Central European Journal of Operations Research (2020) 28:1091–1121
https://doi.org/10.1007/s10100-019-00621-4

A model for locating preventive health care facilities

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Published online: 30 April 2019

Abstract

In this paper, we focus on the problem of locating preventive health care (PHC) facilities. The most important factors that promote participation rates in PHC programs include the establishment of an appropriate infrastructure and the provision of a satisfactory quality of care. For this purpose, we develop a strategic level multi-objective mixed integer linear programming model for locating PHC facilities to ensure maximum participation and provide timely service to potential clients. We, then, apply the model to a case study of locating Cancer Early Diagnosis, Screening and Training Centers in Istanbul, Turkey and solve it considering the forecasted population of each district in Istanbul for the next 15 years. We also perform a sensitivity analysis to quantify the effect of different weighting strategies on the value of each term in the objective function.

Keywords Facility location · Preventive health care · Cancer screening · Goal programming

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1 Introduction

The most efficient and effective way to prevent disease and increase public health is through preventive health care (PHC). PHC services aim to minimize the risk of a serious illness and increase the probability of early diagnosis of serious health conditions. In addition to reducing cancer morbidity and mortality, PHC contributes to the quality of life during treatment by reducing the need for tough treatment methods such as chemotherapy, surgery or radiation therapy. Flu shots, blood tests, antismoking counseling and cancer screening programs are among the most well-known PHC services. In developed and developing countries, governments are exerting considerable effort to accomplish a high level of PHC. One of the required steps to this end is to ensure maximum participation by creating the right infrastructure. According to Baron et al. (2008a)'s study, limited resources and lack of appropriate infrastructure may be considered primary barriers to increasing rate of participation in cancer screening programs. While employed in a range of healthcare areas, PHC services are most frequently used for early diagnosis of cancer.

Cancer, the second leading cause of death after cardiovascular diseases, is a major global public health concern. An estimated 14 million people are diagnosed with cancer annually, and cancer causes 8 million deaths annually. Lung and breast cancers are the most commonly diagnosed cancer types for men and women, respectively, with the highest mortality rates (Torre et al. 2015). Figure 1 depicts the estimated number of cancer cases worldwide in 2012.

The most important cancer control strategy in the twenty-first century is the prevention and early detection of cancer. Early detection involves two basic strategies: early

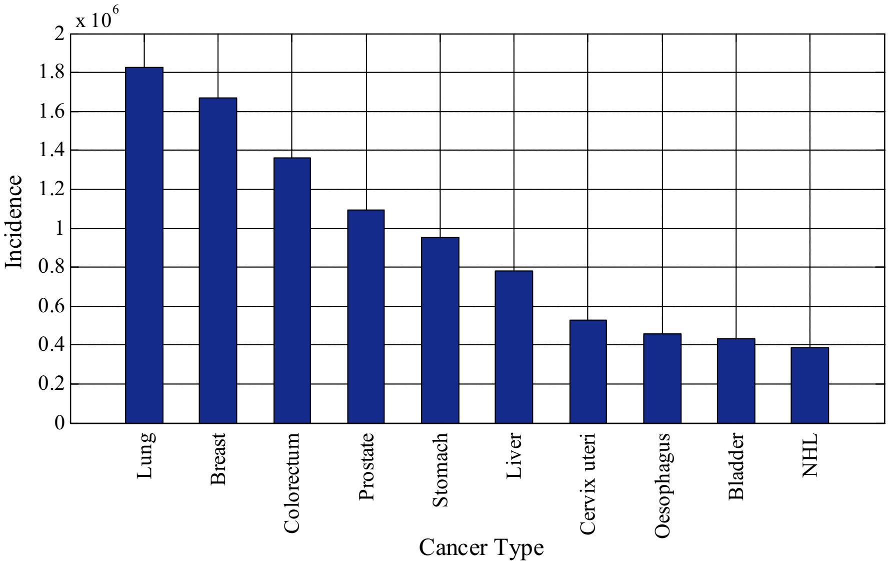

Fig. 1 Estimated number of incident cases, both sexes, worldwide (top 10 cancer sites) in 2012. Data from IARC (2017)

diagnosis and screening. Screening denotes a systematic application of a test for a specific cancer type in a population, displaying no symptoms of illness (asymptomatic) in order to diagnose cancer [World Health Organization (WHO) 2014].

Obviously, the treatment and recovery from illness are easier and less costly when cancer is diagnosed at an earlier phase than a later phase. Different kinds of cancer screening programs, e.g. Breast Cancer (BC) screening, Cervical Cancer (CC) screening, and Colorectal Cancer (CRC) screening, are applied to detect cancer cases even before symptoms arise (Keskinkılıc et al. 2016).

Owing to screening programs and improved treatment methods, mortality caused by BC has declined in recent years in the United States. Mortality rates decreased by 2.3% each year between 1990 and 2003, according to National Cancer Institute's Surveillance Epidemiology and End Results (SEER) program (Ries et al. 2008). As a result of a screening program implemented in Canada, BC mortality rate was reduced by 40% in women aged more than 40 years (Ozmen and Anderson 2008).

There are two types of screenings: *opportunistic* and *organized*. Organized screening is distinguished from opportunistic screening by the way invitations to screening are extended. In organized screening, invitations are extended by centralized registers. In opportunistic screening, however, due to the lack of central registers, invitations to screening depend on the individual's decision or encounters with health care providers (Miles et al. 2004). Opportunistic screening is the unsystematic application of screening tests in routine health services (WHO 2007).

According to WHO (2007)'s guide for early detection of cancer and diseases,

- An effective screening program should be applied to over 70% of the population at risk;
- An appropriate infrastructure has to be in place to offer the screening service periodically;
- Compared with opportunistic or unorganized screening, "organized screening" is more cost-effective; and
- Since organized screening avoids over-treatment and over-screening, it is less harmful to human health than opportunistic screening.

After the Turkish Ministry of Health released cancer screening guidelines in July 2004, Cancer Early Diagnosis, Screening and Training Centers (CEDSTCs) have been established in Turkey (Ozmen et al. 2016). With CEDSTCs, the aim is to execute population-based screening programs for cancers recommended by the WHO. Currently, CEDSTCs provide screening services for breast, cervical and colorectal cancers (Tuncer and Ozgul 2011). However, the quantity and quality of these centers in Turkey are not capable of providing a sufficient level of PHC service to the at-risk population. Although it has been more than 10 years since the initiation of cancer screening programs, the screening rate of breast cancer is still very low, and are mostly performed on an opportunistic basis rather than an organized one (Ozmen et al. 2016). Coverage of screening programs in 2016 was about 35%, 20%, and 25% for BC, CC, and CRC, respectively (Keskinkılıc et al. 2016). Currently, two CEDSTCs provide organized screening services for a population of over 3,000,000 people in the Asian Side of Istanbul, Turkey (KETEM 2017).

In this paper, we focus on the problem of locating CEDSTCs in the Asian Side of Istanbul for an organized population-based screening program. Istanbul is the most crowded city in Turkey hosting a population of 14.8 million. A metropolis bridging the East with the West, Istanbul consists of two sides divided by Bosporus, one of which is the Asian Side. As of 2016, the Asian Side of Istanbul consists of 359 districts with a population of 5,200,460. Currently, there exist six CEDSTCs in Istanbul and only two of them are located in the Asian side of the city.

The target risk groups to be screened in organized screening programs vary according to health policies of the countries. For example; women between the ages of 40–50 in the UK, and 50–70 in Italy and the Netherlands are considered a member of breast cancer risk group (Anttila et al. 2017). Turkish National Cancer Screening Standards have been set by Cancer Control Department, Turkish Ministry of Health (TMoH). The department identified risk groups for breast, cervical and colorectal cancer as "women in 40–69 age group", "women in 30–65 age group" and "men/women in 50–70 age groups" respectively (Keskinkılıc et al. 2016).

The aim of this study is to determine the optimal configuration of CEDSTCs in Asian Side of Istanbul to ensure maximum participation as defined by a pre-determined maximum acceptable waiting time (for service at the facility) and a total setup budget. For this purpose, we developed a multi-objective mixed integer linear program (mo-MILP) model with three objectives. The following properties and challenges have been incorporated into our study on the location challenge for Asian Side CEDSTCs.

- *Multiple objectives* Given a set of population centers, and a set of alternative facility locations in the Asian Side, we aim to develop CEDSTCs configuration which minimizes deviation (1) between maximum possible participation and realized participation, (2) from exceeding the maximum acceptable waiting time, and (3) from exceeding the total setup budget.
- *Multiple target groups and screening programs* CEDSTCs provide screening services for breast, cervical and colorectal cancers. Considering CEDSTCs' multi-purpose employment, we designed our mo-MILP formulation with a capability of meeting multiple types of demand. Additional information is provided in Sect. 3.2.
- *Accessibility* The accessibility of PHC facilities is the most critical factor that influences the tendency of people to participate in PHC screening programs (Verter and Zhang 2015). We used *travel distance* alone as a proxy for the accessibility of a CEDSTC in our model. Additional information on accessibility of the facilities is provided in Sect. 3.3.
- *Gradual coverage* The concept of "location coverage problems" is highly relevant to accessibility concept in the context of PHC location problems. This study replaces the "cover all within a predetermined range and nothing beyond" approach with the gradual cover concept. We used a gradual coverage decay function to implement reduction in accessibility of facilities. Additional information is provided in Sect. 3.4.
- *Congestion* An organized cancer screening program is a follow-up procedure. When limited capacity causes people have to wait for a long time to receive the services, their willingness to participate in subsequent screening programs may diminish significantly. In this study, we determined a maximum acceptable waiting time for

each screening program and minimized the deviations exceeding this threshold to keep congestion under control. Additional information is provided in Sect. 3.5.
- *User choice environment* PHC is a user-choice environment model regarding the allocation of clients to facilities. In our model, we employed deterministic-choice behavior also known as optimal-choice model. In optimal-choice models, fully-informed clients prefer services of the facility with the highest attractiveness (Verter and Zhang 2015). In our model, we assume that each participating individual seeks services of the closest facility considering travel distance as a proxy for the accessibility.
- *Accreditation* In PHC, each facility needs to have a minimum number of clients to retain the accreditation to ensure sufficient quality of care. Although Turkey currently does not impose accreditation criteria for CEDSTCs, we set an accreditation limit taking into account health literature and expert opinions. Additional information is provided in Sect. 3.6.
- *Strategic planning* High costs involving property, expropriation and modern medical equipment make it a long-term strategy to address PHC location problems. Therefore, locating PHC facilities optimally is a strategic challenge for decision makers. The mo-MILP is solved in light of the population growth over the next 15 years that we have calculated to determine optimum CEDSTCs locations to meet the needs. Additional information is provided in Sect. 3.7.

This study contributes to the literature by incorporating the multi-objective, multi-type features of the problem. Although explored separately to some degree, to the best of our knowledge, no existing paper studied the case of PHC network design by considering the issues: (1) PHC facilities with multiple screening capabilities, (2) multiple risk groups, (3) multiple objectives, (4) gradual coverage, (5) congestion, (6) user choice environment, (7) accreditation requirements, and (8) long-term (strategic level) planning, together. Hence, this paper presents a model for such a problem observed in the Asian Side of Istanbul.

The outline of the paper is as follows: It proceeds with a literature review of relevant publications in Sect. 2. It is followed by the assumptions and preliminaries for our mo-MILP in Sect. 3. The mathematical model of the paper is presented in Sect. 4. Numerical results, sensitivity analysis, and discussion concerning the Asian Side of Istanbul are scrutinized in Sect. 5, and finally, conclusions are provided in Sect. 6.

2 Related work

Academic output on determining location of health care facilities began in early 60 s. Hakimi (1964) introduced health care network design into location literature by representing the problem of location on a network for determining the location of police stations and hospitals. There have been many studies on healthcare network design since then. For more information on health care location problems, we refer the interested readers to Daskin and Dean (2004) and Afshari and Peng (2014). They listed review papers, focused on some specific types of health care location problems. Additionally, they present a general guideline with a review for readers to select and apply the methods for health care facility location. Their study provides an updated and comprehensive overview of methods and criteria to locate healthcare facilities.

The problem of locating PHC facilities is a relatively recent field of study in location science literature. Verter and Lapierre (2002)'s paper can be considered the first of its kind published in this area. In their study, a mathematical model is designed to locate PHC facilities that maximize the level of participation to a cancer screening program. They specified a minimum workload limit for facilities to retain accreditation to ensure a sufficient quality of care. Additionally, the results of case studies on Georgia, USA, and Montreal, Canada are reported. Travel distance or travel time to a facility is considered as the only proxy to represent the accessibility of a facility. In their model, partial coverage is adopted to represent reduction in accessibility by the increase of the travel distance or time. However, this model only represents clients' access to facilities on the basis of travel distance or time. The effects of service being offered by facilities have not been factored into their study. In other words, the effects of congestion caused by queues in facilities have not been incorporated into the model.

In another study, Zhang et al. (2009) incorporated congestion into Verter and Lapierre (2002)'s participation modeling by using an $M/M/1$ queue method. They designed a nonlinear programming model so as to maximize the level of participation in a PHC network. Expected total time that comprises the travel, waiting, and service time is used as a proxy for accessibility of a PHC facility. The assumption of each client patronizing the facility with minimum travel distance or time is replaced with patronizing minimum expected total time. Expected total time is chosen instead of total traveling distance or time as the main factor affecting the probability of participation. Since their model was highly nonlinear, they developed four different heuristic solution methods to determine effective locations of PHC facilities. A case study concerning the locations of breast cancer screening centers in Montreal, Canada, is reported.

Afterwards, Zhang et al. (2010) presented a bi-level nonlinear optimization model for similar location problems. They constructed their model as an upper level and a lower level problem. The lower level problem determines the allocation of clients to PHC facilities and upper level problem is designed as a facility location and capacity allocation problem. They presented gradient projection method for the solution of lower level problem and a tabu search procedure for the upper level problem. An illustrative case study in Montreal, Canada, for determining the optimal location of breast cancer screening centers is presented as an application of their model.

Instead of deterministic choice models mentioned above, Gu et al. (2010) proposed a probabilistic choice model for the design of PHC facility networks. They presented a bi-objective model so as to maximize the level of participation to a PHC service. A new measure of accessibility is employed by combining the two-step floating catchment area method, distance factor, and the Huff-based competitive model. They presented an efficient interchange algorithm to determine optimal location of PHC facilities.

In a more recent paper, Zhang et al. (2012) studied the effects of client choice behavior in PHC sector. They formulated two PHC models, namely "optimal-choice" and "probabilistic-choice" models to model clients' choice behavior. In probabilistic-choice model, clients may seek the service of each facility with a certain probability that changes with the attractiveness of facilities. On the contrary, in optimal-choice model, clients patronize only the most attractive facility. In their paper, the proximity to a PHC facility is assumed as the only measure of attractiveness. A genetic algorithm is provided to solve the PHC problem. The two PHC models are used for an illustrative case, the design of a network of breast cancer screening centers in Montreal, to analyze the impact of client choice behavior.

Hosking et al. (2013) proposed a discrete-event simulation model of the CRC screening system in North Carolina, USA. This model is used to analyze the effects of various interventions such as "increasing the number of facilities" on target population group. Aboolian et al. (2015) focused on designing public sector facility networks to determine the optimal number, locations and capacities of facilities so as to maximize the participation to public services. They assumed the expected total time (travel, waiting and service time) at a facility constitutes an efficient proxy for accessibility. They brought out a generic model combining the congestion at the facilities with the customer choice environment that underlies most of the services offered by the public sector. A ε-optimal algorithm targeting the arising nonlinear integer program is presented through a realistic example based on the hospital network of Toronto.

Davari et al. (2015) formulated two models, namely "fuzzy goal programming model" and "fuzzy chance constrained optimization model", designed for PHC network problems. The fuzzy goal programming model is a bi-objective model, limited by budget constraints. The objectives are to maximize participation and equity. This model is modified by fuzzy chance constrained optimization model which represents attractiveness with fuzzy triangular numbers and treats budget constraint as a soft constraint. Both methodologies are used for an illustrative case study in Istanbul, Turkey. In another study, Vidyarthi and Kuzgunkaya (2015), study the impact of directed choice on the PHC facility design under congestion. The authors develop a model which determines the location and the size of PHC facilities with the objective of travel time and congestion minimization. Davari et al. (2016) presented a mixed-integer programming model for designing PHC networks subject to budget constraints and equity considerations. They developed a skewed variable neighborhood search algorithm to solve their proposed model.

The interested reader can also refer to Güneş and Nickel (2015) and Ahmadi-Javid et al. (2017) for a detailed review of healthcare facility location problems. Güneş and Nickel (2015) give an overview of location problems in the contexts of public facility locations, ambulance location and relocation problems, and hospital layout problems. Ahmadi-Javid et al. (2017) categorizes the problems with respect to consideration of uncertainty, multi-period setting, objective function type, modeling and solution approaches, etc.

In this study, we adopted a goal programming approach to solve our multi-objective model. Goal programming, introduced by Charnes and Cooper (1961), is a mathematical programming technique used to deal with multiple (and generally conflicting) objectives. In practice, goal programming uses two different solution approaches, i.e. the weights method, and preemptive method. In the preemptive method, goals are satisfied with an order constructed by their relative importance. This technique is implemented when the importance level of goals is significantly different and a strict prioritization of the goals is possible. In this paper, we employ the former, which aims to minimize the total weighted sum of deviations from the target value of each objective. It should also be noted that, the method minimizes negative deviations from benefit type goals and positive deviations from cost type goals. For details of goal programming, the reader can refer to Charnes and Cooper (1977), Jones and Tamiz (2010) and Schniederjans (2012). Additionally, a summary of goal programming steps is given in Karatas et al. (2018).

All of the discussed relevant works in the literature analyze the problem considering the issues separately. As stated before, we bring several considerations together in this study.

3 Assumptions and preliminaries

PHC facilities (CEDSTCs) in our mo-MILP are modeled as simple $M/M/1$ queuing systems for each screening service (breast, cervical and colorectal cancers). Assumptions and preliminaries considering our model are summarized in the following sections.

3.1 Key assumptions

Our problem carries the basic properties of a stochastic location model with congestion (Berman and Krass 2015). Thus, we make the following key assumptions:

- Each target client group (breast, cervical and colorectal cancer at-risk population) to be screened generates demands in accordance with Poisson distribution.
- Service times at CEDSTCs are exponentially distributed. It should be noted that other distributions, e.g. Erlang-k, Gamma, can also be employed to model service times.
- CEDSTCs are modeled as immobile servers of limited capacity with $M/M/1$ queues. Clients travel to CEDSTCs to seek service.
- Periods of congestion may be experienced at CEDSTCs due to stochastic arrival/server times and limited capacities. Arriving clients enter a queue if the system is busy at the time of arrival.

3.2 Target groups and screening programs

In our problem setting, each CEDSTC provides screening services for all BCs, CCs, and CRCs. Each type of screening program has its own target population group. Table 1 depicts the target group and population in 2016 for the Asian Side of Istanbul in accordance with National Cancer Screening Standards and population data obtained from Turkish Statistical Institute (TSI).

Considering CEDSTCs' multi-purpose employment, we designed our mo-MILP model with a capability of meeting multiple types of demand. We also adopt a risk management approach to quantify the relative weights for each screening service provided by CEDSTCs. For this purpose, firstly, we calculated mortality rates of each cancer type by using "Mortality Rate = (Cancer Deaths/Population) × 100,000" formula in accordance with the "mortality rate" definition in SEER (2017). Thereafter, we determined overall risk values for each cancer type by multiplying the values of

Table 1 Cancer Screening Standards for CEDSTCs. Data from Keskinkılıc et al. (2016) and TSI

Screening program	Sex/age group	Interval (years)	At-risk population
Breast cancer (BC)	Women/40–69	2	1,010,078
Cervical cancer (CC)	Women/30–65	5	1,290,452
Colorectal cancer (CRC)	Men and women/50–70	10	1,159,047

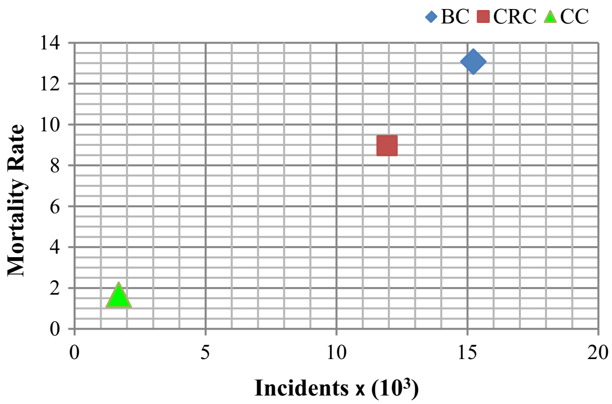

Fig. 2 Estimated number of incident cases and mortality rates in Turkey, in 2012, for breast, colorectal and cervical cancer

Table 2 Relative cancer weights calculated for Turkey in accordance with data from IARC (2017)

Cancer type	Incident	Cancer deaths	Population	Mortality rates	Overall risk	Relative weights
Breast cancer (BC)	15,230	5199	39,771,221	13.07	199,090	0.644
Cervical cancer (CC)	1686	663	39,771,221	1.66	2810	0.010
Colorectal cancer (CRC)	11,930	7158	79,814,871	8.96	106,991	0.346

"cancer incidents" with "mortality rates" which are presented in Fig. 2. Since the term "risk" usually refers to uncertainty about "bad" events, we would expect the risk associated for a certain type of cancer with both mortality rate and cancer incidents. For this reason, among other possible alternatives for deriving a risk measure, we preferred to use the product of the two parameters. Finally, the relative weights are calculated by the normalization of these risk values. The data used to calculate relative weights are presented in Table 2.

3.3 Accessibility

Unlike patients in need of urgent medical care, the potential clients of PHC service do not feel obliged to participate in PHC services provided in the region they reside. Studies in this area show that healthy people tend to use shorter distances for health services when compared to sick people (Weiss et al. 1971). People are not likely to participate to a PHC, unless an appropriate location plan has been made. In PHC literature, accessibility of facilities is considered as a major factor affecting the success of PHC programs. Zimmerman (1997)' survey for identifying factors that affect participation to a PHC service showed that accessibility of facilities is a major factor that influence people's decision to participate. Khan-Gates et al. (2015) also stated in their review paper that long travel distance/times to BC screening facility may dissuade women from participating to an organized screening program.

In PHC literature, several papers such as Verter and Lapierre (2002) and Zhang et al. (2012) used travel distance or travel time alone as a proxy for the accessibility of a facility, in some other papers (Zhang et al. 2009, 2010), authors incorporated congestion into the model by using total expected time (travel, waiting, and service) as a proxy for accessibility. In our model, *travel distance* is used as the proxy for the accessibility. In other words, in this study, we assume that probability of participation decreases with distance between clients and CEDSTCs.

3.4 Coverage

The accessibility measure for PHC facilities is highly relevant to the concept of location coverage problems. In location coverage concept, clients are considered to be fully covered in a pre-specified travelling distance or time of a facility. Nevertheless, the decrease in accessibility of the facilities that occur with the increase in the travelling distance or time is not represented by the concept of location coverage. Instead of full coverage, partial coverage concept is adopted in PHC location models. Various decay functions are presented in PHC network design literature as an implementation of partial coverage. For example; Verter and Lapierre (2002) used a linear decay function while Berman and Krass (2002) presented the gradual coverage decay function employing a step function and Berman et al. (2003) presented the gradual coverage decay model with two pre-specified threshold distances in modelling participation to PHC services. In this paper, we decided to adopt a gradual coverage concept similar to approaches adopted by Berman et al. (2003), Karasakal and Karasakal (2004) and Karatas (2017) to model participation.

We determined two distance parameters d^{min} (minimum critical distance) and d^{max}(maximum critical distance), where $d^{\text{min}} < d^{\text{max}}$ for each population zone. We assume that willingness to a PHC service is (1) complete if a CEDSTC is located within the minimum critical distance d^{min}, (2) to diminish entirely if no CEDSTC is located within the maximum critical distance d^{max}, (3) to diminish partially as the travelling distance increases if closest CEDSTC lies between d^{min} and d^{max}. The level of participation for CEDSTCs located between d^{min} and d^{max} is calculated via

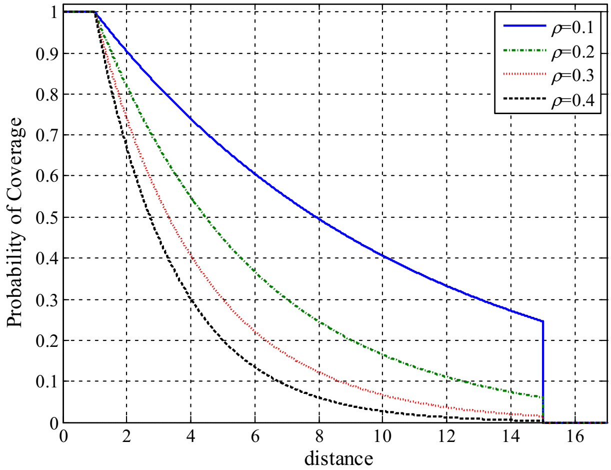

Fig. 3 Example coverage functions for decay constant values of $\rho = 0.1, 0.2, 0.3$, and 0.4, for fixed $d^{\min} = 1$ and $d^{\max} = 15$

a gradual coverage function $f(d_{ij}) \in [0, 1]$ where d_{ij} is the actual travelling distance between population zone i and facility j.

Among several empirical formulas in the literature, e.g. polynomial, exponential, Fermi-type, Elfes, cubic model, after discussing with experts from the TMoH, we adopted an exponential model to serve as an example in the development of our formulation. Using the exponential function, the level of coverage provided by a CEDSTC located at j to the population zone i is expressed as:

$$f(d_{ij}) = \begin{cases} 1, & d_{ij} \leq d^{\min} \\ e^{-\rho(d_{ij} - d^{\min})}, & d^{\min} < d_{ij} \leq d^{\max} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where ρ denotes exponential decay constant. Figure 3 shows example coverage functions for various ρ values.

3.5 Congestion

Stochastic inter-arrival times and service times in facilities may result in congestion. If an instant service is not provided to arriving clients due to congestion, clients may either wait in queue or leave (Berman and Krass 2015).

Most screening programs are follow-up programs. For example, the people in BC risk group should be subjected to BC screening regularly for an implementation of a successful PHC program. Herein, the wait times at screening center queues are a major factor that affect the service quality and patient satisfaction ratios. If the wait times are long due to congestion at facilities, then clients' willingness to participate in a preventive program may decrease for the following screenings.

In facility location literature, the average waiting time at queue is considered an important factor in assessing quality of service. Minimizing average waiting time as a cost term in objective function (Aboolian et al. 2008; Berman and Drezner 2006; Castillo et al. 2009; Elhedhli 2006) or adding a service level constraint to mathematical model to keep average waiting time below a specific threshold (Baron et al. 2008b; Berman et al. 2006; Marianov and Serra 2002; Wang et al. 2002; Zhang et al. 2012) are the most known methods to provide timely service. To ensure a timely service, this paper adopted a hybrid approach which integrates the strengths of the both methods. In particular, we designed our model in such a way that it minimizes the total weighted deviation resulting from exceeding acceptable waiting time threshold.

3.6 Accreditation

The relationship between volume of clinical activity and quality of care is considered as a major factor in health care services. Or and Renaud (2012) report in their paper that higher volume of clinical activity results in a better quality of care. Most PHC services also require a minimum workload for each facility to retain accreditation, except when there are no extra health policy decisions for sparsely populated zones. For example, for BC screening programs, U.S Food and Drug Administration (FDA) set a minimum of 960 mammograms in 24 months as a minimum workload for a radiologist to retain FDA accreditation (FDA 2001).

Minimum accreditation standards for British Columbia and U.K. are 3000/year and 5000/year, respectively (Güneş et al. 2014). In their study, Kan et al. (2000) suggest a minimum of 2500 interpretations per year for a mammography technician to stay sharp for better cancer detection rates. Similarly, European Union has set the criteria that each endoscopiest has to exercise at least 300 colonoscopy applications for CRC screening annually (Keskinkılıc et al. 2016).

Currently, no such accreditation limits are identified for the CEDSTCs' screening programs in Turkey. To ensure a sufficient level of service quality and efficient use of public funding, after consulting with experts, we determined minimum workloads for each screening programs implemented by CEDSTCs. In this paper, minimum workloads for BC, CC, and CRC screening programs are set as 2500/year, 2000/year and 1000/year, respectively.

3.7 Strategic planning

High costs involving property, expropriation and modern medical equipment make it a long-term strategy to address PHC location problems. Therefore, locating PHC facilities optimally is a strategic challenge for planners. Decision makers seek to make profitable investments by planning for new facilities to remain in place and operational for a long period of time. Thus, an efficient facility location planning must not only to meet the needs of current system but also the future needs that may emerge in long-term arising from factors such as population growth or environmental changes.

In this perspective, we solve the mo-MILP considering the population of each district in Asian Side of Istanbul for the next 15 years. We employed the "Double

Exponential Smoothing Using Holt's Method (DESUHM)" (Holt 1957) to forecast demand for the next 15 years, as calculated based on the previous years' population data obtained from TSI.

DESUHM, explained in "Appendix", is a forecasting method used to predict future demands that follow an upward or downward linear trend in the past. Since the past years' TSI population data follow a linear trend, DESUHM method can be used effectively to forecast future demands for the CEDSTCs. There exist some research which compare the performance of different forecasting techniques. For example, Nazim and Afthanorhan (2014) perform a detailed comparison of several techniques to forecast population, and they find out that Holt's method performs best among them. Similarly, Ryu and Sanchez (2003) evaluate forecasting methods and find out that Holt's method performs best among others that were not designed for seasonal data.

4 Mathematical model

In this step, we have developed a mo-MILP location model. The model is formulated with sets and indices, parameters, variables, constraints and objective function as explained below.

4.1 Sets and indices

$i, j, j' \in I$	Set of nodes that represent the population zones (districts) and candidate locations for facilities (CEDSTCs)
$k \in K$	Set of cancer screening programs
$n \in N$	Set of years in the strategic planning period
$g \in G$	Set of goals in the objective function

4.2 Parameters

h_{ikn}	Fraction of potential clients of screening program k residing at node i at year n
λ_{kn}	Number of potential clients who require type k PHC service over the entire network (Poisson distributed with a rate of λ per unit of time) for year n
μ_k	Common service rate of screening program k (exponentially distributed)
t_k	Time threshold for "acceptable expected waiting" time for potential clients who require service of screening program k
u_k	$(= 1/t_k)$ surplus service rate of screening program k to ensure expected waiting time at CEDSTC is below time threshold t_k
d_{ij}	Distance between population zone i and candidate location j
$d^{\max}$	Maximum critical distance that an individual would travel for PHC (No coverage outside $d^{\max}$)
$d^{\min}$	Minimum critical distance (demand is fully covered within $d^{\min}$)
Δ	A large positive number (i.e. $\Delta = \max\{d_{ij} : i, j \in I\}$) (this parameter is used in constraint (4) to ensure clients seek the service of closest facility)
acc_k	Accreditation limit for screening program k

P_i Maximum probability of participation of clients residing in population zone i when travel distance is no more than $d^{\min}$

c_{ijkn} Expected rate of clients of cancer screening program k from population zone i who would seek service of facility j at year n ($c_{ijkn} = f(d_{ij})P_i h_{ikn}\lambda_{kn}, \forall i, j \in I, k \in K, n \in N$)

m Setup cost of a CEDSTC

B Total available setup budget

ω_g Weights assigned by the decision maker (for each goal $g \in G$)

θ_g Normalization factors (for each goal $g \in G$)

γ_k Relative weights (for each cancer screening program k)

4.3 Decision variables

x_{ij} $\begin{cases} 1, & \text{if population zone } i \text{ is served by a facility at site } j \\ 0, & \text{otherwise} \end{cases}$

y_j $\begin{cases} 1, & \text{if a facility is open at site } j \\ 0, & \text{otherwise} \end{cases}$

dev^{r+}_{jkn} Positive deviation resulting from exceeding surplus service capacity to ensure expected waiting time is below the specified time threshold t_k

dev^{p-}_{ikn} Negative deviation associated with realized and maximum possible participation

dev^{b+} Positive deviation associated with total setup budget B

4.4 Constraints

4.4.1 Assignment constraints

The technical constraint set (2) ensures that each population zone is serviced by one CEDSTC. Note that, even if the center is assigned to a CEDSTC, there might be no participation due to the accessibility and accreditation (minimum workload) constraints.

$$\sum_{j \in I} x_{ij} = 1, \quad \forall i \in I \tag{2}$$

4.4.2 Location/allocation constraints

Constraint set (3) stipulates that a population zone can only be served by an open CEDSTC.

$$x_{ij} \leq y_j, \quad \forall i, j \in I \tag{3}$$

4.4.3 Proximity constraints

In accordance with our assumptions in Sect. 3, constraint set (4) guarantees that each population zone is assigned to its closest open facility. In other words, we assume that each participating individual seeks services of the closest facility.

$$\sum_{j' \in I} d_{ij'} x_{ij'} \leq \left(d_{ij} - \Delta\right) y_j + \Delta, \quad \forall i,\ j \in I \tag{4}$$

4.4.4 Capacity and accreditation constraints

Constraint set (5) imposes the minimum workload requirements. The stability of the queueing model on opened CEDSTCs requires that the service rate is strictly larger than the arrival rate. Hence, a CEDSTC cannot be established at candidate location j unless arrival rate of clients of type k screening program exceeds the minimum workload requirement denoted by acc_k. It should also be noted that, the clients and servers (screening devices) are not related with each other. Each type of screening program has its own target population group and features. Therefore, we do not adopt the concept of "total service rate", but rather use individual service rates for each screening program.

$$\mu_k \geq \sum_{i \in I} c_{ijkn} x_{ij} \geq acc_k y_j, \quad \forall j \in I, \quad k \in K, \quad n \in N \tag{5}$$

4.4.5 Cost deviation from exceeding budget

The objective pursued by most of the studies dealing with resource allocation is to minimize fixed and variable costs associated with locating the new facility (Tsouros and Satratzemi 1994). In our case, we define our "*facility setup cost*" as the sum of fixed costs of installing facilities. Constraint set (6) measures deviations from the budget as follows:

$$\sum_{j \in I} m y_j - B - dev^{b+} \leq 0 \tag{6}$$

4.4.6 Accessibility constraints

The best-case scenario is to reach max participation level that can be formulated as $P_i \lambda h_i$. Constraint set (7) measures the gap between the realized participation and maximum possible participation to be used in the objective function.

$$\sum_{j \in I} c_{ijkn} x_{ij} - P_i \lambda_{kn} h_{ikn} + dev_{ikn}^{-p} \geq 0, \quad \forall i \in I, \quad k \in K, \quad n \in N \tag{7}$$

4.4.7 Congestion constraints

In our model, it is important to keep *expected waiting time* for each facility below *acceptable waiting time*. Since the system is an $M/M/1$ queue, constraint set (8) measures the deviation of rates resulted from the difference between expected waiting time and tolerable waiting time for each facility. This constraint adopts a similar approach implemented by Wang et al. (2002) to model congestion. In particular, Wang et al. (2002) use an upper bound on permissible expected waiting time for customers and calculate the surplus service capacity to ensure that expected waiting time at facility is less than the upper bound. In our case, we allow exceeding the tolerable waiting time and measure this surplus by the deviational variables.

$$y_j u_k + \sum_{i \in I} c_{ijkn} x_{ij} - y_j \mu_k - dev^{r+}_{jkn} \leq 0, \quad \forall j \in I, \quad k \in K, \quad n \in N \tag{8}$$

4.4.8 Variable type declarations

Constraint sets (9)–(12) declare variable types and domains.

$$x_{ij} \in \{0, 1\}, \quad \forall i, \ j \in I \tag{9}$$

$$y_j \in \{0, 1\}, \quad \forall j \in I \tag{10}$$

$$dev^{b+} \geq 0 \tag{11}$$

$$dev^{p+}_{ikn}, dev^{r-}_{jkn} \geq 0, \quad \forall i, \ j \in I, \quad k \in K, \quad n \in N \tag{12}$$

4.5 Objective function

The multi-objective function, given by Eq. (13), attempts to minimize three terms. The first term measures the average total weighted deviation resulting from the gap between the realized and maximum possible participations incurred over the planning period. The second term represents the total deviation resulting from exceeding the expected acceptable waiting time at facilities averaged over the planning period. The third term represents the deviation resulting from exceeding the budget.

$$\begin{aligned} \min_{\substack{\mathbf{x},\mathbf{y},\\ \mathbf{dev}^r,\mathbf{dev}^p,\mathbf{dev}^b}} \quad z = & \frac{1}{n} \sum_{n \in N} \left(\omega_1 \theta_1 \sum_{k \in K} \gamma_k \sum_{i \in I} dev^{p-}_{ikn} \right) \\ & + \frac{1}{n} \sum_{n \in N} \left(\omega_2 \theta_2 \sum_{j \in I} \sum_{k \in K} dev^{r+}_{jkn} \right) + \omega_3 \theta_3 dev^{b+} \end{aligned} \tag{13}$$

In our model, the objective function has three goals, $g \in \{1, 2, 3\}$, each of which has its own weights and normalization factors represented as ω_g and θ_g, respectively. ω_g are the decision weights given by decision makers considering the environmental factors such as available budget or customer satisfaction. Multi-objective models may give out unbalanced results due to the different magnitudes of objectives unless a proper normalization method has been implemented. Thus, as used by Razi and Karatas (2016), we implemented θ_g as normalization factors which are calculated by using normalization method presented in Grodzevich and Romanko (2006, p. 93). This method has been proposed to scale weighted sum objective functions in multi-objective models. In this method, two special points, namely Nadir and Utopia, are calculated in the solution space. Nadir and Utopia points are the upper bound (denoted by z_g^N) and the lower bound (denoted by z_g^U) on each objective g. These points are used for the calculation of normalization factors via the formula $\theta_g = 1 \Big/ \left(z_g^N - z_g^U\right)$.

5 Results and discussion

In this section, we report our results relating to the location problem of CEDSTCs in the Asian Side of Istanbul. We employ MATLAB® R2013a to implement the DESUHM method to forecast future population data and use CPLEX 12.2.0.2 to solve the optimization problem. In the frame of the information mentioned above, our model used the following data.

5.1 Problem data

5.1.1 Population zones and candidate facility sites

The Asian Side of Istanbul consists of 359 districts. In this study, we used the medians of each district as population zones and candidate facility locations, which are presented in Fig. 4.

5.1.2 Demand (potential clients) data for 15 years planning period

We used the population data of each of these districts covering recent years and DESUHM method to forecast the number of potential clients for each cancer screening program provided by CEDSTCs. The data used in forecasting is based on the TSI-provided population data of Istanbul for the years 2006–2016.

Figure 5 shows the annual forecasts for the number of potential clients for each type of cancer screening service between the years 2017–2031.

The aggregate number of clients that seek the service of BC, CC or CRC screening programs in the Asian Side of Istanbul is assumed to follow a Poisson distribution. We assume that, excluding the holidays and weekends, there are approximately 250 working days annually and 8 working hours per day. Thus, we can calculate the number of potential clients per hour for each screening program as "total number of potential clients/250/8". For instance, considering 1,063,330 women in BC risk group residing in the Asian Side of Istanbul in 2017, the hourly demand λ can simply be calculated as

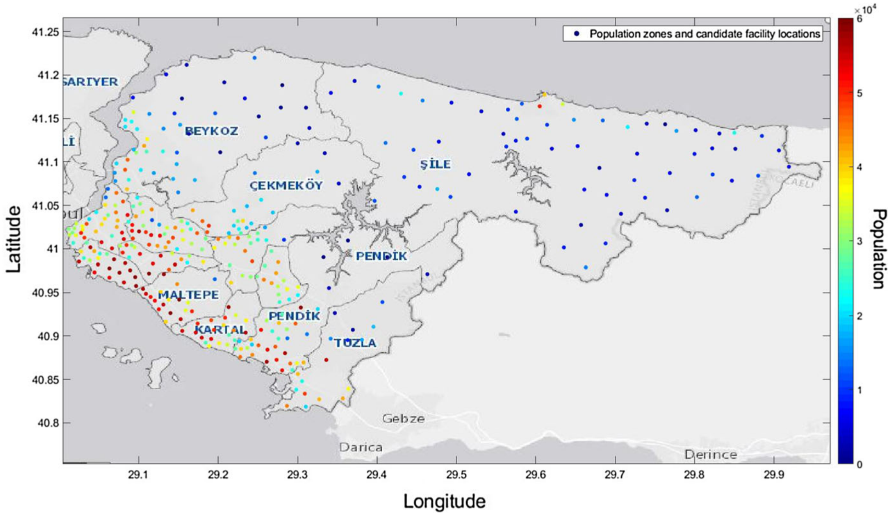

Fig. 4 Actual population zones and candidate facility locations for CEDSTCs in the Asian Side of Istanbul. Each population zone (and candidate facility location) is represented by a disc

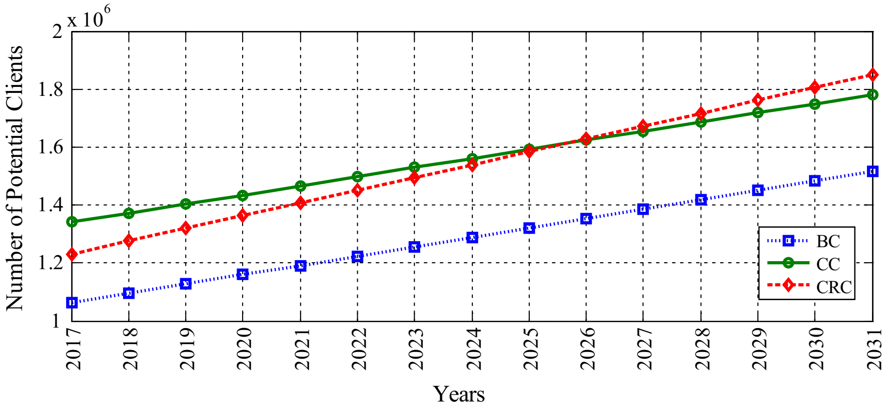

Fig. 5 Number of potential clients of cancer screening services calculated via DESUHM forecasting method

$\lambda = 1{,}063{,}330/250/8 = 265.83$. Table 3 illustrates the calculated hourly demand data for the following 15 years for each screening program.

5.1.3 Service rate, waiting time threshold and accreditation requirement

In accordance with the criteria discussed in Sect. 3 and after consulting with experts, we determined the server time, waiting time threshold and accreditation parameters as mentioned in Table 4. In the table, waiting time thresholds include waiting times at queue and at service.

Table 3 Estimated hourly demand for each cancer screening service for years 2017–2031

Cancer type	Years													
	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2031
BC (clients/h)	265.83	273.83	281.84	289.92	298.00	306.14	314.29	322.43	330.58	338.72	346.87	355.02	363.16	371.31
CC (clients/h)	134.18	137.25	140.32	143.47	146.62	149.77	152.92	156.07	159.22	162.37	165.52	168.67	171.82	174.97
CRC (clients/h)	61.58	63.77	65.96	68.15	70.34	72.54	74.76	76.98	79.19	81.41	83.62	85.84	88.06	90.27

Table 4 Service rate, waiting time threshold and accreditation requirement parameter values

Parameter	Cancer type		
	BC	CC	CRC
Service rate (μ)	5 clients/h	6 clients/h	2 clients/h
Waiting time threshold (t)	45 min	45 min	60 min
Accreditation limit (acc)	2500 clients/year	2000 clients/year	1000 clients/year

5.1.4 Weights

Under expert guidance and keeping in mind that the importance of participation for public health services always supersedes the budget and waiting time factors, we determined the decision weights, ω_g, for our three goals in the objective function as 0.5, 0.3 and 0.2 for the objective function goals 1, 2 and 3, respectively. Additionally, using the normalization technique described in Sect. 4.5 we calculated the normalization factors θ_g as 0.0417, 0.00579 and 0.00587. Lastly, the relative weights, γ_k, described and calculated in Sect. 3.2 are 0.644, 0.346 and 0.010 for BC, CC and CRC, respectively.

5.1.5 Other parameters

The setup budget (m) for the installation of a single CEDSTC is determined as 2.2 million Turkish Liras (TL) (1 Euro$\approx$6 TL as per February 2019 published figures), based on a detailed market research on cancer screening equipment and construction costs. For the project, the budget allocated for installing all CEDSTCs is 120 million TL.

We determined the two distance parameters $d^{\min}$ (minimum critical distance) and $d^{\max}$ (maximum critical distance), described in Sect. 3.4, as 0.5 and 8 km., respectively. In our gradual coverage function (1), we set $\rho = 0.1$. We further assumed maximum probability of participation, P_i, for each type of cancer screening program within minimum critical distance as 0.95.

5.2 mo-MILP model results

Based on the above mentioned data, we obtained the solution shown in Fig. 6. The disks and squares in the figure indicate the population zones and CEDSTCs to be accredited, respectively.

The mo-MILP model is solved to optimality on a computer with Intel(R) Xeon(R) CPU E5-2620 v3 @2.40 Ghz processor, 128 GB memory and Microsoft Windows 7 64-Bit Operating System. We implement models in General Algebraic Modeling System (GAMS©) environment and solve them with CPLEX 12.2.0.2 using default settings.

According to this solution, 63 CEDSTCs need to be accredited with a 15.5% excess over the total budget goal (approximately 18 million TL). The total number of potential

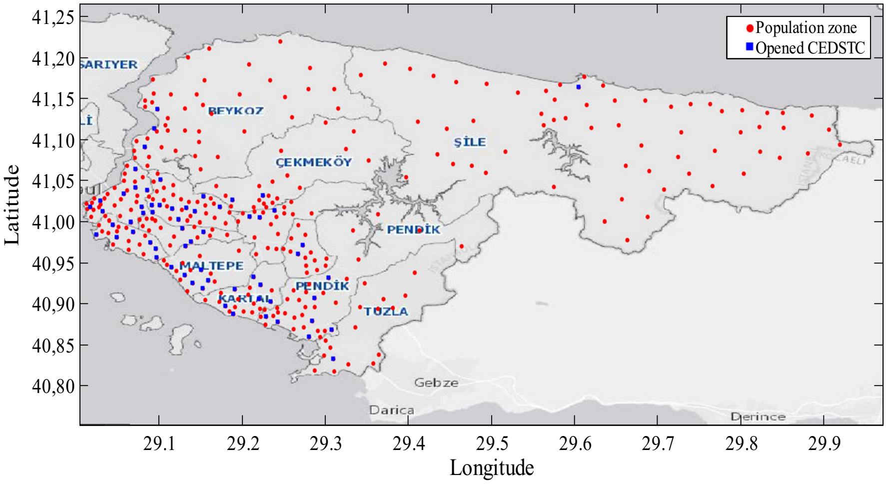

Fig. 6 Accredited CEDSTCs in the Asian Side of Istanbul

clients per hour for each cancer screening services and mo-MILP results are reported in Table 5. As can be seen from the Fig. 6, the CEDSTCs requiring accreditation are located in highly populated western and southern districts. For the sparsely populated northern districts, our model activates a single CEDSTC located roughly in the mid-north of the Asian Side of Istanbul.

Figure 7a, b exhibit the participation ratio and the participation values per hour for each cancer screening program for the 15 years planning period, respectively. The participation ratios represented in Fig. 7a shows small decreases annually. However, at the end of planning period, it is consistently higher than 70%, the threshold accepted as success criteria by WHO. Figure 7b illustrates the hourly participation values for each cancer screening service. Herein, we can observe that the annual increase in participation values realizes as expected, in accordance with the population growth represented in Fig. 5. In other words, as the population grows through years, so do the participation levels.

Graphs in Fig. 8 exhibit the deviation data for the next 15 years obtained via mo-MILP solutions. In Fig. 8a the participation deviations resulting from the gap between the realized and maximum possible participation are represented; and in Fig. 8b, rate deviations that occur from exceeding the specified time threshold are demonstrated. As expected in this paper, the participation deviations which are represented in Fig. 8a evolve linearly due to population growth, which itself evolve linearly also as observed from Fig. 5. The annual average rate deviations are reported in Fig. 8b. Herein, we observe the deviations at very low values, i.e. varying between 0 and 0.15 clients/h. It should be noted that the values in this figure represent the average excess deviations over the waiting time threshold for accredited CEDSTCs.

According to Fig. 8b, CC screening waiting times do not excess the time threshold until the year 2026. Thereafter, the waiting times start to go up. For BC, the screening program starts at a slightly higher excess rate, while gradually going down until 2025,

Table 5 Summary of results

Type of screening service	Model results	Years														
		2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
BC	Total # of potential clients per hour (λ)	265.8	273.8	281.8	289.9	298	306.1	314.2	322.4	330.5	338.7	346.8	355	363.1	371.3	379.4
	Participation per hour	215.4	221.4	227.5	233.8	240	246	252.4	258.6	264.8	271.1	277.4	283.5	289.7	296	302.2
	Participation ratio (%)	81	80.8	80.7	80.6	80.5	80.3	80.3	80.2	80.1	80	79.9	79.8	79.7	79.7	79.6
	Deviation from max possible participation	50.34	52.4	54.26	56.1	57.96	60.07	61.84	63.81	65.76	67.61	69.46	71.49	73.4	75.31	77.19
	Deviation of rates resulted from exceeding waiting time threshold	0.95	0.5	0.36	0.21	0.14	0.1	0.07	0.07	0.18	0.3	0.43	0.67	1.26	2.86	4.85
CC	Total # of potential clients per hour (λ)	134.1	137.2	140.3	143.4	146.6	149.7	152.9	156	159.2	162.3	165.5	168.6	171.8	174.9	178.1
	Participation per hour	108.9	111.2	113.5	115.8	118.1	120.4	122.7	125.2	127.4	129.9	132.3	134.6	136.9	139.3	141.7
	Participation ratio (%)	81.2	81	80.9	80.7	80.5	80.4	80.2	80.2	80	80	79.9	79.8	79.7	79.6	79.5
	Deviation from max possible participation	25.21	25.99	26.78	27.63	28.5	29.29	30.13	30.83	31.74	32.47	33.22	34.03	34.83	35.59	36.41
	Deviation of rates resulted from exceeding waiting time threshold	0	0	0	0	0	0	0	0	0	0.26	0.76	1.27	1.96	2.69	3.53
CRC	Total # of potential clients per hour (λ)	61.5	63.7	65.9	68.1	70.3	72.5	74.7	76.9	79.1	81.4	83.6	85.8	88	90.2	92.4
	Participation per hour	49.8	51.5	53.2	55	56.7	58.4	60	61.7	63.5	65.2	66.9	68.6	70.3	72	73.7

Table 5 continued

Type of screening service	Model results	Years														
		2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
	Participation ratio (%)	81.4	80.9	80.8	80.7	80.7	80.7	80.5	80.3	80.2	80.2	80.1	80	79.9	79.8	79.7
	Deviation from max possible participation	10.75	11.72	12.22	12.73	13.13	13.56	14.1	14.68	15.2	15.62	16.2	16.7	17.24	17.72	18.25
	Deviation of rates resulted from exceeding waiting time threshold	2.14	2.03	1.98	1.95	1.97	2.11	2.35	2.67	3.12	3.66	4.34	5.05	5.9	6.87	7.91
Total	Total # of potential clients per hour (λ)	461.6	474.8	488.1	501.5	514.9	528.4	541.9	555.4	569	582.5	596	609.5	623	636.5	650
	Participation per hour	374.3	384.2	394.3	404.6	414.9	425	435.3	445.6	455.8	466.2	476.6	486.7	497	507.4	517.7
	Participation ratio (%)	81	80.9	80.7	80.6	80.5	80.4	80.3	80.2	80.1	80	79.9	79.8	79.7	79.7	79.6
	Deviation from max possible participation	87.27	90.61	93.77	96.86	100.02	103.46	106.65	109.84	113.12	116.28	119.38	122.76	125.95	129.15	132.31
	Deviation of rates resulted from exceeding waiting time threshold	3.09	2.53	2.34	2.16	2.11	2.21	2.42	2.74	3.3	3.96	5.03	6.48	8.43	11.69	15.45

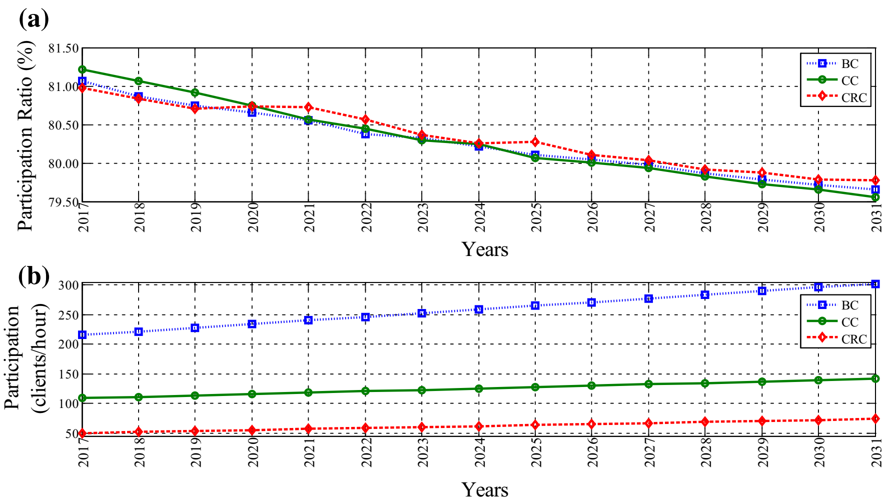

Fig. 7 **a** Participation ratio and **b** participation values per hour for each cancer screening program through 15 years planning period

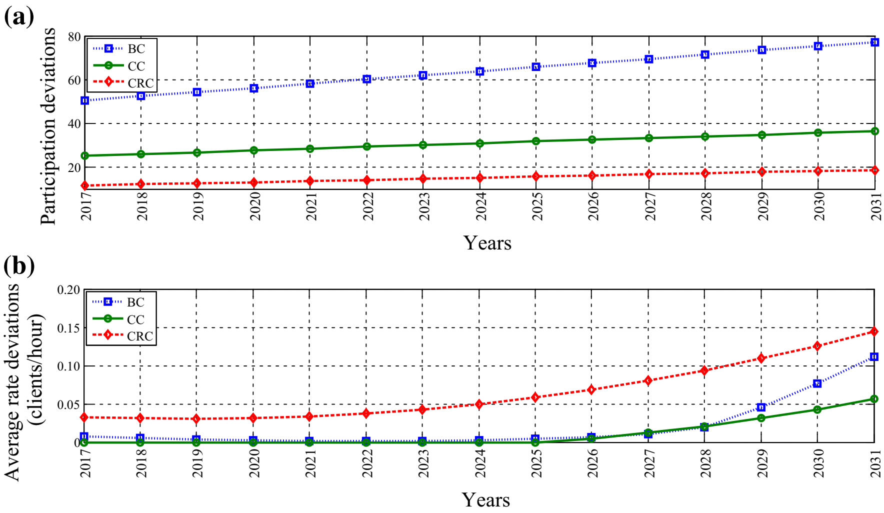

Fig. 8 **a** Participation and **b** rate deviations for each cancer screening program through 15 years planning period

a case which we consider acceptable as our model aims for a long-term solution of 15 years. After that, waiting times become longer and rates go up over the years.

Among the three cancer types covered in the study, the average rate deviations are highest for CRC. Similarly to BC rates, the CRC deviation rate slightly decreases until 2020, to 1.95, after which it consistently goes up.

To summarize; the study comes up with a solution targeting the three cancer types which succeed in satisfying over 70% of the potential demand and boasts keeping waiting time-related dissatisfaction at low levels. It is observed in the table that waiting time for three cancer types consistently increases after 2026. In light of this, the healthcare officials may be advised to plan measures for post-2026 period, such as establishing additional CEDSTCs, increasing capacities of then-existing CEDSTCs, or as suggested above, implement a mobile CEDSTC program for the northern area. Moreover, to attain higher participation, mobile screening services may be planned seasonally and delivered to North districts, where the service coverage is relatively limited.

5.3 Sensitivity analysis

We reported the results of our model for the specific objective function component weights $\omega_1 = 0.5$, $\omega_2 = 0.3$, and $\omega_3 = 0.2$. Decision makers from TMoH may also request the optimal CEDSTC location schemes for different weights or parameter values. For this reason, we perform two different sets of sensitivity analysis. In the first group, we assess the performance of each objective function component under different weighting strategies. In the second group we evaluate the performance under different participation functions. We achieve this by using different, ρ, exponential decay constant values and maximum participation probabilities (P_i).

The first group analysis aims to assist decision makers by reporting the trade-offs in different prioritization and weighting strategies. In this analysis, we also violated the expert judgment that participation is always of higher importance than the budget and waiting time factors. In particular, we based our analysis on the weight assigned to the first term of the objective function, i.e. deviation from the maximum possible participation, and generated 12 cases. We test the performance of each objective function term for $\omega_1 = \{0, 0.1, 0.2, \ldots, 1\}$ and, except case 1-6, we assume that for a given ω_1, ω_2 and ω_3 are equal and these weights sum up to 1. Case 1-6 corresponds to the weights adopted in our original solution. Table 6 summarizes the results for each test case.

First, the results for cases 1-1 to 1-4 reveal that, when $\omega_1 \leq 0.3$ there is no shortage on budget. However, this comes at the cost of lower participation. Relatively low deviation from the acceptable waiting time (second term) is possibly due to low participation. Additionally, cases 1-1 and 1-2 are dominated by case 1-3. Second, the data shows that it is possible to decrease the total deviations for the first and second terms to 17 and 0.410 clients/h, respectively, at the cost of a 40% budget exceedance. Another interesting observation is the sharp declines in terms 1 and 2 along with a sharp rise in term 3 between cases 1-11 and 1-12. Nonetheless, in all settings it is encouraging to observe that the deviation from the maximum possible participation tends to get smaller if decision makers allocate higher budget expenditures for public healthcare services. We conclude that weights used in our original solution (case 1-6) leads to a compromise solution with reasonable deviations from all three terms.

The second group analysis aims to evaluate the response of the model under different participation functions by varying parameters ρ and P_i. In particular, we run experiments for a full factorial design of $\rho = \{0.2, 0.3, 0.4\}$ and $P_i = \{0.75, 0.85,$

Table 6 Results of first sensitivity analysis

Test case #	Objective function component weights			Component 1	Component 2	Component 3
	ω_1	ω_2	ω_3			
1-1	0.0	0.50	0.50	179.839	0.680	0.0
1-2	0.1	0.45	0.45	178.845	0.703	0.0
1-3	0.2	0.40	0.40	158.061	0.621	0.0
1-4	0.3	0.35	0.35	154.239	0.735	0.0
1-5	0.4	0.30	0.30	123.516	0.802	8.0
1-6	0.5	0.30	0.20	109.829	0.882	15.5
1-7	0.5	0.25	0.25	104.851	0.902	14.2
1-8	0.6	0.20	0.20	95.086	0.862	18.1
1-9	0.7	0.15	0.15	90.209	0.882	18.6
1-10	0.8	0.10	0.10	90.126	0.693	22.2
1-11	0.9	0.05	0.05	75.795	0.602	26.5
1-12	1.0	0.00	0.00	16.989	0.410	40.6

Table 7 Results of second sensitivity analysis

Test case #	ρ	P_i	Component 1	Component 2	Component 3
2-1	0.2	0.75	267.839	0.170	1.00
2-2	0.2	0.85	250.845	0.222	0.03
2-3	0.2	0.95	188.061	0.343	0.00
2-4	0.3	0.75	323.211	0.101	5.03
2-5	0.3	0.85	285.616	0.102	0.00
2-6	0.3	0.95	290.321	0.0	0.00
2-7	0.4	0.75	423.102	0.0	12.29
2-8	0.4	0.85	296.965	0.0	9.19
2-9	0.4	0.95	232.001	0.0	9.11

0.95}. The value of each objective function component for all generated 9 cases is reported in Table 7. It should be noted that in this group of experiments we used our default weights as $\omega_1 = 0.5$, $\omega_2 = 0.3$ and $\omega_3 = 0.2$.

The numerical results in Table 7 reveal that for smaller ρ and P_i, the average total weighted deviation resulting from the gap between the realized and maximum possible participations incurred over the planning period increases while total deviation from the expected acceptable waiting time decreases. This is an expected outcome since smaller ρ and P_i values result in a decreased coverage performance yielding less participation. The decrease in participation also brings low deviation from the acceptable waiting time (second term). In specific increasing ρ from 0.2 to 0.3 increases the value of the first component by 27%. An additional increase from 0.3 to 0.4 yields an additional 5% increase on average. It is interesting to note that for

$\rho = 0.4$ the second component takes a value of 0 while the budget deviation (component 3) is relatively high. This can be explained by the tradeoff between the waiting time and budget, i.e. lowered waiting times occurring at the cost (exceeded budget).

6 Conclusion

In this paper, we have presented a strategic level multi-objective model developed to determine the optimal configuration of CEDSTC locations in the Asian Side of Istanbul by considering expected population growth in the next 15 years period. We designed our model taking into account the CEDSTCs' multi-purpose employment with a capability of meeting multiple types of demand.

In our model we minimized the average deviations between maximum possible participation and realized participation, average deviations exceeding the maximum acceptable waiting time and deviations from exceeding the total setup budget, taking into account the 15 years planning period. In this perspective, we solve our mo-MILP model considering the population growth forecast of each district in Asian Side of Istanbul for the next 15 years. We employed the DESUHM method to forecast the demands for the next 15 years according to the TSI-published population data.

Considering that the accessibility of PHC facilities is one of the key factors that influence the willingness of people to participate, we used travel distance as a proxy for the accessibility of a CEDSTC. Due to lack of data, we assumed that the probability of participation for each type of cancer screening programs decreases with distance. We used a gradual coverage decay function to implement reduction in accessibility of facilities. We employed deterministic-choice behavior, also known as optimal-choice model. In our model, we assume that each participating individual seeks services of the closest facility considering travel distance as a proxy for the accessibility. We also adopted a risk management approach to quantify the relative weights for each screening service in the optimization model.

In the previous section, we presented model parameters and results. Based on our assumptions and parameter values, we obtained an efficient solution for locating CEDSTCs in the Asian Side of Istanbul. According to our solution, 63 facilities need to be accredited with a 15.5% excess over the total budget (B) goal. We reported participation ratio, participation values, and deviation values for the next 15 years. Our solution as designed based on these factors attains an average of over 79% participation rate for these three cancer types throughout the 15 years planning period. Additionally, to increase the participation rate and service quality, we suggest establishing additional CEDSTCs after 2026 and delivering mobile screening services to low populated North districts where the expected coverage is relatively low.

We believe that, although providing technical support in terms of facility, equipment and other types of resources is crucial for increasing participation to screening programs, the sustainability and success of public health through PHC also relies on education level and socioeconomic status of the population. The participation can also be increased through other actions such as pre-screening reminders, postal reminders, personalized reminders for non-participants, general practitioner endorsements, public service ads, etc.

The limitation of this study is that, there exists no empirical data which explains a realistic participant accessibility measure to PHC services. Therefore, our study is based on the assumption that the participation probabilities follow a gradual coverage concept as explained in Sect. 3.4. Although this function may not be the same for different populations and cultures, a future work may research patient behaviour for attending PHC services. As another future work, analytic models derived for such purposes can be tested or improved by simulation models that run under stochastic environments.

Appendix

DESUHM (Holt 1957) uses two smoothing constants, α and β, and two smoothing equations that calculate the value of intercept and the slope. The equations and parameters (see Table 8) used in this method are explained below.

$$S_t = \alpha D_t + (1-\alpha)(S_{t-1} + G_{t-1}) \tag{14}$$

$$G_t = \beta(S_t - S_{t-1}) + (1-\beta)G_{t-1} \tag{15}$$

In Eq. (14), the most current value of demand, D_t, is averaged with the summation of S_{t-1} and G_{t-1} to calculate the value of intercept at time t, S_t. In Eq. (15), the new value of the S_t is used to update the value of slope, G_t, by averaging $S_t - S_{t-1}$ with the previous value of G_{t-1}. Same values can also be used for the smoothing constants; but in most applications, $\beta \leq \alpha$ equation is preferred for better stability. The forecast of the nth period at time t, is formulated as $F_{t,t+n} = S_t + nG_t$.

Table 8 Parameters used in DESUHM equations

Parameter	Definition
S_t	The value of the intercept at time t
G_t	The value of the slope at time t
D_t	The most current observation of demand
S_{t-1}	The prior forecast of the current demand, which is the previous intercept
G_{t-1}	The value of the intercept at time $t-1$

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