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Planning Strategies for Home Care services

Euroopan unioni
Euroopan sosiaalirahasto

Elinkeino-, liikenne- ja ympäristökeskus

Vipuvoimaa EU:lta 2007–2013

Pohjois-Karjalan ammattikorkeakoulu

Savonia ammattikorkeakoulu

LOREN IPSUM DOLOR

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NORTH KARELIA UNIVERSITY OF APPLIED SCIENCES

VASKE-project

2012

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ISBN 978-952-275-054-9 (pdf)

North-Karelia University of Applied Sciences
VASKE-project

Joensuu, Finland 2012

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ABSTRACT

In this paper we examine the savings potential of alternative planning strategies for home care services by means of two case studies. The problems are solved by commercial routing software and the results are demonstrated on data collected from a sparsely populated area in East Finland. The obtained empirical results show significant improvement potential. The worker productivity can be increased by 25.9–68.9% compared to current practice and the instant time at patient can be increased up to 75.8% of the shift length. The results also suggest that more efficient plans are possible in case the planning is done based on half-day shifts. Compared to other elderly care models, the results show that optimized home care is over twenty times cheaper, even in case of frequent visits and distant patient locations.

1 INTRODUCTION

In recent years population ageing has moved into a top place of the policy agenda in industrialized countries. As more and more people live to a high age, demand for home care services is increasing rapidly. Worldwide, there are 600 million people aged 60 and over, and this number will double by 2025 (World Health Organization 2009). At the same time, the proportion of active workforce is getting lower, resulting in less tax payers and income.

Home and community-based care programs have been growing due to the preferences of elderly clients to remain in their homes (Bauer, 1996). While the issue of cost-effectiveness in the nation's home and community-based programs and nursing homes is a continuous topic of discussion (Chiu et al, 2001; Doty, 2000; Grabowski, 2006), in practice, effective program operation strategies have been limited (Kim and Kim, in press).

Table 1 gives an overview of the expected demographics in Finland. The first part of the table reports the ratio of inactive to active citizens for five cities in East Finland and the next three rows do the same for two counties in East Finland and the entire country. According to the table, in some communes the proportion of elderly will be doubled in the near future and will be clearly larger than the size of work-aged population.

Table 1. Proportion of population aged <15 and >65 to population aged between 15 and 64 in 2010-2040.

	2010	2020	2030	2040
Lieksa	62.4	101.8	137.1	130.6
Iisalmi	53.4	74.1	88.8	87.1
Kiuruvesi	64.6	83.2	100.9	99.5
Sonkajärvi	60.5	87.9	112.4	111.1
Vieremä	59.4	75.0	86.8	86.2
Pohjois-Karjala	54.2	73.9	88.4	86.1
Pohjois-Savo	54.3	71.8	84.7	84.1
Whole Finland	51.6	65.4	73.0	73.4

Elderly people have varying degrees of need for assistance and medical treatment. It is advantageous to allow them to live in their own homes as long as possible, since a long-term stay in a nursing home can be much more costly for the social insurance system than a treatment at home providing assistance to the required level. According to Eveborn et al. (2009), on average, a place in a retirement home costs 49 500 euros annually, whereas home care costs 20 300 euros. This is comparable with the cost levels observed in Finland; the cost of treatment in a communal facility such as hospital or retirement home costs about 150 euros per day and the average cost of home care per patient is 12 300 euros (Nakari 2013). In Finland there is also third option between retirement home or hospital and living at home, called 24h service housing. It refers mainly to living in home-like conditions but in central location and together with other patients. The average cost level of service housing in Finland about 120 euros per day (Savon Sanomat 2009). These are the key cost levels to which home care should be compared to. Apart from aging population and pressure to contain the costs e.g. chronic pathologies and numerous medical and technological advances have affected the increase of the home care sector. In Finland it is also a public policy to support living at home as long as possible.

Home care refers to the combination of home nursing and home services. The aim is to provide the care and support needed to assist people, particularly elderly people, people with physical or learning disabilities and people who need assistance due to illness to live as independently as possible in their own homes. Home nursing refers to primary health care outpatient services, such as blood pressure and blood sugar measurement, the administration of medication into dispensers, and the removal of stitches. Support services, on the other hand, include meal, dressing, cleaning, safety, maintenance, bathing, and transportation services, as well as services that facilitate social interaction. In Finland communes are responsible to organize the home care either by themselves or through outsourcing the services to private companies.

The home care sector typically has a very unpredictable demand for service. Moreover, the duration of the service is highly volatile. This creates a tension between the size of the workforce and the operational costs. In recent years there has been a lot of discussion about the scarcity of resources devoted to the home care of the elderly and work pressure and salary conditions for the staff (e.g. http://www.cbc.ca/news/canada/nova-scotia/story/2012/08/09/ns-northwood-homecare-workers-strike.html). The numbers tell a different story: productivity in home care is typically low (Groop 2012).

One of the main problems currently is that the service requirements for home care are bigger than what is possible with the existing resources and planning strategies (Groop 2012). This has a big impact on the well-being and motivation of the nurses and thus productivity. Here the key issue is to increase the productivity to increase the instant time at customer and that way service quality. To gain productivity increases, optimization based planning has a key role, but it should be embedded in a larger managerial effort to reduce indirect work and carefully analyze the existing care plans in personal level.

Very often, the visit time at customer is strictly limited by tight time windows in the care plans. As a consequence, morning periods can be very busy and there is slack time in the afternoon. In many cases the tight time windows are unnecessary from the customer viewpoint and can be loosened without impact on service quality. Figure 1 illustrates the workload at different times of the day. The figure shows that in addition to tight time windows that probably can be loosened, up to 43% of the morning peaks are caused by visiting customers that need to be visited only rarely, 0–4h or 5–10h per month or occasionally and thus for sure have flexibility in their visit time windows.

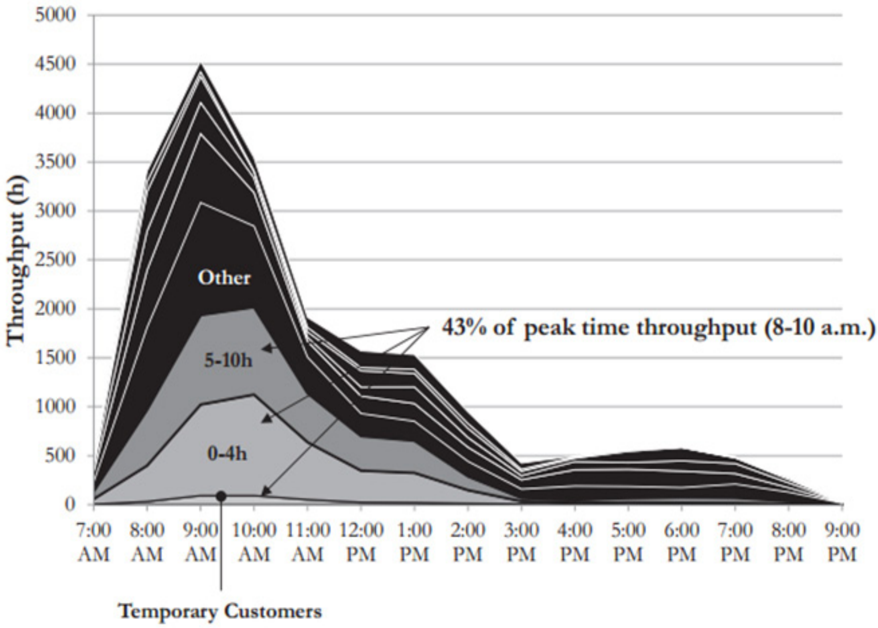

Figure 1. Relative load contribution of visits with different frequencies (Groop 2012).

Despite the high and rapidly increasing importance of the home care optimization, the academic literature is rather limited. Begur et al. (1997) report a realistic decision support system for optimizing home care operations. The system is based on simple standard heuristics and the authors report 20 000$ annual saving for a set of 7 nurses. Eveborn et al. (2006) present a decision support system called LAPS CARE, specifically designed for home care staff planning. Case study results from Sweden demonstrate 20% and 7% savings potential in transportation and total costs, respectively. According to Eveborn et al. (2009), on the average LAPSCARE has increased operational efficiency by 10-15%. Bertels and Fahle (2006) present an approach (PARPAP) combining linear programming, constraint programming and meta-heuristics for the optimization of home health care routes. The model is solved by a construction heuristic that generates an initial solution and two improvement heuristics.

Akjiratikarl et al. (2007) apply a particle swarm optimization metaheuristic that is combined with a variant of an insertion heuristic and simple local searches to home care operations in UK. The authors report 48-73% reductions in distance cost compared to current manual practice. Bräysy et al. (2009) used a commercial software, based on a library of heuristics and report 36.8–71.1% savings in the required workforce with Finnish home care data. Nickel et al. (2012) suggest a two-phase method where long- and short-term planning are separated and present a constraint programming, large neighborhood search and tabu search heuristics to solve the problem. Real life data is used but no real comparison to current practice is provided. Koeleman et al. (2012) aim to provide a model to deal with the personnel planning problem in home care service facilities in a stochastic setting. They cast the problem as a Markov decision problem and determine the optimal patient admission policies and size of the workforce. Actual routing model is omitted from their study. Rasmussen et al. (2012) consider a single day problem and model it as a set partitioning problem with side constraints and develop an exact branch-and-price solution algorithm. The authors consider also temporal dependency issues and multi-objective planning that includes e.g. nurses' preferences and service level.

In this paper, we present two case studies on home care optimization in sparsely populated areas in East Finland. In these areas, exceptionally large proportion of aging population (see Table 1), long distances and below average infrastructure make efficient home care a big challenge. Our main goal is to estimate the improvement potential of optimization based planning. In addition, we analyze various planning strategies to provide general guidelines. More precisely, we e.g. investigate the impact of resource pooling, i.e., having all workforce in a single pool instead of assigning them first to fixed bases or service areas and the impact of modern communication technology that enables starting and ending the tours at customer site instead of a given base. One of the most interesting issues is the impact of different work shift lengths to operational efficiency. The empirical results show a significant, over 60% improvement potential, compared to current practice. The instant service time at customer wrt. total shift length can be almost doubled through optimization. Based on the obtained results, we also analyze the cost level of home care and compare it to alternative care models to provide guidelines for elderly care.

The remainder of this paper is organized as follows. In the next section we shall define the solved home care optimization problem in more detail. In Section 3 we shall describe shortly the applied solution approach and the problem data and results are discussed in Section 4. Finally, conclusions are drawn in Section 5.

2 PROBLEM DESCRIPTION

From the viewpoint of optimization, the key underlying problem in the home care optimization is the vehicle routing problem (VRP). The VRP (see e.g. Toth and Vigo (2001) for details) consists of defining an optimal set of routes for vehicles in order to serve a set of customers. There are many variants of the problem, but the common objective is to minimize the total travel time and size of the fleet. Also other constraints, such as time windows, dynamic demand and vehicle capacity can exist. Different vehicle routing problems are among the most difficult combinatorial optimization tasks.

In practice, the care workers travel from their homes or bases to deliver care to their allocated clients at a specified time or within a specified time-window, and then return home or base after finishing their visits. The maximum work time limit (e.g. 8h) work per day per nurse is usually imposed. Generally, the time-windows of high-level tasks are tighter than those of low-level tasks, because high-level tasks are more critical. Apart from minimizing the required nurses, a key objective is to minimize time used for traveling. The total traveling distance is the sum of the distance from the care worker's home or base to the first client, the distances between the successive clients and the distance from the last client back to the worker's home or base. This basic setting corresponds to the definition of well-known VRP with time windows (see e.g. Bräysy and Gendreau 2005a,b). In practice, the time windows are not absolutely restrictive as a certain amount of flexibility is allowed. Time window violations are actually quite common, but customers are informed by phone. For related literature on soft/flexible time windows, we refer to Figliozzi (2010).

Typically, each customer requires several visits within a given interval that can vary from a few hours to days or even weeks. A personal plan is made for each customer, based on his/her needs. The time interval in which a customer receives service is decided according to the needs and wishes of the customer and other real-life limitations. Typically the care plan is and must be made for several weeks ahead, resulting in need to plan for several repeated visits to same customer during the planning period. Often there is flexibility in defining the actual visit day, resulting in another VRP variant called periodic VRP (see e.g. Hemmelmayr et al., 2009 for details).

A related issue to the long-term planning is the continuity of care. It means that if possible, the same nurses should always visit the same patients. To our best knowledge, there is no direct research on the topic from optimization viewpoint, but it can be modeled in rather straightforward way through compatibility constraints (see Bräysy and Hasle 2012 for more details). The same compatibility constraint is used to match the nurses' skills, equipment etc. with the customer. This is important because the personnel have a maximum number of working hours per day and different levels of education and different skills (such as nurses and practical nurses), often aimed at performing specific tasks. In addition, one should match or define correct vehicle for each route and consider heterogeneous vehicle fleet including e.g. car, bike or bus with various travel times in exact road network

Another complication, compared to traditional vehicle routing, consists of temporal dependencies between visits (Dohn et al., 2011). The temporal dependencies constrain and interconnect the routes of the nurses. One temporal dependency is synchronization (Bredström and Rönnqvist, 2008). For instance, synchronisation of two visits is used when a citizen needs help to get in or out of bed. Here two nurses are required at the same time. The overlap temporal dependency is, for example, seen when a nurse has to pass on a key to the next nurse. The temporal dependencies minimum difference and maximum difference are for example used when a nurse starts the washing machine at a customer and a following nurse (perhaps the same) empties the washing machine at the same customer. The visits need to be separated by, say, 2 hours, but not more than 4 hours. The same issue arises also if the same customer must be visited for care reasons more than once a day and the optimal timing of each visit must be defined. For example in Finland there are cases where a customer is visited 6 times per day. Another way to deal with multiple visits per day would be to define different non-overlapping time window to each visit, but it results practically always to unnecessary and useless waiting time at customer.

In our study the only optimization objective was to increase the productivity of the nurses resulting in short-term to more time at patients. But other objectives such as maximum patient and staff satisfaction could also be simultaneously considered. Related to this, one may e.g. consider customer preferences regarding visit time windows, preferred nurses/patients and balanced workload. Also, visits are often associated with a priority and it is important to only reschedule and cancel less significant visits.

In addition to the VRP component, home care optimization includes also staff planning component that has practically been ignored both in literature and practice. Apart from planning the customer visits for a given planning period ahead, one should at the same time plan the corresponding work shifts, including shift start and end times as well as breaks and rest periods and holidays such that related work regulations are followed and if possible workers' preferences are also taken into account. In the literature this entity is called the nurse rostering problem (Ernst et al., 2004, Lü and Hao 2012).

The above described home care optimization problem were implemented in the R2 commercial software of Procomp Solutions Ltd. The R2 solver is designed to deal with a large variety of real-life optimization problems, including all three levels of decision making from strategic to operational. The key feature of the software is its ability to solve very large-scale problems through intelligent modeling of the various constraints and objectives that enable linear scaling with the problem size. The software model includes support e.g. to long-term and real-time planning, multiple objectives (e.g. cost, service level, balanced work division), shift planning (including e.g. optimized break handling and worker skill level), case dependent service times, various transportation modes, service area optimization, base optimization, complex capacity and time window handling and many detailed issues such as maximum time at vehicle, required equipment management, safe route planning, optimal route timing and detailed cost impact analysis. For more details on these features, we refer to Bräysy and Hasle (2012).

The R2 solver is based on a set of published heuristic algorithms that are adapted to handle complex real-life problems and carefully implemented and tuned to gain high efficiency. The initial solution is generated with a variant of the cheapest insertion heuristic of Solomon (1987). The initial solution is further improved with the chain-exchange local search procedures of Bräysy (2003) that are guided by the threshold accepting metaheuristic by Bräysy et al. (2009) to escape local minima. In addition, a large neighborhood search heuristic (Pisinger and Røpke, 2007) is applied periodically to further improve the solution. To optimize the number of routes/shifts, ejection pool heuristic of Nagata and Bräysy (2009) is applied during the improvement phase. The allocation of periodic orders is done with a variant of the method by Tarantilis et al. (2012). For more details on the solution method, we refer to Bräysy and Dullaert (2011).

3 EMPIRICAL DATA AND RESULTS

3.1 Data

Empirical data was collected from a rather small and sparsely populated communes located in East Finland in 2011–2012. The collected data is derived from real care plans from which one representative 7-day week data was chosen for the first case and a two-week data set was selected for the second case. The first data consists of 268 different customers, most of them requiring multiple visits during the week. The total number of visits during the planning period is 1390. The total required instant service time at customer equals 479 hours in the planning period, corresponding to over 60 full day work shifts. The number of bases is two. In the second data there were 1162 different customers that required 18127 visits during the two week period. Here the number of bases is seven and there were in total 1222 visits that required two nurses simultaneously (in the first data there was only one such customer). For each visit, we obtained information on the address, time window, required service time and required nurse skill level or synchronization (two nurses at the same time). For each nurse information is stored on his/her home base.

In addition to collecting data on the care plans, data on the actualized care corresponding to the same plan and period was also collected. The collected data includes time used at customer, time used for traveling, distance traveled and arrival times at each customer location. The visit frequency, i.e., how many times a customer is visited during the 7-day week is illustrated in Figure 2. Here the last column includes also frequencies above 7.

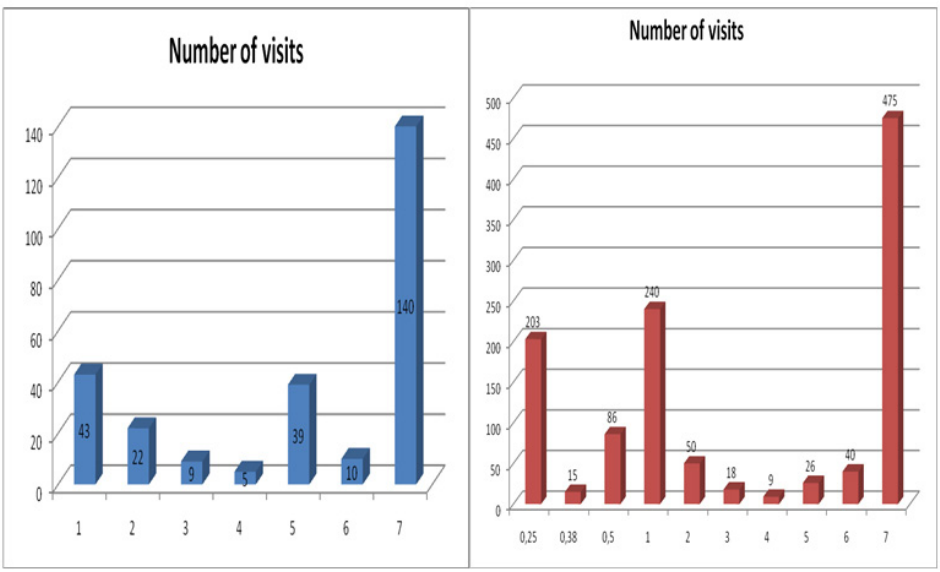

Figure 2. The visit frequencies within a 7-day week in first (left) and second data (right).

Figure 2 clearly shows that the vast majority of the customers in our case is visited at least once a day or once per work day. Another important customer group is those that are visited once a week. In the second data there are also a significant number of customers visited once in four weeks (corresponding to value 0.25 in the figure). In Figure 3 we illustrate the time window widths or flexibility before and after a multi-professional team analyzed the care-plans from the viewpoint of time window criticality. This process was carried out with the first data only and the key goal was to reduce the morning peaks and increase efficiency and well-being of the nurses that way.

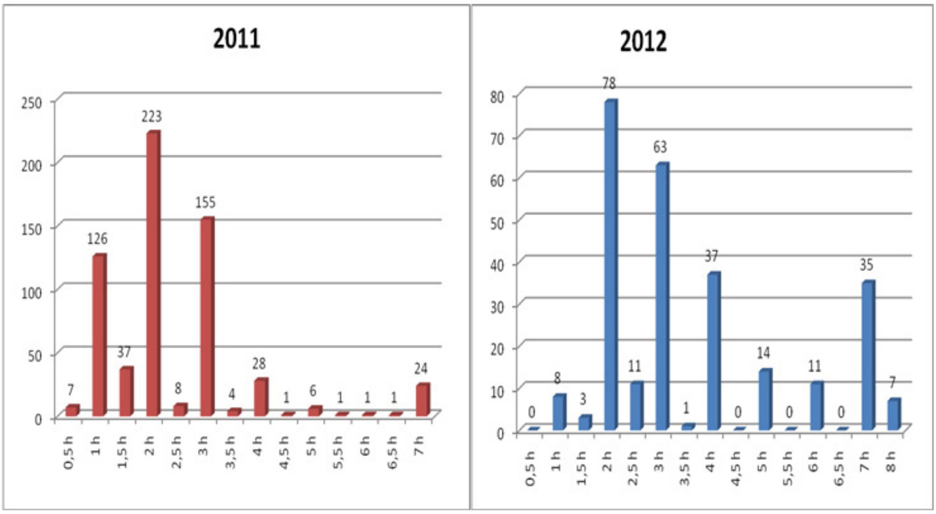

Figure 3. The width of visit time windows

The results were quite significant. For example, before the change 83% of the visits had time windows whose width was less than 3h. After the analysis the same percentage dropped to 61%. Correspondingly, the number of orders in 3h-8h time window increased from 36% to 63%. According to obtained feedback, the change clearly improved the well-being and attitudes of the nurses. According to the figure, even after the readjustment of care plans, a large majority of the customers have rather tight time windows. Only 2.6% of the customers have a full day time window, whereas one third of the customers have a time window of 2h or less. The time window widths of the second data are illustrated in Figure 4.

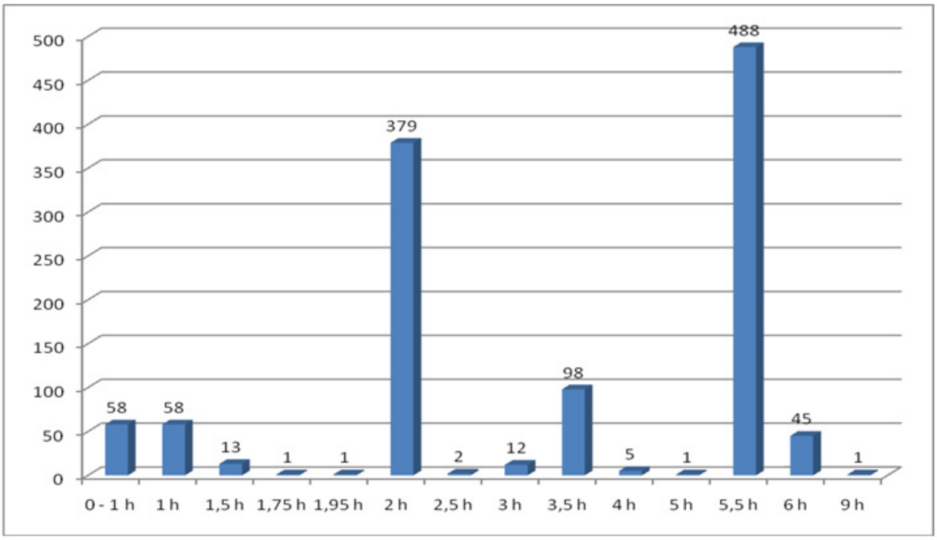

Figure 4. The time window widths in second data

According to Figure 4, in the second dataset the proportion of customers with wider time windows is larger, but still a large majority of the customers have very tight visit time windows. In Figure 5 we illustrate the geographical dispersion of the customers and the base locations (marked with squares). As one can see from the figure, the distances to some individual customers are quite long, in some cases up to 100 km causing many of the customers to be rather isolated. The lake between the bases in the first data make joint planning also challenging by growing the distance between the bases.

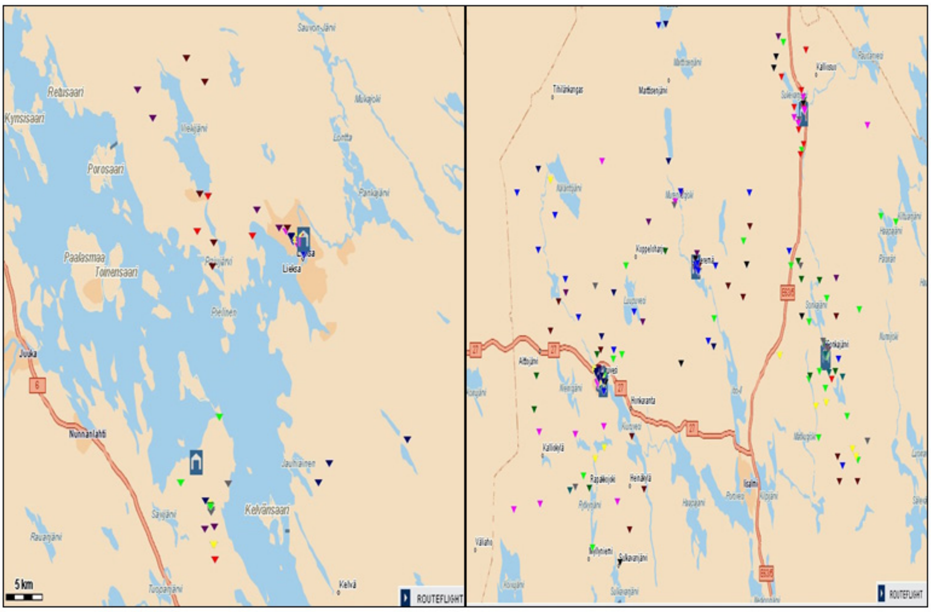

Figure 5. The geographical location of customers in the first (left) and second (right) data.

The test runs were executed on a Intel Xeon X5460 (3.16 GHz) computer with 12 Gb memory. The routes were calculated on real road network, based on DIGIROAD maps and the modified shortest path algorithms of Bauer et al. (2010). The travel times were calculated assuming that each nurse has a car in use and considering the actual speed limits and turning and parking impacts in the road network.

3.2 Results

Due to the periodic nature of the problem, limited data, some sparsely visited customers and slight weekly variance in the set of visited customers, direct comparison between actualized plan and the optimized plan total values is not possible. To be more precise, in the optimized plan the set of customers may differ from the set of customers in the actualized plan. For example, if we have a customer that must be visited once in two weeks, optimization may allocate the visit to latter week, whereas in the actualized plan the patient can be served on the first week. As the data on the actualized plans was obtained only from one week period, a direct comparison over full planning period is not possible. And the optimization should be based on plan data, not historical data on current practice to set the time windows, service times, requirements etc. correctly. They should be based on the care plan, not current practice. Given that large majority of the customers are visited very frequently and workload between the weeks is balanced, the difference is small and does not impact the result interpretations. To enable a fair comparison, we calculated three key efficiency measures:

1) Number of customer visits per hour
2) Service time at customer, as a % of the total shift length
3) Traveled distance per customer

The comparison between the current practice and the various optimization scenarios in Tables 2 and 4 is based on these measures. The first one is used as the key efficiency measure that is reported in the last column. In addition to actual direct service work at patients' homes, nurses' workday comprises numerous indirect tasks. Apart from driving, breaks and booking work that are considered directly in our optimization model, there are a lot of other tasks such as planning, meetings, communication, laboratory and medication work etc. According to a detailed work time survey by Nakari (2013) all the other indirect tasks not considered in our model require 15% of the total work time. Majority of these missing indirect tasks are time-flexible and can be allocated to efficient positions within the workday. In the efficiency improvement percentages of the last column, we have considered also all indirect work to illustrate the realistic improvement potential.

Table 2 reports the results to the first dataset. The first optimized scenario in Table 2 includes the current service areas. This means that each nurse is allowed to serve only customers in his or her pre-defined service area that is given as input parameter to optimization. These pre-defined service areas are identical to the ones used in the current practice. In all other optimized scenarios, the service area limitation is omitted to reflect the increased schedule flexibility when abandoning current practice. We have defined 3 different maximum shift lengths in Table 2, from 3h to 8h to illustrate the impact of shift length limit to generating efficient route plans. In the first five scenarios, we assume that each route starts and ends at a base. In the last two scenarios this limitation is omitted and a route can start and end at customer location. The key idea is to illustrate the potential of modern ICT technology, such as mobile devices and electronic keys that make it possible to operate without base visits.

Table 2. Comparison between optimization scenarios and current practice.

Scenario	Shift length/h	Service areas	Team bases	Time at patient %	Km/ patient	Improvement %
Current	8	YES	YES	39.8	1.32	0
Scenario 1	8	YES	YES	57.0	1.27	26.9
Scenario 2	8	NO	YES	68.9	1.23	53.9
Scenario 3	4	NO	YES	70.4	1.57	57.7
Scenario 4	3	NO	YES	68.4	1.98	55.6
Scenario 5	8	NO	NO	68.9	0.65	53.9
Scenario 6	4	NO	NO	75.8	0.56	68.9

According to Table 2, considering the number of visits per hour, a 26.9% productivity improvement to current practice is possible even if current service zones are kept in place. If the pre-defined service zones are removed, 53.9% improvement in productivity is possible compared to current practice. This means that either the same group of nurses could handle 53.9% more patients, or the same number of patients could be handled by 53.9% less nurses or the service level, i.e., time at customer could be increased by the same amount. This is largely explained by the fact that in current practice the non-productive slack time not allocated to customer service or indirect work is nearly 30% of the work time. As mentioned above, these improvement percentages include all direct and indirect work as well as accurate travel times, break durations etc. Despite the long distances, the results show that the travel times play only a very small role from the total time use perspective.

The fourth scenario of the table indicates that the service efficiency and time at customer can be further increased slightly if the planning is done in half-day shifts, whereas reducing the shift length to 3h results in worse solutions. Ignoring the bases and starting and ending the shifts at customer location directly has practically no impact on the required workforce or imminent time at customer, but it reduces the distance by 47% in 8h shift case. However, if 4h shifts are used as in last scenario, up to 15% efficiency improvements are possible. This result in mainly due to the nature of the home care operations, with restricting time windows, multiple visits per day and in some cases multiple nurse requirement. Here one must remember that planning on half-day basis does not prevent the same nurse to take two half-day shifts on the same day or e.g. work the other half of the shift somewhere else, like hospital. It is only a planning strategy.

In Table 3 we analyze the costs of the different treatment models according to Finnish cost data in euros. More precisely, we demonstrate the daily cost per patient and the total cost of 268 patients in one week. The used salary levels are obtained from Taloussanomat (2011) and other cost data from several Finnish communes.

Table 3. Cost analysis of elderly care models

	Cost per day	Total cost per week
Average cost in Finland	33.7	63 240
Real cost + optimized plan	6.1	11 444
Service housing	120	225 120
Communal facility	150	281 400

When analyzing the results in Table 3, one must bear in mind that the cost of home care is dependent on the frequency and duration of the visit. In the studied communes in East Finland, the visit frequency was relatively low, less than once per day, which partially explains the lower cost of the optimized plan wrt. average cost in Finland. Another explaining factor is that the real costs of home care are clearly lower than budgeted costs, even if all cost types are taken into account. This may be partially explained by very high administrative overhead. The real costs are based on average salary of home care nurse according to Taloussanomat (2011) and regulatory social premiums as well as maximum allowed km-allowance of 45 cents per kilometer. As the food, medication and living costs are paid the patients in case of home care, the other costs related e.g. to equipment remain very limited and account only about 5.5% of the total costs (Nakari, 2013). One should also note that here the optimized costs refer to using the bases and standard 8h working day, so even lower costs could be obtained through other planning scenarios. Despite this, the optimized home care is over 20 times cheaper than other alternatives. This result clearly shows the importance of optimized home care as the primary treatment model for elderly.

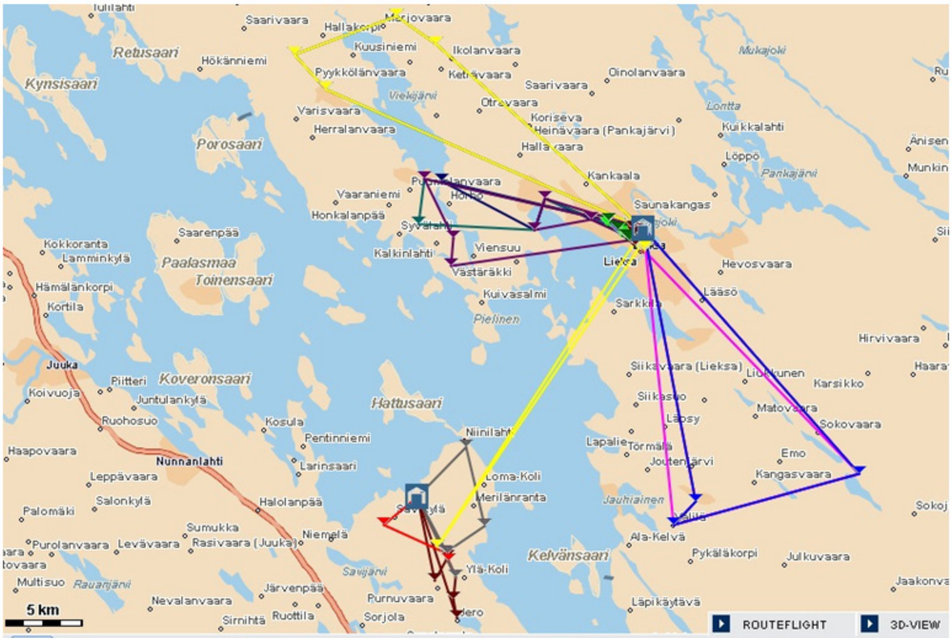

Figure 6. Optimized routes with 4h shift length and two bases on a given day.

The optimized routes with 4h shift length are illustrated in Figures 6 and 7 with and without considering the base traveling. To facilitate the illustration, straight lines are used. In practice, e.g. the yellow route naturally follows roads to get to the other side of the lake. According to Figure 6, it seems effective to combine distant customers to same route and even customers from another base area, despite the need to travel around the lake. Even though this incurs extra traveling, it also enables more efficient resource use. In Figure 7 the long depot traveling is avoided, but combining the customers in different service areas appears still beneficial.

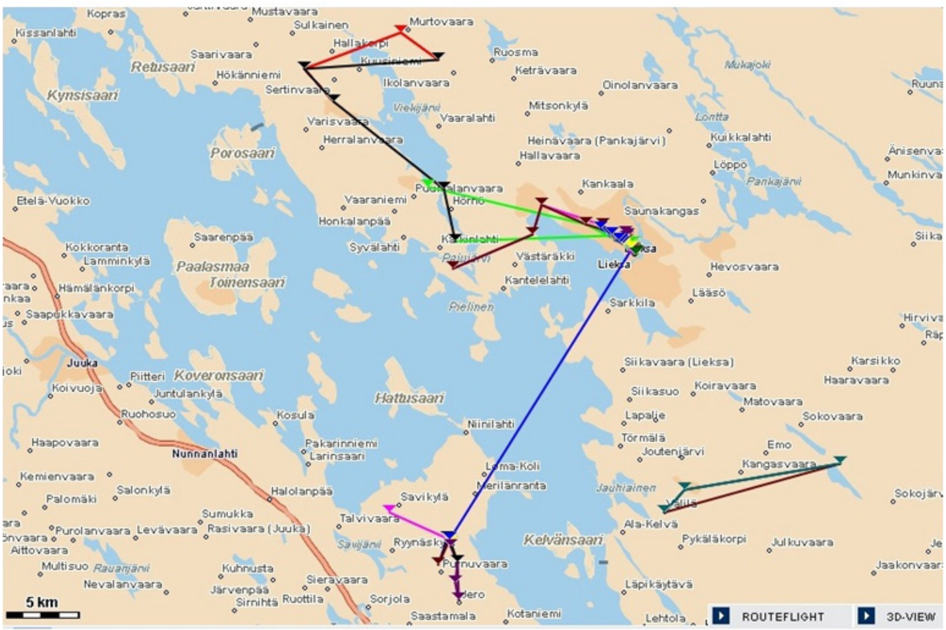

Figure 7. Optimized routes with 4h shift length without home bases.

In Table 4 we illustrate the results to the second dataset. Here only two optimization scenarios were calculated, mainly to show the potential of optimization in another, larger case with many bases.

Table 4. Optimization results to second dataset.

Scenario	Shift length/h	Service areas	Team bases	Time at patient %	Km/patient	Improvement %
Current	8	YES	YES	38.7	2.39	0
Scenario 1	8	NO	YES	62.8	1.16	33.3
Scenario 2	4	NO	YES	72.5	1.25	55.6

According to Table 4, with 8h days the productivity can be increased by 33.3% and instant service time at customer can be growed up to 62.8%. At the same time the traveled distance is more than halved. Compared to results in Table 2, the savings potential is here in the same level. Through 4h shifts, the efficiency can be further increased by over 20%, indicating that with more bases, shorter entities are more efficient. The optimized routes with second dataset are illustrated in Figure 8. The figure clearly shows that despite the large number of bases, it is important to combine customers located at different depot areas.

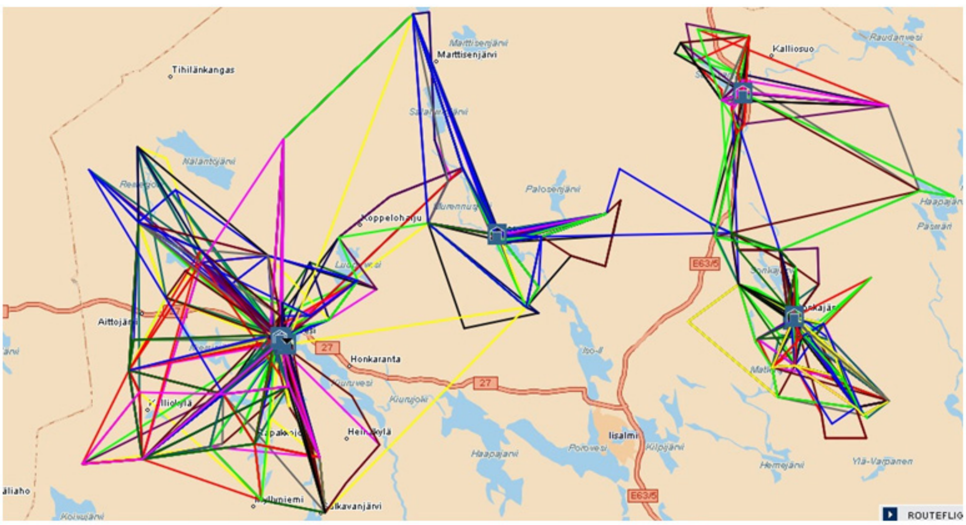

Figure 8. Optimized routes to second case.

4 CONCLUSIONS

We have focused on the home care operations in a sparsely populated area. Apart from comparing optimized results with the current practice, we also analyzed several different optimization scenarios. The results indicated a 26.9%–68.9% improvement to current practice, depending are the current service area limitations considered and used shift length. The results also indicate that starting the tours from customer site, instead on given base or depot makes it possible to reduce the traveled distance by more than half. An interesting new finding was that considerably higher productivity and higher relative instant time at customer is possible via planning through half-day shifts instead of traditional full-day shift planning. The conducted cost analysis revealed that optimized home care can be over twenty times cheaper than alternative care models, even with patients requiring intensive care. We also noticed that in addition to basic operational planning, one should use optimization also for other important tasks such as personnel skill management and development and service planning, i.e., what services should be offered in each case and by whom. These shall be part of our future study.

ACKNOWLEDGEMENTS

This research was part of ESR-supported VASKE-project, see http://vaskehanke.blogspot.fi/. We gratefully acknowledge this support.

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