](#page-21-0)). Blais et al. ([2003\)](#page-19-0) were the firstknown researchers to study districting in home health care. In the problem they study, the service region of a community health clinic in Montreal is to be partitioned into six districts staffed by multi disciplinary teams. The selection of districts is based on five criteria: indivisibility of subunits, respect for city boundaries, contiguity of resultant districts, the ability of nurses to travel easily within the district to which they are assigned, and workload balance. The first three criteria are strictly enforced, while travel ''mobility'' and workload balance are addressed using a weighted objective function. Mobility is approximated by summing centroid-to-centroid travel distances between subunits assigned to each district, where travel distances are calculated as the shortest time path between centroids using public transportation and walking. The authors point out that because patients in subunits are visited on tours, this mobility measure does not accurately reflect actual distance traveled, but does serve as an adequate proxy. Workload is measured as the time spent visiting patients and traveling between patient visits, with travel between visits estimated using historical data. Districts having workloads outside an allowable range are penalized in the objective function. A tabu search procedure that considers two types of local search moves is used to solve the districting problem. To reach a new solution in a given iteration, a subunit can be moved from its current district into an adjacent district, or two subunits in adjacent districts can be swapped. The solution obtained via the tabu search procedure achieved decreased nurse transportation time for the Montreal health clinic instance, and was implemented to the health clinic's satisfaction.

Bennett [\(2009\)](#page-19-0) studies a home health nurse districting problem, but observes that measuring nurse workload as the number of patient visits a nurse performs does not reflect the actual amount of time required to visit the patients. Longer travel times are required to visit patients in large, sparsely populated districts than in small, densely populated districts. A method is developed for approximating expected daily travel time in each district. Then, a measure for district workload is used that includes time spent performing active patient care and expected time spent traveling between patient visits. A district is feasible only if it is contiguous and the total nurse visit time and expected travel time are within lower and upper bounds on district target workload. Because the contiguity and workload balance considerations would require nonlinear constraints if handled within the core optimization problem, the authors use a set partitioning formulation, where the objective is to minimize nurse travel within the selected districts. A solution method is developed that combines ideas from column generation and heuristic local search methods. The method begins with a subset of feasible districts obtained via a clustering heuristic and solves the linear relaxation of the set partitioning formulation. Then, the dual variable values associated with the linear relaxation solution are used to guide the search for improving columns to add to the subset of feasible districts. New columns are created through the types of local

search moves described in Blais et al. [\(2003](#page-19-0)). Solutions obtained using the hybrid approach are shown to require less nurse travel, on average, than those obtained using pure local search.

Lahrichi et al. ([2006\)](#page-20-0) observed that due to changes in a home health agency's patient census over time, the districting problem must be periodically solved if balanced workloads among nurses are to be preserved. Three years after the districting solution developed in Blais et al. ([2003\)](#page-19-0) was implemented at the Montreal health clinic, Lahrichi et al. analyzed the clinic's operation data and discovered workload imbalance (Lahrichi et al. [2006](#page-20-0)). The average number of patients seen per nurse per month was 15.3 patients in the ''busiest'' district, and 9.9 patients in the least busy, a 35% discrepancy. Because frequent re-solving of the districting problem presents administrative challenges, the authors suggest that a dynamic patient to nurse assignment approach that considers both the district boundaries and current nurse workload should be developed.

Lahrichi and Hertz ([2009\)](#page-20-0) developed such an approach to address the shortcomings, a static districting solution presents. Instead of solving a districting problem, they take a districting solution as input, and solve a patient to nurse assignment problem in which nurses are allowed to travel outside of the district to which they are assigned to visit patients. A weighted objective function is used to minimize overload (the amount by which a target is exceeded) according to three nurse workload measures: case load, visit load, and travel load. Case load is a function of the number of patients in each category assigned to a nurse, where patient categories differ according to the amount of nurse effort required. Visit load is a weighted sum of the visits a nurse must perform, where each visit is weighted by its complexity. Travel load measures the number of visits a nurse performs outside of his or her assigned district, and weighs each associated visit according to an approximation of the travel distance required. The authors formulate the multi-objective problem as a mixed integer program with nonlinear constraints and a quadratic objective. A tabu search procedure is developed where the allowable local search moves involve changing the assignments for single or multiple patients and nurses. Computational experiments suggest it is possible to reduce the case loads and visit loads of nurses if the nurses are allowed to visit patients in nearby districts. The approach is cited as an alternative to frequent re-solving of the home health nurse districting problem.

11.3.3 Home Health Supply Chain

Studies in the operations research literature that focus on the home health supply chain are few. In Chahed et al. ([2000\)](#page-20-0), an operations planning problem encountered in the home chemotherapy supply chain is studied. The application is relevant in the French health care system, where patients can elect to receive chemotherapy in their homes, but the drugs must be prepared in specific, licensed facilities. The drugs that are administered have short shelf-lives and are highly individualized for each patient, complicating the joint production–distribution planning problem. The authors present a model and solution approach that can be used to minimize production and delivery costs when only a single nurse route may be used to distribute and administer the drugs. They describe model extensions that incorporate various capacity constraints and patient service considerations, such as multiple nurses, patient time windows, and patient priorities corresponding to urgency of care.

Supply chain practices frequently employed by home health care agencies are characterized in Bennett and Mason [\(2011](#page-19-0)). In 2010, the authors administered a survey to 132 home care agencies nationwide in order to determine how product and information flow through the home health supply chain, and how various home health supply chain configurations perform. It was discovered that 50% of responding agencies act as intermediaries in the distribution channels of their respective supply chains. As described in [Sect. 11.2.3](#page-7-0), the implication is that nurses become involved in non-clinical supply chain responsibilities such as picking and delivering supplies to patients. As evidence, 40% of responding agencies report that their nurses visit the agency at least three times per week to obtain supplies.

11.4 Recent Developments

New technologies are emerging that have the potential to impact the way in which home health care is delivered. Remote monitoring devices, sometimes referred to as telehealth devices, collect biometric data from patients in their homes and transmit it to remote servers, where it can be accessed and reviewed by health care professionals. The systems can also send patient reminders and provide patient education. Thus, the devices provide continuous access to health care services, and facilitate patient communication with their caregivers via tools such as videoconferencing. These devices have been shown to increase operational efficiency and improve care outcomes. In a survey conducted by Fazzi Associates and Philips regarding the impact of telehealth in the home care industry, 49.7% of responding agencies reported a decrease in the number of in home visits performed as a result of telehealth adoption, and 88.6% reported an increase in quality outcomes (Fazzi and Ashe [2008](#page-20-0)). If telehealth videoconferences replace a number of in home visits to each patient, or to qualified patients, an agency can provide care to a larger number of patients without increasing their mobile nurse workforce. Nursing capacity must be allocated to monitoring the incoming transmissions and conducting videoconferences, but time spent traveling is eliminated. Despite the potential benefits of telehealth, reimbursement has been identified as a top barrier to implementation, according to a survey of health care decision makers conducted by Intel (Burt [2010\)](#page-20-0). Many health insurance providers do not reimburse home care agencies for the devices they distribute to enrolled patients, nor the health care providers conducting the videoconferences. Developments regarding telehealth

reimbursement in home health care should be closely monitored, as models presented in [Sect. 11.2](#page-2-0) do not currently incorporate the option to use such devices.

11.5 Applications and Results

In this section, applications and results found in the literature for the operational problem of routing and scheduling nurses and the tactical problem of developing home health nurse service districts are presented.

11.5.1 Home Health Nurse Routing and Scheduling

Results from the HHNRS literature summarized in Table [11.2](#page-11-0) are described in this section. Each paper reviewed solves the daily scheduling problem of assigning visits to nurses and optimizing individual nurse routes.

The spatial decision support system developed in Begur et al. ([1997](#page-19-0)) enables schedulers at home health agencies to interact with a GIS-based automatic scheduling tool to assign patient visits to nurses and develop nurse routes, with the objective of minimizing total travel. The system was implemented for a home health agency with a 2700 square mile service region, 40 patient visits per day, and seven nurses. Savings resulting from system implementation are estimated as \$20,000 per year, including travel costs, nurse staffing requirements, and paperwork time and cost.

The decision support system developed in Eveborn et al. ([2006\)](#page-20-0) also enables users to interact with a GIS-based software tool to create daily nurse schedules. The daily scheduling problem is solved with the objective of minimizing travel time and penalty costs associated with violation of properties such as time windows and nurse continuity. The system was implemented for a home health agency with 28 employees of seven skill levels and 150 patients distributed throughout a 1.2 square mile region. The heuristic approach based on repeated matching obtains solutions in under 3 min on a standard 700 MHz PC. When compared with solutions produced manually, the software achieves 20% travel savings and reduces operational planning time by an estimated 7%.

The optimization component of an additional home health nurse scheduling software is described in Bertels and Fahle ([2006\)](#page-19-0). A combination of tabu search (TS), simulated annealing (SA), and constraint programing (CP) methods are used to assign nurses to visits and optimize individual routes. Results are presented for a variety of test instances with 80–200 patients, 200–600 visits per day, and 20–50 nurses that work between 5 and 9 h/day. Durations for patient visits range from 6 to 72 min, and have associated time windows up to 3 h width. The test instances are run on a Pentium III-933 PC with 512 MB RAM. Initial feasible solutions specifying routes for each nurse are obtained using CP in less than 2 min on average. When SA and TS are initialized without a feasible solution, they either produce no feasible solution, or worse solutions than CP. When SA and TS are allowed to improve an initial feasible solution from CP until a total runtime of 900 s is reached, TS terminates with an improving solution in all instances, while SA only terminates with improving solutions in 8 out of 12 sets of instances.

A particle swarm optimization (PSO) construction and improvement heuristic is used in Akjiratikarl et al. [\(2007](#page-19-0)) to assign visits to nurses and optimize nurse routes, such that travel is minimized and capacity and time window constraints are not violated. The authors test the heuristic on five instances with 100 visits per day, 50 patients, and 12 nurses. Test instances were run on a Pentium M processor with 1.6 GHz CPU speed and 512 MB RAM. In approximately 3.5 min on average, the PSO algorithm produces solutions that achieve 11 to 31% travel savings when compared with manually prepared solutions. The PSO algorithm also outperforms solutions produced using a previously developed proprietary software.

11.5.2 Home Health Nurse Districting

Three of the papers described in [Sect. 11.3.2](#page-11-0) present computational results for the models and corresponding solution approaches developed for HHND and related problems. The model developed in Blais et al. [\(2003](#page-19-0)) utilizes a weighted objective function that includes a travel-minimizing and workload-balancing component. A tabu search heuristic is used to divide a service region containing 36 subunits into 6 districts. The heuristic produces a solution in less than 300 CPU seconds on a Sun Enterprise 10000 (400 MHz). The authors compare the heuristic solution to one developed manually, and determine the distribution of workload is more uniform in the heuristic solution. The mean number of annual home visits performed per district in both solutions is 5201, while the standard deviation is 872 visits for the manual solution and 111 for the heuristic solution. The authors also report that travel time per district, expressed as a percentage of daily workload, is reduced from 18% in the manual solution to 16% in the heuristic solution.

The model developed in Bennett [\(2009](#page-19-0)) approximates HHND solution cost as the total expecting daily routing costs in all districts. Workload balancing is addressed through lower and upper bound constraints on time spent with patients plus expected time spent traveling in each district. A heuristic combining ideas from column generation and neighborhood search is used to divide a 5500 square mile service region comprised of 156 subunits into 32 districts, each to be staffed by a team of five nurses. Solutions are compared to those produced using a local search heuristic. When workload is constrained to be within $\pm 10\%$ of target expected workload, the column generation based heuristic is able to improve an initial feasible solution by 9.3%, and outperforms the local search heuristic by 4.8%. When workload bounds are relaxed, such that workload must be within $\pm 15\%$ of the target, expected daily routing costs are reduced by an additional 1.3%. With less strict workload balancing requirements, the column generation based heuristic again outperforms the local search heuristic, producing solutions with 5.6% lower expected daily routing costs. For both heuristics, solutions are obtained in \3 min for all instances.

The problem solved by Lahrichi and Hertz [\(2009](#page-20-0)) is a patient to nurse assignment problem, so the results cannot be directly compared to HHND solutions obtained in Blais et al. ([2003\)](#page-19-0) and Bennett ([2009\)](#page-19-0). A mixed integer program is used to assign patients to nurses with the objective of minimizing a weighted sum of three workload measures: case load, visit load, and travel load. A tabu search heuristic is developed to obtain solutions for a number of instances that each have two resource types and five patient types. The largest instance is comprised of 26 nurses, 36 subunits, six districts, and 1413 patients. To enable comparison of heuristic solutions with optimal values, the authors first solve instances with no case load constraints (the resulting model is linear) using CPLEX. The solutions produced by CPLEX and the tabu search heuristic are very similar, especially when travel load is heavily weighted in the objective function. An interesting insight from the computational study is that visit overload can be almost eliminated when nurses are allowed to perform visits in districts to which they are not assigned. This comes at a cost of increased travel, but the amount is difficult to quantify, because the authors measure travel load as a function of number of trips to adjacent subunits without providing actual distances. When the tabu search heuristic is used to solve instances that include case load constraints, it is observed that case load balancing can be achieved without too much expense in terms of travel load or visit load imbalance.

11.6 Future Directions

Future research directions are identified in the categories of logistics planning problems, work measurement, and design of incentive schemes.

11.6.1 Logistics Planning Problems

Of the problems presented in this chapter, the operational planning problem of home health nurse routing and scheduling has received the most attention in the literature. However, no study to date has simultaneously considered the nurse assignment and visit time assignment problems while addressing the dynamic, periodic, and consistent aspects of resulting routing problems. A possible explanation for this apparent gap in the literature is the lack of consensus among health care providers regarding how nurse and time consistency should be modeled. For example, is it preferable to minimize the number of different visit windows assigned to a patient throughout their duration of care, or instead to minimize the maximum difference between any two visit windows; i.e., which alternative in the

Option	# windows assigned Difference between windows (h)
$\{0800-0900, 0800-0900, 1600-1700\}$ 2	
$\{0800-0900, 0900-1000, 1000-1100\}$ 3	

Table 11.3 Evaluating visit window consistency for example three-visit patient

example in Table 11.3 is preferred? And, is nurse consistency strictly preferred over time consistency, or is there an acceptable trade off between the two objectives? Posing these questions to various home care agencies may result in different answers, as the industry is highly segmented and agencies tend to be unique in their operations. For example, some agencies allow their nurses to self schedule patient visits, while others do not. In order for models and solution methods developed by the scientific community to be most applicable, the extent to which nurse and visit window consistency are prioritized must be better understood. To this end, research that surveys home health agencies and patients to determine preferences, or clinical research that determines the impact of home health nurse consistency on patient care outcomes, could be useful in guiding future research. Furthermore, a comprehensive routing and scheduling tool with the flexibility to evaluate various consistency policies and their impact on nurse efficiency would provide important information to home health planners as they develop operating policies.

11.6.2 Work Measurement

Work measurement studies are needed to describe how home health nurses spend time during the workdays. Average home health care staff productivity, as measured by visits per day, is 4.95 for Registered Nurses and 6.02 for Licensed Practical Nurses (NAHC [2007\)](#page-21-0). Average visit length ranges between 30 and 60 min, depending on visit and patient characteristics (Payne et al. [1998\)](#page-21-0). The remaining portion of the home health nurse workday comprises tasks such as driving, completing documentation, engaging in case management and follow-up, and performing supply chain related duties. Quantifying time per day home care nurses spend on each type of task would provide useful input for the models described in [Sect. 11.2](#page-2-0). For example, home health nurse districting models described in [Sect. 11.2.2](#page-4-0) often constrain nurse workload per district to be within allowable bounds. The total amount of time nurses spend working per day would provide a more accurate approximation of workload than simple measures such as patient visit count. Also, models for evaluating the cost of various supply chain configurations, described in [Sect. 11.2.3](#page-7-0), require an estimate of nurse time spent performing supply chain duties.

11.6.3 Design of Incentive Schemes

As a primary provider of post-acute care, home health care is uniquely positioned to engage in partnerships with hospitals and other acute care providers to coordinate care delivery. Effective incentive schemes are needed to facilitate these collaborations. In a 2010 survey sponsored by Wyatt Matas & Associates, home care providers and industry leaders were asked to choose the biggest opportunities for home care to elevate its position within the health care continuum from a list of options. Three of the most frequent selections were chronic care and disease management, reimbursement for post-episode care management, and reimbursement for telehealth (Matas [2010](#page-20-0)). Various initiatives are included in the Patient Protection and Affordable Care Act of 2010 for the creation of innovative payment models that encourage collaboration and integration across the health care continuum. Beginning in 2013, Medicare payments to hospitals with high rates of preventable readmissions for heart attack, heart failure, and pneumonia patients will be reduced (Berenson and Zuckerman 2010). Studies have shown that using home health to assist with the daily management of chronic disease decreases risk for hospitalizations (Hughes et al. [1997](#page-20-0)). Thus, hospitals may turn increasingly to home care agencies to manage post-discharge patient care in an attempt to reduce readmissions. Additionally, Centers for Medicare and Medicaid Services is piloting a bundled payment system for an episode of care that begins three days before a hospitalization and ends 30 days after discharge (Berenson and Zuckerman 2010). Research addressing the design of incentive schemes is needed to determine the appropriate sharing of revenue in bundled payment systems.

References

- AHRQ (2007) National and regional estimates on hospital use for all patients from the HCUP nationwide inpatient sample (NIS): 2007 outcomes by patient and hospital characteristics for all discharges. [http://hcupnet.ahrq.gov/HCUPnet.jsp.](http://hcupnet.ahrq.gov/HCUPnet.jsp) Accessed 4 November 2009
- Akjiratikarl C, Yenradee P, Drake P (2007) PSO-based algorithm for home care worker scheduling in the UK. Comput Ind Eng 53:559–583
- Begur S, Miller D, Weaver J (1997) An integrated spatial DSS for scheduling and routing home health care nurses. Interfaces 27:35–48
- Bennett AR (2009) Home health care logistics planning. Dissertation, Georgia Institute of Technology, USA
- Bennett AR, Erera A (2011) Dynamic periodic fixed appointment scheduling for home health. IIE Trans Healthc Syst Eng 1(1):6
- Bennett AR, Mason S (2011) Characterizing the home health supply chain. Working paper CIHL HH 11-01, Center for Innovation in health care Logistics. University of Arkansas, USA
- Berenson R, Zuckerman S (2010) How will hospitals be affected by health care reform? Timely analysis of immediate health policy issues. Robert Wood Johnson Foundation, Princeton
- Bertels S, Fahle T (2006) A hybrid setup for a hybrid scenario: combining heuristics for the home health care problem. Comput Oper Res 33:2866–2890
- Blais M, Lapierre S, Laporte G (2003) Solving a home care districting problem in an urban setting. J Oper Res Soc 54:1141–1147
- Bozkaya B, Erkut E, Laporte G (2003) A tabu search heuristic and adaptive memory procedure for political districting. Eur J Oper Res 144:12–26
- Buerhaus P, Staiger D, Auerbach D (2000) Implications of an aging registered nurse workforce. J Am Med Assoc 283:2948–2954
- Burt J (2010) Intel survey shows positive impact of telehealth technology. [http://www.eweek.](http://www.eweek.com/c/a/Enterprise-Networking/Intel-Survey-See-Positive-Imp act-of-Teleheath-Technology-469358/) [com/c/a/Enterprise-Networking/Intel-Survey-See-Positive-Imp act-of-Teleheath-Technology-](http://www.eweek.com/c/a/Enterprise-Networking/Intel-Survey-See-Positive-Imp act-of-Teleheath-Technology-469358/)[469358/.](http://www.eweek.com/c/a/Enterprise-Networking/Intel-Survey-See-Positive-Imp act-of-Teleheath-Technology-469358/) Accessed May 2010
- Cabana MD, Jee SH (2004) Does continuity of care improve patient outcomes. J Fam Pract 53(12):974
- Caro F, Shirabe T, Guignard M, Weintraub A (2004) School redistricting: embedding GIS tools with integer programming. J Oper Res Soc 55:836–849
- CDC (2009) At a glance 2009: chronic disease—the power to prevent, the call to control. Technical report Centers for Disease Control and Prevention. National Center for Chronic Disease Prevention and Health Promotion, Atlanta
- Chahed S, Marcon E, Sahin E, Feillet D, Dallery Y (2000) Exploring new operational research opportunities within the home care context : the chemotherapy at home. Health Care Manage Sci 12(2):171–191
- CMS (2008) Home health quality initiatives. Technical report. Centers for Medicare and Medicaid Services, 7500 Security Boulevard, Baltimore MD, 21244
- D'Amico S, Wang SJ, Batta R, Rump C (2002) A simulated annealing approach to police district design. Comput Oper Res 29:667–684
- Eveborn P, Flisberg P, Ronnqvist M (2006) LAPS CARE—an operational system for staff planning of home care. Eur J Oper Res 171:962–976
- Fazzi R, Ashe T (2008) National study on the future of technology and telehealth in home care. Philips and Fazzi Associates, USA
- Ferenc J (2010) Time well spent? Assessing nursing supply-chain activities. Mater Manag Health Care 19(2):12–16
- Garfinkel R, Nemhauser G (1970) Optimal political districting by implicit enumeration techniques. Manag Sci 16(8):B495–B508
- Groer C, Golden B, Wasil E (2009) The consistent vehicle routing problem. Manuf Serv Oper Manag 11(4):630
- Haugland D, Ho S, Laporte G (2007) Designing delivery districts for the vehicle routing problem with stochastic demands. Eur J Oper Res 180:997–1010
- Hess SW, Samuels SA (1971) Experiences with a sales districting model: criteria and implementation. Manag Sci 18(4):41–54
- Hess S, Weaver J, Siegfeldt H, Whelan J, Zitlau PA (1965) Non-partisan political redistricting by computer. Oper Res 13:998–1006
- Hojati M (1996) Optimal political districting. Comput Oper Res 23(12):1147–1161
- Hughes SL, Ulasevich A, Weaver FM, Henderson W, Manheim L, Kubal JD, Bonarigo F (1997) Impact of home care on hospital days: a meta analysis. Health Serv Res 32(4):415–432
- King C (2010) To your health: Intel and GE's joint venture. <http://www.ecommercetimes.com/>. Accessed 30 August 2010
- Lahrichi N, Hertz A (2009) A patient assignment algorithm for home care services. J Oper Res Soc 60(4):481–495
- Lahrichi N, Lapierre S, Hertz A, Talib A, Bouvier L (2006) Analysis of a territorial approach to the delivery of nursing home care services based on historical data. J Med Syst 30(4):283
- Matas (2010) Survey for envisioning the future of homecare. Technical report, Wyatt Matas and Associates, 1776 I Street NW, 9th Floor, 20006, Washington
- Mehrotra A, Johnson E, Nemhauser G (1998) An optimization based heuristic for political districting. Manag Sci 44(8):1100–1114
- Nachtmann H, Pohl E (2009) The state of health care logistics: cost and quality improvement opportunities. Technical report, Center for Innovation in Health care Logistics, University of Arkansas, USA
- NAHC (2006) Home care profit margins update. Technical report, National Association for Home Care and Hosipce, Washington, DC
- NAHC (2007) Basic statistics about home care. Technical report, National Association for Home Care and Hospice, 228 Seventh St SE, 20033, Washington
- NAHC (2009) Study shows home health care workers drive nearly five billion miles to serve elderly and disabled patients. Technical report, National Association for Home Care and Hospice, 228 Seventh St SE, 2003, Washington
- Payne S, Thomas C, Fitzpatrick T, Abdel-Rahman M, Kayne H (1998) Determinants of home health visit length: results of a multisite prospective study. Med Care 36(10):1500–1514
- Ricca F, Simeone B (2008) Local search algorithms for political districting. Eur J Oper Res 189:1409–1426
- Rich J (1999) A computational study of vehicle routing applications. PhD dissertation, Rice University, USA
- Steeg JM (2008) Mathematical models and algorithms for home care services. PhD dissertation, Fraunhofer Institute for Industrial Mathematics
- Steven H, Landers MD (2010) Why health care is going home. New Engl J Med 363:1690–1691
- Super N (2002) Who will be there to give care? The growing gap between caregiver supply and demand. White paper, National Health Policy Forum of The George Washington University, Washington, DC
- UPS (2009) UPS corporate responsibility: a commitment to safety, every day. [http://](http://responsibility.ups.com/safety/index.html) responsibility.ups.com/safety/index.html. Accessed 3 November 2009
- US (2004) Projected population of the united states, by age and sex. [http://www.census.gov/](http://www.census.gov/population/www/projections/usinterimproj) [population/www/projections/usinterimproj](http://www.census.gov/population/www/projections/usinterimproj). Accessed 27 April 2011
- Zoltners A, Sinha P (1983) Sales territory alignment: a review and model. Manag Sci 29(11): 1237