Chapter 1
Home Care Services Delivery: Equity Versus Efficiency in Optimization Models

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Abstract Home Care Services (HCS) delivery is a quite recent and challenging problem motivated by the ever increasing age of population and the consequent need to reduce hospitalization costs. Integer Linear Programming (ILP) models have been recently proposed in [5] to formulate a very general HCS problem, with the aim at balancing the operator workload. In fact, in Home Care setting "equity" criteria are crucial to guide the decisions. "Efficiency" criteria, i.e., the minimization of the operating costs, are essential as well. The aim of this paper is thus to compare equity criteria versus efficiency criteria in HCS. Preliminary computational results on a set of real instances are presented and analysed. Specifically, two alternative "balancing" objective functions are compared via optimization and simulation, by showing their impact on diverse relevant Quality of Service indicators, including cost indicators.

1.1 Introduction

Nowadays, the ever increasing average age of population, at least in industrialized countries, and the increased costs for the consequently required care, compel the medical care units to offer Home Care Services (HCS) in an attempt to limit costs. Elderly people have in fact varying degrees of need for assistance and medical

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treatment, and it may be advantageous to allow them to live in their own homes as long as possible. In addition, medical treatments carried out at patients home impact favorably on their quality of life. Therefore, HCS are a cost-effective and flexible instrument in the social system.

Interestingly, in Home Care setting the minimization of the operating costs, that is a common objective of the stakeholders (either private or public) providing the service, is not the only objective to be taken into account to guide the Home Care decisions. In fact, another objective typically used in HCS is the balancing of the utilization factor among the operators, where the *operator utilization factor* is the total workload of the operator in the considered planning horizon over his/her maximum possible workload. In order to achieve this objective, one possibility is to maximize the minimum operator utilization factor. Hereafter this balancing objective function will be referred to as *maxmin*. Anyway, an alternative balancing function may be defined, which consists in minimizing the maximum operator utilization factor. This alternative function will be indicated as *minmax*. Both formulations have been proposed in [5]. In the context of assignment decisions in HCS, the *maxmin* criterion has been also investigated in [9].

The aim of this paper is to compare the two balancing objective functions in an extensive way. Specifically, *maxmin* and *minmax* are compared both via an optimization approach and also via a simulation experimentation performed on a set of real HCS instances, by showing their impact on diverse relevant Quality of Service (QoS) indicators. This set of QoS indicators includes the mean operator utilization factor over the considered planning horizon, the corresponding range, i.e. the difference between the maximum and the minimum operator utilization factors, and the daily variation of the operator utilization factor. In addition, in order to provide a hint about the influence of such equity measures on the HCS efficiency, QoS indicators related to the operated service time and the operator travelled time are also investigated.

The results of the preliminary computational experiments are very interesting. In fact, they show that the *maxmin* criterion is able to return more balanced HCS solutions, in the sense that the difference between the maximum and the minimum operator utilization factors is smaller than the one returned by *minmax*. The *maxmin* criterion is also preferable in balancing the operator traveling time and service time. This is true not only by looking at the overall planning horizon, which is a week in our experiments, but also at a daily level. Such stronger equity achievements are obtained for not too high a price in the increased mean operator utilization factor, mean operator service time and mean operator traveling time. On the other hand, the *minmax* criterion appears to be more suitable for the minimization of the operating costs since it always returns solutions with the smaller total travelled time.

The achievements above have been shown first in a deterministic setting, via optimization, and then confirmed by the simulation experiments, where the robustness of the computed HCS solutions against travel time and service time variability has been evaluated.

The plan of the paper is the following. In Sect. 1.2 we introduce the HCS problem, and describe the two alternative objective functions *maxmin* and *minmax* [5]. In Sect. 1.3 we describe the HCS dataset, and present the computational campaign. Then, in Sect. 1.4 preliminary computational results are presented and commented. Observations about future researches conclude the paper.

1.2 The HCS Problem

In this paper we address a relevant optimization problem arising in HCS. Given a planning horizon W, which is a week in the considered experiments, a set of patients with an associated *care plan*, i.e. weekly requests each of them demanding a specific ability or *skill* to be operated, and a set of operators also characterized by a specific skill, the problem asks to schedule the patient's request during the week, assign the operators to the patients by taking into account the compatibility between request and operator skills, and determine the tour each operator has to perform in every day of the week. Each tour must start at the operator's premises and come back to the operator's premises.

Specifically, the *care plan* associated with patient j specifies the type and, for each type, the number of visits required by j in the planning horizon W. Two types of visits are considered: *ordinary requests* (requiring an ability or *skill 1*), and *palliative requests* (requiring an ability or *skill 2*). Accordingly, it is assumed that each operator has skill 1 or skill 2, and that a hierarchical structure of the skills exists, such that an operator with skill 2 can work all the requests, whereas operators with skill 1 can work only requests of skill 1.

In the considered HCS problem the scheduling of the patient requests in W, the operator assignment and the routing decisions are offered through a new modelling device, called *pattern*. We assume in fact that the patient's requests are operated according to a set P of a priori given patterns. Specifically, for each pattern $p \in P$ we define $p(d) = 0$ if no service is offered at day d, while it is $p(d) = 1$ or $p(d) = 2$ if a visit of skill 1 or 2, respectively, is operated according to pattern p on day d. Only one visit per day can be operated. Several pattern generation approaches can be proposed to generate a subset P of patterns rather than considering the entire set of all possible patterns. The motivation to generate a good but limited set of patterns stems from the fact that the cardinality of P influences the size of the resulting optimization models. In this paper we refer to a flow pattern generation approach, which is based on the solution of an auxiliary network flow problem, and which proved to be very effective in selecting a small number of patterns of good quality, according to the results in [5].

Given the input data above, the studied HCS problem consists in assigning a pattern from P to each patient j, so scheduling the requests of j, expressed by his/her care plan, during the planning horizon (*care plan scheduling*), in assigning operators to each patient j, for each day where a request of j has been scheduled (*operator assignment*), and in determining the tour of each operator for each scheduled day (*routing decisions*). In addressing these three groups of decisions, the skill constraints, that is the compatibility between the skills associated with the patient's requests and the skills of the operators, have to be taken into account as well as other relevant Quality of Service requisites.

Observe that the Home Care context under investigation involves joint assignment, scheduling and routing decisions over W. In the state-of-the-art literature Home Care problems are usually solved in cascade: first the operators are assigned to the patients; second, the schedule of each operator is determined. Some optimization models that extend Vehicle Routing Problem (VRP) formulations have been proposed, but generally they deal with a daily planning horizon. To the best of our knowledge there are only three exceptions [2, 6, 10]. However, no exact approach is proposed there to solve the overall problem, but two-stage solution approaches are presented. In fact, in the literature tailored metaheuristic approaches are usually proposed to solve Home Care problems rather than exact approaches.

On the other hand, as outlined before, here the Home Care problem is solved by jointly addressing assignment, scheduling and routing decisions over W, by suitably generalizing the VRP, and specifically the Skill VRP [3, 4], from which it inherits the skill based structure.

New Integer Linear Programming (ILP) formulations have been proposed in [5] to formulate the stated HCS problem, by considering two balancing objective functions, and preliminary computational results have been reported in a deterministic setting. Let O denote the set of the operators available in W, while O_d be the subset of the operators available on day d, for each d in W. Let t_{ij} denote the traveling time from patient i to patient j along the link (i,j) of the logistics network, with A denoting the link set. Finally, let t'_j be the service time at patient j, and D_t indicate the workday length of operator t. Then the *maxmin* objective function can be defined as follows:

$$\max m$$

$$D_{td} = \sum_{(i,j)\in A} (t_{ij} + t'_j) \cdot x_{ij}^{td}, \; \forall d \in W, \forall t \in O_d$$

$$\frac{\sum_{d\in W} D_{td}}{|W| \cdot D_t} \geq m, \qquad \forall t \in O,$$

where $|W|$ is used to denote the width of the planning horizon W. The decision variables x_{ij}^{td} take value 1 if the operator t travels along (i,j) on day d, and 0 otherwise. Therefore, D_{td} represents the workload of operator t on day d, expressed as the sum of the service times and the traveling times on day d. m is an auxiliary variable which, in a standard way, is introduced to linearize the objective function. In fact, m estimates from below the utilization factor of each operator, expressed as the weekly workload of the operator over his/her maximum possible workload in W: by maximizing m, then the model maximizes the minimum operator utilization factor. In a similar way we define the alternative balancing objective function *minmax*: in such a case, we minimize the auxiliary variable m which, now, estimates from above the utilization factor of each operator.

The aim of this paper is to enhance the computational results in [5] by performing a deeper comparison of the criteria *maxmin* and *minmax*, also investigating their impact on efficiency indicators. In the simulation setting, the robustness of the HCS solutions returned by the two balancing criteria will be stressed under scenarios of service time and traveling time variability. This will be the subject of the next two sections.

1.3 The HCS Dataset

The real data used in this work have been provided by one of the largest Italian public medical care unit operating in the north of Italy, and they have been already used in [8]. The HCS instances are characterized by a geographical area which comprises five or eight municipalities where patients are located. In regards to the patients, we selected 2 weeks in the time period (2004–2008), i.e. a week in January 2006 (hereafter denoted by *January 2006*) and a week in April 2007 (hereafter denoted by *April 2007*), and we then selected subsets of patients with a care profile in that week. Specifically, for the January 2006 week, patients are 40 or 60, whereas for the April 2007 week, patients are 50 or 80. Patient's demand had been computed by looking at the scheduling implemented by the provider: specifically, for each skill, the requested number of visits in our instances is set equal to the real number of visits performed by operators of that particular skill. This choice is supported by the fact that the provider never used operators with skill different from the skill required by a visit. As already indicated, two skills are considered for operators and patient's requests: *ordinary*, corresponding to skill 1, and *palliative*, corresponding to skill 2. The geographical area under consideration is characterized by 11 operators and a subset of them is selected in our instances according to the number of patients: when the number of patients is 40, 4 operators are chosen; when the patients are 50 or 60, the number of operators is fixed to 5, while for 80 patients 6 operators are selected. In all the instances only one operator of skill 2 (with workday duration equal to 6 h) is selected, while the remaining operators are all characterized by a workday duration of 8 h and skill 1. For a given combination of number of municipalities, number of patients and number of operators, three instances are generated by randomly selecting the desired number of patients among the available patients. The instances are thus identified by a string reporting the following fields separated by a "-" character: the week, the number of municipalities, the number of patients, the number of operators, the instance identifier in the group (i.e. 0, 1 or 2) and the objective function used which can be *maxmin* or *minmax*. As an example "Jan06-5-40-4-0-maxmin" refers to a week in January 2006, 5 municipalities, 40 patients, 4 operators, instance number 0 and *maxmin* objective function. Summarizing, for each of the 2 weeks, 2 values for the number of municipalities are combined with 2 values for the number of patients and for each of these combinations 3 instances are generated, thus giving rise to 12 instances for each week. The resulting 24 instances are run with the 2 alternative objective functions.

In all the generated instances, the traveling times t_{ij} have been computed via Google Maps for the inter-municipalities distances, while they have been set equal to 3 min for the intra-municipalities distances, consistently with the provider indications. Furthermore, according to the medical care unit indications, the service time has been fixed to 30 min (i.e. $t'_j = 30$ min).

The 48 optimization runs have been performed on a AMD Opteron(tm) Dual Core Processor 246 (CPU MHz 1991.060). The solver is CPLEX 12.4 with a time limit of 12 h and a memory limit for the branch and bound tree of 1 GB. On the other hand for the simulation experiments, which are based on a discrete event simulation model integrated with the optimization models, VBA has been used as the integration environment, and Rockwell Arena13 as the simulation platform. Referring to the simulation length, we performed 30 simulations runs for each instance, which is a fairly large number [7]. In total we thus performed 1,410 simulation runs.

1.4 Computational Results

1.4.1 Optimization Results

Tables 1.1 and 1.2 report a comparison between the solutions obtained with the two alternative objective functions in terms of some QoS indicators: (1) the Coefficient of Variation CV, which measures the day-by-day variability of the operator utilization factor; (2) *WeeklyST*; (3) *WeeklyTT*; and (4) *WeeklyWT*. The last three indicators refer respectively to the service time, the travelling time, and the workload of the operator in W, over his/her maximum possible workload. Therefore, *WeeklyWT* represents the operator utilization factor. For each quality indicator the mean value computed over the operators and the width of the range between the maximum value of the indicator and the minimum value of the indicator are given respectively as "Mean" and "Range" columns. For the traveling time, the percentage of the total travel time with respect to the total working time is also given in column "All". For all the quality indicators except for CV, mean values are given as percentage.

To provide a more formal definition of CV, let $\overline{D}_t$ be the average daily workload of operator t, i.e. $\overline{D}_t = \sum_{d=1}^{|W|} D_{td}/|W|$ and denote with $S(D_t)$ the standard deviation of the daily workload of operator t. Then the Coefficient of Variation of operator t is defined as follows:

$$CV_t = \frac{S(D_t)}{\overline{D}_t}.$$

In Tables 1.1 and 1.2, the "Mean" and "Range" columns under the multicolumns CV refer, respectively, to the mean value of CV_t over t, and to the difference between the maximum and the minimum of such values over t.

The data in Tables 1.1 and 1.2 correspond to the best solutions given by the optimization solver within the given time limit; these solutions are very close to

Table 1.1 January 2006 – optimization results (values in % except for *CV*)

	CV		WeeklyST		WeeklyTT		WeeklyWT		
	Mean	Range	Mean	Range	Mean	Range	All	Mean	Range
Jan06-5-40-4-0-maxmin	1.06	0.34	18.75	2.50	7.80	2.28	7.87	26.55	0.26
Jan06-5-40-4-0-minmax	1.46	0.53	18.65	0.42	3.90	0.13	3.90	22.54	0.54
Jan06-5-40-4-1-maxmin	0.99	0.69	18.85	4.17	7.95	1.17	7.96	26.80	3.63
Jan06-5-40-4-1-minmax	1.17	1.14	18.85	5.42	6.91	2.46	6.89	25.76	6.79
Jan06-5-40-4-2-maxmin	1.06	0.63	17.92	5.42	7.70	0.92	7.72	25.61	4.63
Jan06-5-40-4-2-minmax	1.15	1.19	17.92	5.42	6.84	0.79	6.82	24.76	6.21
Jan06-5-60-5-0-maxmin	1.09	0.59	21.83	12.92	8.38	1.42	8.35	30.21	12.92
Jan06-5-60-5-0-minmax	1.39	1.07	21.83	17.92	8.84	3.71	8.88	30.68	19.79
Jan06-5-60-5-1-maxmin	1.15	0.88	20.75	18.75	7.78	1.63	7.73	28.53	19.13
Jan06-5-60-5-1-minmax	1.51	1.28	20.75	21.25	7.88	2.54	7.85	28.63	22.46
Jan06-5-60-5-2-maxmin	1.14	0.54	20.92	3.33	7.88	2.88	7.98	28.79	0.54
Jan06-5-60-5-2-minmax	1.37	0.36	20.92	3.33	6.64	3.29	6.76	27.56	0.21
Jan06-8-40-4-0-maxmin	0.97	0.61	20.42	2.92	10.34	2.94	10.42	30.75	0.07
Jan06-8-40-4-0-minmax	1.03	0.96	20.31	1.25	6.92	1.29	6.89	27.23	0.33
Jan06-8-40-4-1-maxmin	0.93	0.84	20.52	17.08	9.33	0.10	9.33	29.85	17.03
Jan06-8-40-4-1-minmax	1.06	0.74	20.52	27.08	8.47	7.17	8.46	28.99	31.96
Jan06-8-40-4-2-maxmin	1.13	0.39	19.06	8.75	7.79	3.42	7.92	26.85	5.33
Jan06-8-40-4-2-minmax	1.25	0.54	19.06	12.50	6.66	3.67	6.76	25.72	11.71
Jan06-8-60-5-0-maxmin	1.04	0.34	22.83	5.42	10.66	1.72	10.71	33.50	3.69
Jan06-8-60-5-0-minmax	1.12	0.87	22.83	6.67	9.11	4.46	9.13	31.94	8.68
Jan06-8-60-5-1-maxmin	1.21	0.44	21.25	11.25	8.64	1.90	8.70	29.89	9.39
Jan06-8-60-5-1-minmax	1.33	0.72	21.25	16.25	8.15	6.21	8.27	29.40	15.63
Jan06-8-60-5-2-maxmin	1.12	0.56	22.42	14.58	10.54	1.25	10.53	32.96	13.94
Jan06-8-60-5-2-minmax	1.10	1.10	22.42	22.08	9.51	7.25	9.50	31.92	25.82

the optimum ones except for instance Apr07-5-80-6-1. Furthermore, computational results on instance Apr07-8-80-6-0 are not reported since *minmax* failed to provide a feasible solution within the time limit.

The main achievements related to this deterministic scenario can be summarized as follows. By considering *WeeklyWT*, i.e. the operator utilization factor, its mean value for the *maxmin* criterion is usually greater than the mean value returned by the *minmax* criterion, although their difference is often small. On the other hand, the range of *WeeklyWT* for the *maxmin* solutions is almost always substantially smaller than the one returned by *minmax*. The same kind of relationship can be observed for the day-by-day variability of the operator utilization factor. For *CV*, this relationship is true also considering the mean values.

Concerning the two main components contributing to the operator workload it is possible to observe that, whereas the mean percentage service time is about the same for the two objective functions, the range of *WeeklyST* is often substantially smaller for the *maxmin* solutions. A similar trend, although in a weaker form, can be observed by considering the range of *WeeklyTT*. However, as expected, the total

Table 1.2 April 2007 – optimization results (values in % except for *CV*)

	CV		WeeklyST		WeeklyTT		WeeklyWT		
	Mean	Range	Mean	Range	Mean	Range	All	Mean	Range
Apr07-5-50-5-0-maxmin	0.53	0.61	25.42	5.83	8.99	4.51	9.09	34.41	1.32
Apr07-5-50-5-0-minmax	0.68	1.14	25.42	4.58	7.73	3.51	7.84	33.15	2.32
Apr07-5-50-5-1-maxmin	0.59	0.29	25.33	2.92	8.13	3.00	8.20	33.47	0.17
Apr07-5-50-5-1-minmax	0.78	1.05	25.33	2.92	4.81	2.00	4.81	30.14	2.88
Apr07-5-50-5-2-maxmin	0.53	0.46	28.25	10.00	9.69	3.47	9.77	37.94	6.53
Apr07-5-50-5-2-minmax	0.58	0.68	28.25	16.25	7.16	5.58	7.21	35.41	18.03
Apr07-5-80-6-0-maxmin	0.55	0.43	33.19	17.92	11.07	2.58	11.07	44.26	16.42
Apr07-5-80-6-0-minmax	0.89	1.10	33.19	25.42	9.22	5.29	9.21	42.41	28.74
Apr07-5-80-6-1-maxmin	0.48	0.37	33.82	4.17	13.01	4.26	13.13	46.83	0.37
Apr07-5-80-6-1-minmax	0.69	0.41	34.03	16.67	10.64	6.92	10.72	44.67	18.17
Apr07-5-80-6-2-maxmin	0.61	0.60	33.47	13.33	11.78	2.46	11.76	45.25	12.28
Apr07-5-80-6-2-minmax	0.87	1.53	33.47	27.08	9.51	9.00	9.53	42.98	32.19
Apr07-8-50-5-0-maxmin	0.55	0.32	27.42	8.33	11.58	1.67	11.61	39.00	6.67
Apr07-8-50-5-0-minmax	0.69	0.50	27.42	8.33	9.47	2.85	9.57	36.89	6.49
Apr07-8-50-5-1-maxmin	0.59	0.72	26.00	7.50	9.55	4.56	9.41	35.55	8.39
Apr07-8-50-5-1-minmax	0.87	1.20	26.00	10.00	8.12	3.63	8.08	34.12	13.03
Apr07-8-50-5-2-maxmin	0.79	0.34	21.33	2.50	8.19	2.54	8.21	29.53	0.08
Apr07-8-50-5-2-minmax	0.82	0.51	21.33	0.42	4.96	1.24	5.00	26.29	0.87
Apr07-8-80-6-1-maxmin	0.62	0.45	33.26	30.83	13.00	3.44	12.90	46.27	33.03
Apr07-8-80-6-1-minmax	0.70	0.58	33.40	55.42	11.02	15.79	11.01	44.43	64.81
Apr07-8-80-6-2-maxmin	0.64	0.62	31.39	27.08	12.55	6.72	12.33	43.94	32.56
Apr07-8-80-6-2-minmax	0.89	0.71	31.39	33.33	10.04	4.67	9.91	41.43	37.79

traveling time spent by the operators during the week is usually smaller in the solutions returned by the *minmax* criterion.

Therefore, as already outlined, in a deterministic setting and for the tested instances, *maxmin* appears to be preferable in balancing the operator percentage traveling time and the operator percentage service time, and therefore the operator utilization factor. This is true not only by looking at the overall planning horizon, but also at a daily level. Such stronger equity achievements are obtained for not too high a price in the increased average quality indicators. On the other hand, *minmax* always returns solutions with the smaller total travelled time for the operators. Therefore, it appears to be more suitable for the minimization of the operating costs, which are measured here in terms of travelling costs.

1.4.2 Simulation Results

The simulation model reproduces the activities of the operators for each day of the week. However, now the travel times t_{ij} and the service times t'_j are realization of random variables. Concerning their randomness, since the provider did not collect data relevant to service and travel times, we could neither use empirical distributions, nor fit theoretical distributions to real data. Hence, to randomize these times we have multiplied the standard values of the service and travel times by numbers randomly sampled from triangular distributions (called TRIA), according to the formulas below, where N denotes the set of the patients:

$$\tilde{t'}_j = t'_j \bullet TRIA(0.9, 1, 1.1),\ \forall j \in N$$
$$\tilde{t}_{ij} = t_{ij} \bullet TRIA(0.8, 1, 1.5),\ \forall (i, j) \in A.$$

The use of triangular distributions is coherent with the recommendations of [7], who suggest using finite distributions to avoid sampling excessively large and meaningless times. In addition, triangular distributions have been successfully applied by [1] to model travel times in a similar setting.

The simulation experiments have been conducted with a threefold aim:

- To verify whether the randomness of the service and travel times can lead to overtime, and therefore to additional costs for the provider; observe that overtime could happen especially in case of not evenly balanced workload among the operators, during the week and/or across the days;
- To understand if *maxmin* and *minmax* lead to solutions that significantly differ in terms of overtime;
- To determine how the randomness of travel and service times impacts on the quality indicators presented in Sect. 1.4.1.

Referring to the first point, for each of the 23 instances and for both *maxmin* and *minmax*, we have calculated the mean values and the standard errors, across the 30 replications, of the total weekly overtime. Hence, for each instance, we have performed a one-sided independent t-test to ascertain whether the mean value (M), across 30 replications, of the weekly overtime (*AllWeeklyOT*) could be considered significantly larger than zero. In other terms, we have tested the alternative hypothesis $H1 : M(AllWeeklyOT) > 0$ against the null hypothesis $H0 : M(AllWeeklyOT) = 0$. For all these tests we were not able to reject the null hypotheses at a significance level $\alpha = 0.05$. It led us to conclude that for all the instances the overtime is never significantly different from zero, regardless of the objective functions considered. Actually, even in the worst case (i.e. considering the maximum of the individual replication maxima values), the overtime is smaller than 4 min/week. This fact implies that both objective functions allow avoiding undesirable daily workload peaks that would lead to overtimes. It is worth to observe, however, that for the investigated instances the operator utilization factor is rather small (see Tables 1.1 and 1.2), and therefore overtimes may be difficult to emerge. Since the overtime is always very close to zero for the tested instances, the comparison between the overtimes associated with *maxmin* and *minmax* is not meaningful.

It does make sense, instead, to assess the impact that the time randomness may have on the system performance. We have thus calculated, for all the quality indicators in Sect. 1.4.1, the mean, the standard deviation and the 95 % two-sided

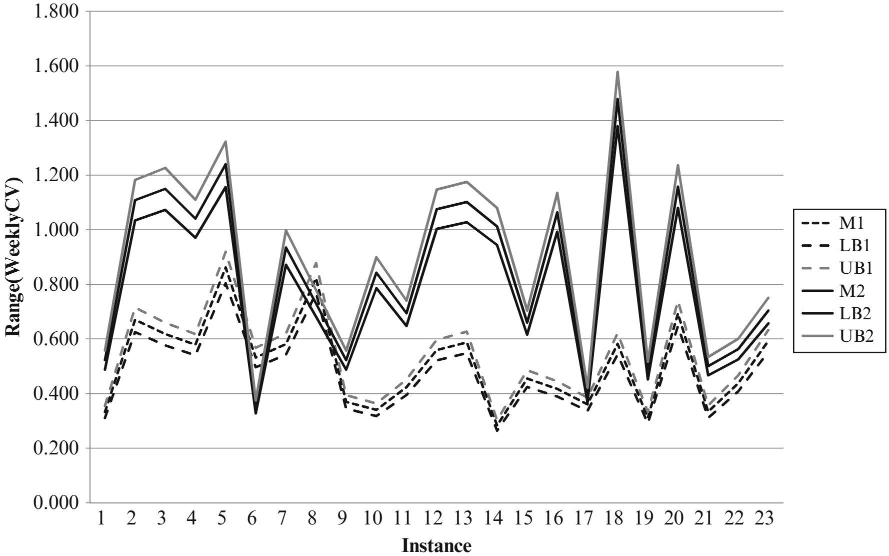

Fig. 1.1 Confidence intervals for the range of daily variability

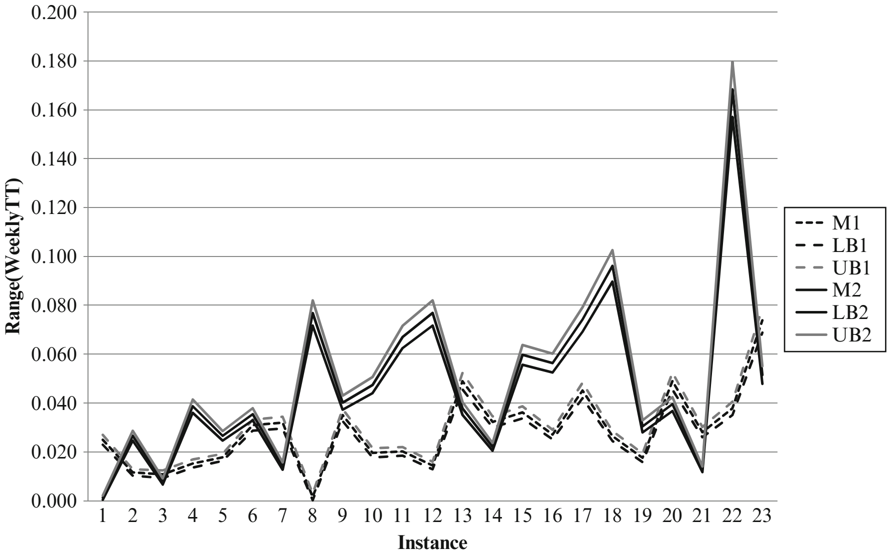

Fig. 1.2 Confidence intervals for the range of *weeklyTT*

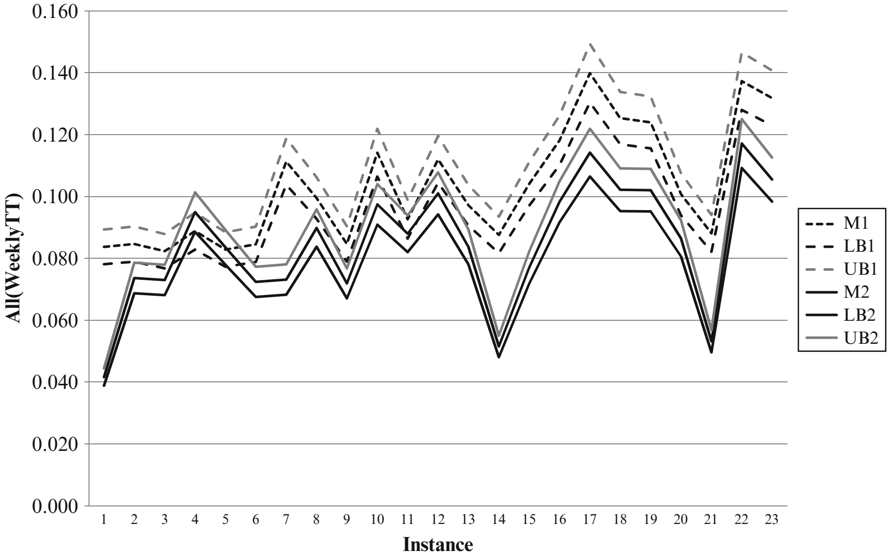

Fig. 1.3 Confidence intervals for the total percentage traveling time

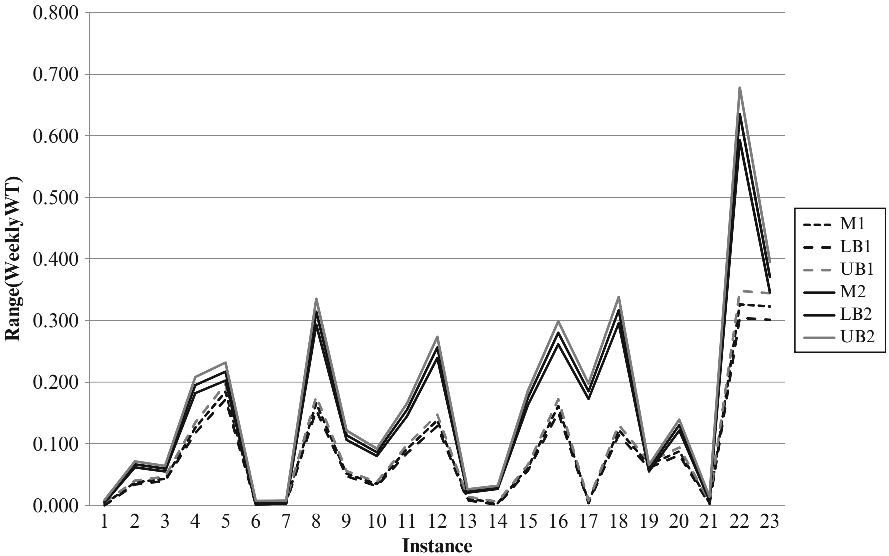

Fig. 1.4 Confidence intervals for the range of operator utilization factor

confidence intervals for the mean. Due to space constraints, hereafter we shall present only the results related to the range of *CV*, *weeklyTT* and *weeklyWT*, by adopting a graphical representation. A graph is provided also for *AllWeeklyTT*. Specifically, each graph refers to one indicator and presents, for each instance and for both the *maxmin* (1 – dashed lines) and *minmax* (2 – regular lines) objective functions: (i) the mean value of the indicator (M); and (ii) the upper (UB) and lower (LB) bound of the confidence intervals for the mean.

Concerning this last point of the simulation study, the main achievement is that, by observing the equity and the efficiency indicators of the system in a stochastic environment, and calculating the confidence intervals for each indicator, the same trend already observed in a deterministic setting appears to be confirmed also in the presence of randomness of travel and service times, as shown in the figures below.

1.5 Future Research

It is worth pointing out that the ones presented in this paper are preliminary results of a study that will be expanded in several ways, especially regarding the simulation experiments. Firstly, the simulation model will be used to assess the robustness of the HCS solutions returned by the optimization models, against the times randomness, in settings characterized by higher resource utilization levels. In these settings, in fact, deviations of the times from their expected values likely cause overtimes and can even prevent operators to ultimate their daily tours. Second, the simulation model will be used to test the output of optimization models developed in context where patients can be visited only in certain time windows. In these contexts, in fact, the times randomness in addition to lead to overtime, can prevent the operators to match their appointments. Finally, the simulation model will be used to study the performance of systems where patient-operator mismatches can occur, thereby determining the need to dynamically reschedule the tours of one or more operators.

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