Applied Computing and Intelligence
https://www.aimspress.com/journal/aci

Applied Computing and Intelligence
6(1): 79–88.
DOI: 10.3934/aci.2026005
Received: 20 March 2026
Revised: 06 May 2026
Accepted: 06 May 2026
Published: 11 May 2026

Research article

Social and health care services as a two-objective optimization problem

Pasi Fränti*

School of Computing, University of Eastern Finland, Joensuu, Finland

* **Correspondence:** Email: franti@cs.uef.fi.

Academic Editor: Chic-Cheng Hung

Abstract: Optimizing health care services can be considered as an optimization problem, but what exactly should we optimize? We present the problem as a two-objective optimization problem, minimizing cost and maximizing quality. The challenge is that, even if we had concrete quality indicators for all health care sectors, it is not clear how we would solve it. In this paper, we discuss alternative scenarios for solving the problem and the pitfalls we should avoid.

Keywords: health care services; optimization

1. Introduction

Optimizing health care services is a challenging problem that decision-makers struggle with. Jones and Jones [1] listed 16 items, including definable ones such as deciding on locations for major hospitals, as well as very abstract ones such as creating collaborative IQ.

In the literature, parts of health care services have been addressed as optimization problems. Examples include staff worktime scheduling, accessibility problems, optimizing health station locations, minimizing patient length of stay, and organizing home take care services. Each addresses an individual component by defining the goal via an explicit objective function, which is then optimized by an algorithm. They provide improved solutions to the parts they address. However, the other parts are strongly interrelated, and the existing approaches do not model the optimization of the health care system as an entity.

To model the health care system, the challenges are: (1) how to model the system, (2) identify its key components, (3) measure the success, and (4) how to optimize the overall system. In practice, we can optimize an existing system only by making small local changes, often with unpredictable consequences. Optimizing the overall system jointly can be very challenging.

In this paper, we define the optimization of the health care system via two higher-level objectives:

(1) Quality of care;
(2) Cost of the services.

The problem can then be addressed as a two-objective optimization problem.

The rest of the paper is organized as follows: In Section 2, we provide a brief review of the optimization problems addressed in the literature regarding the individual components of health care services. In Section 3, we propose our model and discuss how it could be optimized. In Section 4, we discuss an alternative approach that leaves the optimization to market forces, in contrast to algorithmic optimization, which reflects central government decisions.

2. Optimization of health care services

Scheduling is a classical optimization problem that is easier to identify and has therefore been widely studied in the literature. Abdalkareem et al. [2] identified several scheduling problems, including patient admission scheduling, nurse scheduling, operating room scheduling, and surgery scheduling, among others.

Accessibility is another common problem. It consists of two components: the location of the health station and the delay in getting treatment. The main benefit of accessibility is early diagnoses for preventive health care [3].

Optimizing health station locations has been widely addressed in the literature. A good clustering algorithm [4] (see also the web tool [5]) can yield accurate and stable clustering results, but the choice of objective criterion significantly affects the results. Logistically, better locations closer to patients were favored in [4], suggesting a single, downtown, centralized health station rather than those in suburban areas. At the same time, the algorithm suggested new health stations in smaller neighboring towns, see Figure 1.

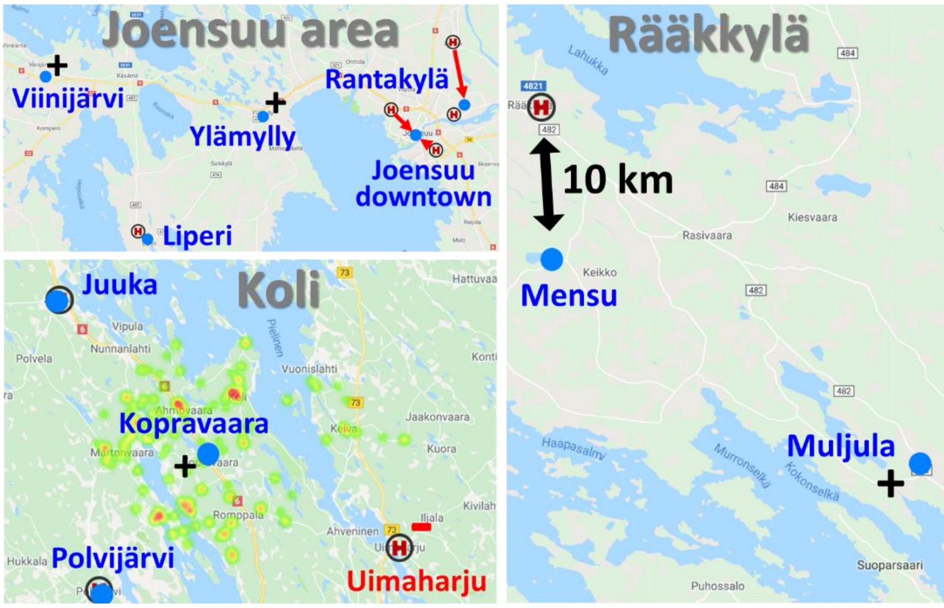
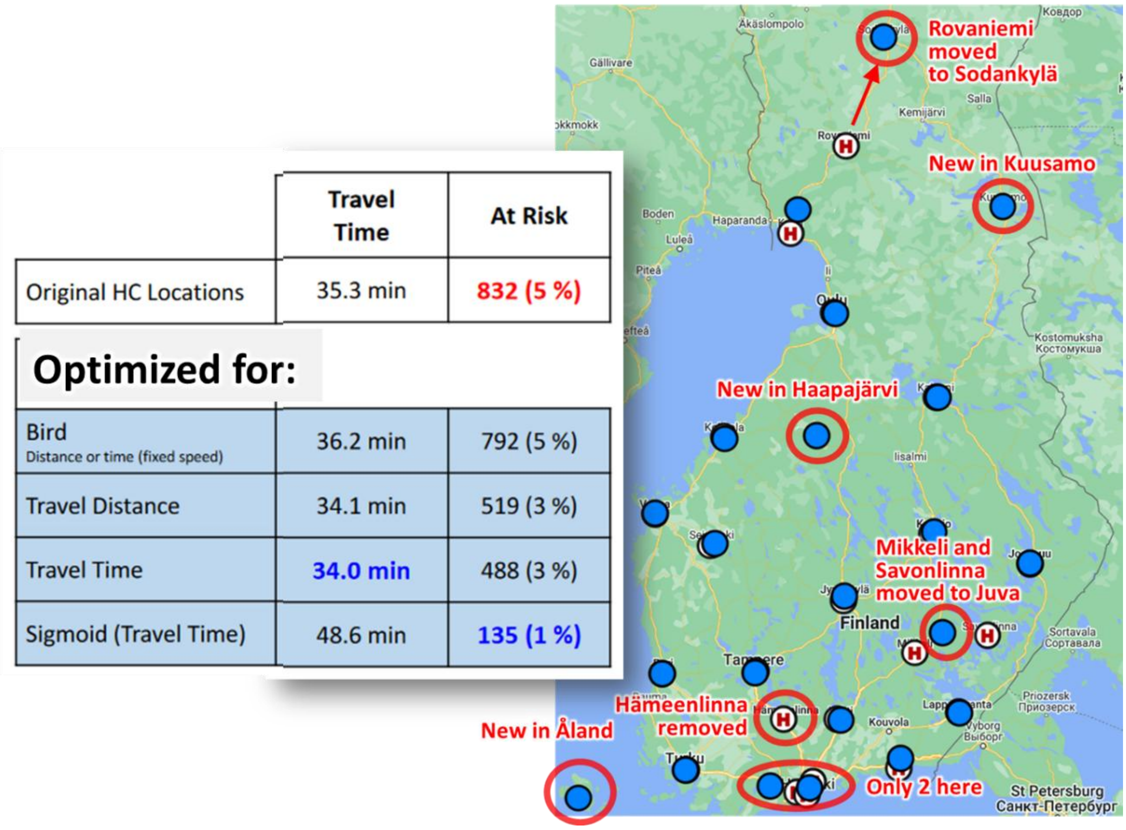


Figure 1. Clustering has been used to suggest theoretically better locations for the health centers [4].

Optimizing the location has also been modeled as a maximum coverage location problem by maximizing the number of patients within a given distance threshold [6]. However, it led to an increase in total travel time [7], as shown in Figure 2. It is therefore more sensible to minimize travel time directly.



	Travel Time	At Risk
Original HC Locations	35.3 min	832 (5 %)
Optimized for:		
Bird Distance or time (fixed speed)	36.2 min	792 (5 %)
Travel Distance	34.1 min	519 (3 %)
Travel Time	34.0 min	488 (3 %)
Sigmoid (Travel Time)	48.6 min	135 (1 %)

Figure 2. The locations of hospitals with percutaneous coronary intervention (PCI) capability were optimized by maximizing the number of patients within 45 minutes door-to-door reach in [7]. Maximizing coverage reduced the number of patients at risk from 5% to 1%, but at the cost of increasing travel time from 35 min to 48 min.

The locations cannot be determined solely based on emergency needs. Physicians working in the smaller units might not have enough tasks for their specialization. It would be better to optimize the overall services. In addition to the location, we should also consider work shift scheduling and the matching of the needs and the services provided by each unit:

(1) Specializations of the physicians available;

(2) Needs for the service at the place.

Not every unit needs to have all services available. The services offered at each health station can differ, see Figure 3. This leads to a complex overall optimization problem that includes facility locations and work-shift scheduling. Analyzing the co-occurrence of diseases [8] might help identify related specializations, as shown in Figure 4.

To optimize overall health care services, the key challenge is determining which objective function to optimize.

Eriskin et al. [9] proposed three objectives during the COVID-19 pandemic: the number of rejected patients, travel distance, and installation cost of pandemic hospitals. Total cost has been another common objective. Xiang et al. [10] minimize total cost and maximize total preference satisfaction, Goodarzian et al. [11] minimize total cost and service time, and Fu et al. [12] minimize total cost and delay of treatment. Decerle et al. [13] aimed to balance the workload by minimizing the maximum difference in working time among caregivers.

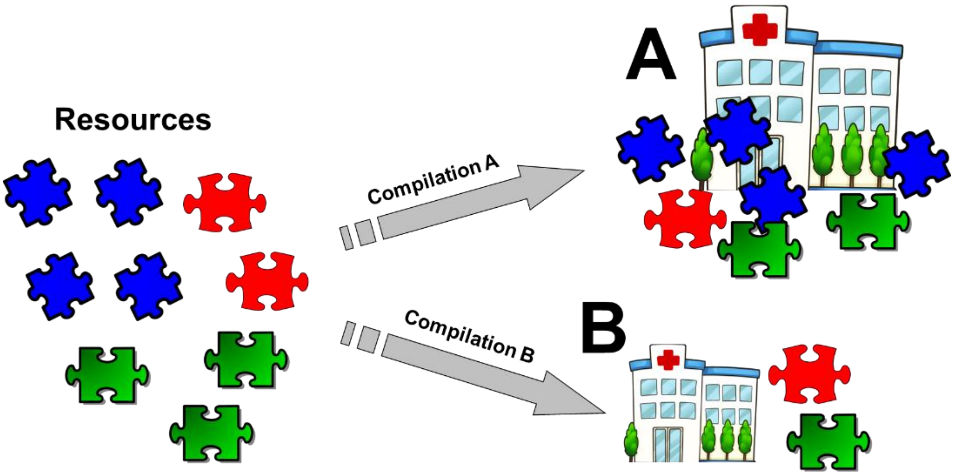


Figure 3. Instead of the facility allocation problem, we should consider the combination of the health care services offered in each health center. The optimization should allow a dynamic combination of the overall services.

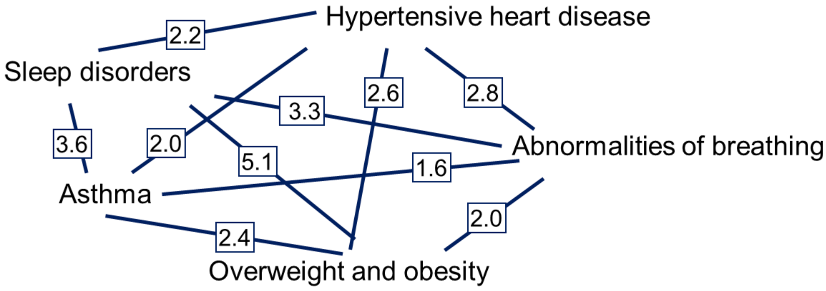


Figure 4. Analyzing disease co-occurrences can help optimize health care. Many correlations are well-known, but new connections between diseases can be found [8].

The problem has also been addressed via agent-based simulation [14]. Cabrera et al. [15] used simulation to optimize healthcare emergency departments (EDs) based on minimum patient length of stay (LOS) as the evaluation metric. Ordu et al. [16] proposed combining forecasting, optimization, and simulation.

Once the problem has been defined, it can be solved by a suitable optimization algorithm, of which evolutionary computing is the most common. The problem can also be simplified by unifying multiple objectives into a single objective using a weighted-sum approach.

The health care station is not the only component of the overall service. Part of the service includes home care, where nurses and helpers visit the homes of selected patients who can manage at home but need regular help, see Figure 5.

Optimizing these services can be modeled as a traveling salesperson or vehicle routing problem, but in practice, it is much more complex. We call it the touring nurse problem, which involves jointly optimizing worker-to-task allocation, routing, and task scheduling. For example, if a diabetes patient needs an injection, we must send a qualified nurse within the specified time window, as shown in Figure 6.

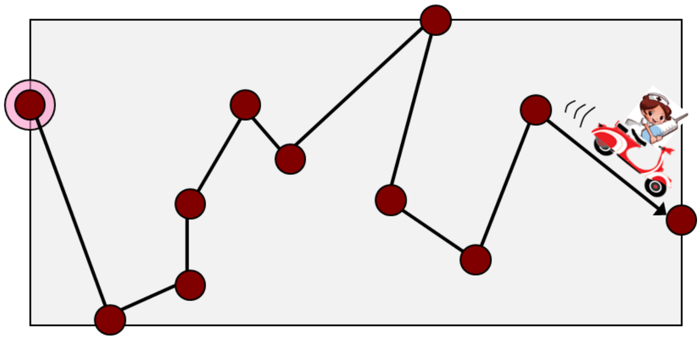


Figure 5. Home care services involve a routing problem where the service provider must visit customers within a given time window.

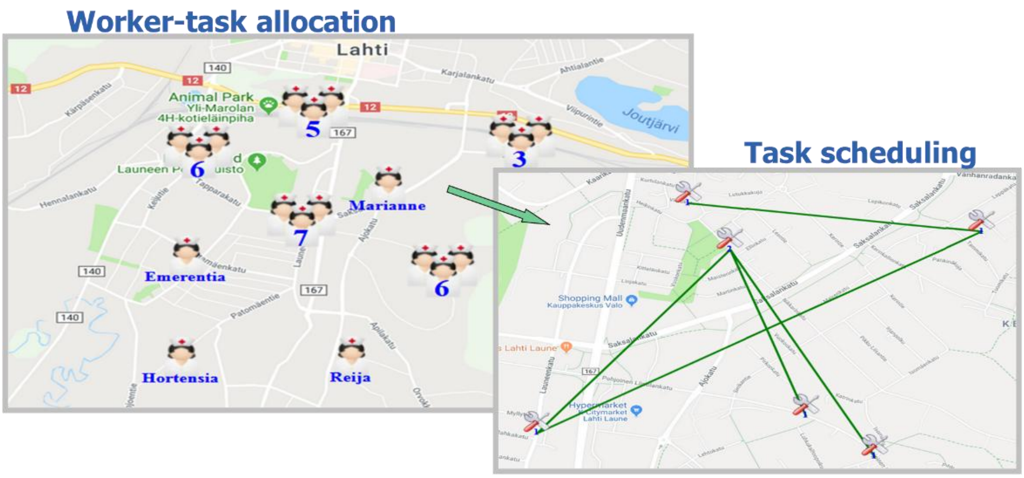


Figure 6. Home take care services include both work scheduling and route allocation problems.

3. Two-objective optimization

The individual problems discussed in the previous section are important components in the health care system. However, they are interrelated. Improving one would evidently have a consequence for the others. One cannot solve one without considering the effect on others.

To address this complexity, we define two higher-level objectives: *quality* and *cost*. These are the two main criteria that matter to people and decision makers. Following this view, we next define health care optimization as a two-objective optimization problem with these objectives:

(1) Quality of care;
(2) Cost of the services.

The model's benefit is its simplicity. If we can measure the objectives, we can analyze the results and consequences of any system. A disadvantage is that the quality-of-care objective is very abstract, and defining concrete measures can be hard. The cost of services is easier to estimate, even if the exact prediction is not possible.

The early discussion of quality of care lacked physician participation, and many reacted with anger, skepticism, or indifference [17]. Early proposals, such as those by Campbell et al. [18], suggested rather abstract concepts, such as the ability to access effective care, to maximize health benefits.

The Agency for Healthcare Research and Quality (AHRQ) [19] has also summarized the quality of care into six domains: safety, effectiveness, patient-centered, timely, efficient, and equitable. For example, safety means that the care that is intended to help the patient should not cause harm. These are still rather abstract concepts and would require concrete indicators to evaluate their quality. Some practical measures can be found on their web page.

It might be tempting to convert the two-objective problem into a single-objective problem. However, unifying quality of care and cost at the same scale would require magically converting quality of care into euros. For example, how many euros would one premature death due to mistreatment or delay be worth? It involves ethical choices and political decisions, which are very hard for any decision-maker.

Instead of unifying the objectives, we next discuss what the two-parameter optimization would mean in practice.

The typical approach in multi-objective optimization is to create a set of alternative solutions. The choice of practice is then left to the decision-maker, based on how much they value quality and how much they value cost. There might also be a strict upper limit for the cost that cannot be exceeded, and the optimization would then be to find the best solution in terms of quality within the given budget.

Figure 7 illustrates the set of solutions created by some optimization algorithm (typically an evolutionary algorithm). The example has two objectives: the quality of the service and the cost savings compared to current services if the new solution were implemented.

A solution is called Pareto-optimal if it is better than another solution by at least one objective. Suppose the blue solution has a quality of 4.3 according to some hypothetical indicator. This value is better in quality than the other solutions to the right along the Pareto front. It also has more savings than the other solutions to the left. The Pareto-optimal solutions constitute the Pareto front, which is represented by the curve in Figure 7.

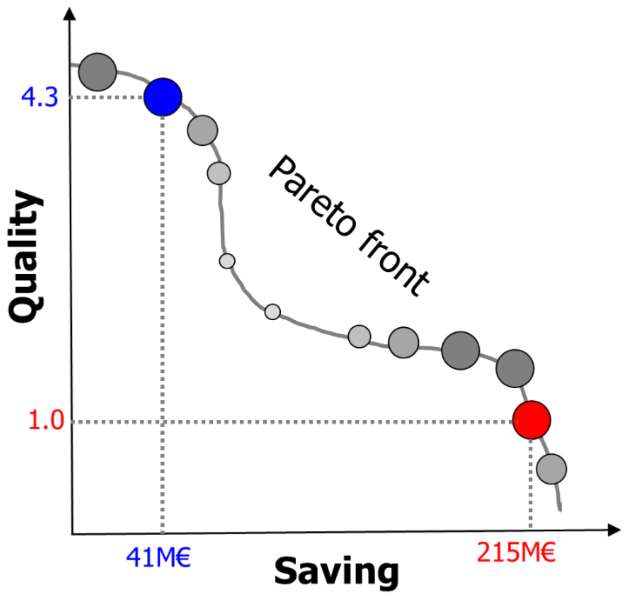


Figure 7. Two Pareto-optimal solutions. The blue one has a high quality indicator of 4.3, but leads to only 41 M€ savings. The red one has a low quality indicator of 1.0 but leads to large 215 M€ savings.

The set of solutions can be stored and used later. If the budget increases, we can change to a solution higher along the Pareto front, leading to higher quality. Or vice versa, a budget cut may force us to change the solution to a lower one along the Pareto front, leading to lower costs and quality; at least in theory.

In practice, two neighboring solutions in the Pareto-optimal fronts can be very different. This is especially true if an evolutionary algorithm, such as a genetic algorithm, was used in the optimization. We may then need to extend the set of solutions to include additional sub-optimal solutions that are easier to reach via small changes to the current solution, see Figure 8.

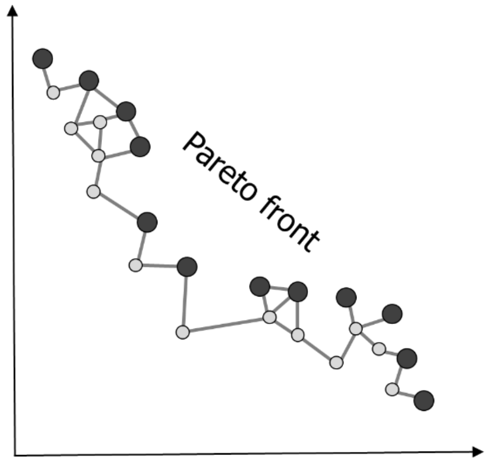


Figure 8. Moving between solutions along the Pareto front may require storing sub-optimal solutions that differ only slightly from their neighbors. The links indicate solutions that are neighbors in this regard.

4. Optimizing by the market forces

Optimization is complex and very difficult to solve algorithmically with any meaningful objective functions. We simplified the optimization to only two objectives, which could be solved if reliable functions were defined.

Algorithmic optimization aligns well with centralized, government-controlled operations, but privatizing the health care sector has been a long-standing trend, with exactly this in mind. An alternative approach is therefore to rely on market forces. It relates to evolutionary optimization, but without the explicit use of objective functions. Instead, it relies on supply and demand. The idea is that demand creates supply, and quality and cost are indirectly controlled by customer behavior, which selects services that are either cheaper or of better quality. The customer evaluates and decides how much to value price over quality. The fittest suppliers survive. In this approach, decision-makers would rely more on simulations than on optimization algorithms.

But would it work in practice? Are market forces fit for optimizing health care services as well? Two extreme scenarios are shown in Figure 9. Minimizing cost is trivial: no services, no cost, but the quality of care would become nonexistent. Maximizing the quality of care is also possible by establishing health stations everywhere, but this would be unaffordable due to the high cost. Narratives of populist politicians tend to be bipolarized and focus on such extremes.

The idea behind privatization is to let market forces optimize the price and quality of services. In markets, there are supply (sellers) and demand (buyers). In the health care system, the patient is the buyer (customer), and the service provider is the seller. Customers will buy the products they consider worth the price. Expensive and poor-quality products will get out of the market as customers stop buying them. The competition will create better services, leading to higher quality of the health care services at a lower cost. That is, if the market forces work as they are supposed to.

However, the health care market does not work exactly like that. It is more complex. In addition to the buyer and seller, there is a middleman (the government) that collects funds from citizens and pays most of the costs to the service providers, see Figure 10. This triangle leads to different behavior and side effects, which we are less aware of.

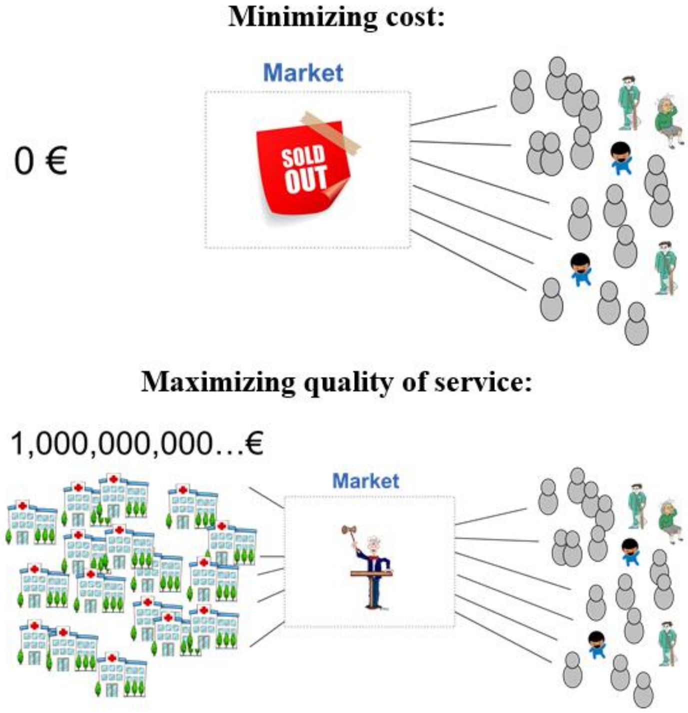


Figure 9. Two extreme scenarios for a market-driven approach. Minimizing cost leads to no services, whereas maximizing quality is unaffordable.

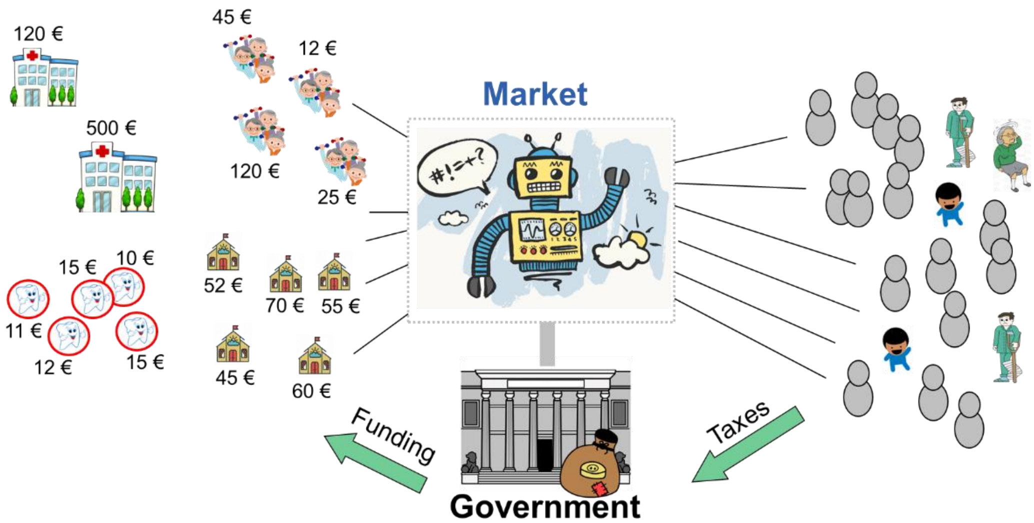


Figure 10. The marketplace for health care services involves three parties: the service providers (sellers), the patients (buyers), and the middleman (the government), which pays (most of) the bills.

5. Conclusions

We have presented the optimization of health care services as a two-objective optimization problem. If the quality of care can be reliably measured, we can derive a set of Pareto-optimal solutions using a good optimization algorithm. An alternative strategy would be to let market forces optimize. This requires modeling the system with the middleman (government). It leads to potentially interesting research questions that could be addressed through simulations.

Use of AI tools declaration

The author declares he has not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

Pasi Fränti is an Editor-in-Chief for Applied Computing and Intelligence and was not involved in the editorial review and the decision to publish this article.

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