Fostering long-term care planning in practice: extending objectives and advancing stochastic treatment within location-allocation modelling

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Abstract: Many countries are currently concerned with the planning of networks of Long-Term Care (LTC), which requires considering a multiplicity of policy objectives and anticipating the impact of key uncertainties. Nevertheless, location-allocation literature has not been modelling key health policy objectives, and the use of stochastic planning models entails low practical usability due to prohibitive computational times. This study tackles these issues by proposing an approach that supports the reorganization of LTC networks (in terms of services location, capacity planning and patients allocation) while exploring different health policy objectives and considering uncertainty within a reasonable computational time, leading to the development of a stochastic multi-objective mathematical programming model – the *LTCNetPlanner*. The *LTCNetPlanner* builds upon health economics and policy concepts to model the maximization of health and wellbeing together with cost- and equity-related objectives within location-allocation literature. Concerning uncertainty, a scenario-based stochastic approach is developed and alternative scenario reduction methods enabling a faster model resolution are explored within the *LTCNetPlanner*. Specifically, it is proposed a novel *Morphol-KMG method* able to reduce the number of scenarios while accounting for experts' knowledge. A case study in the Great Lisbon region is explored, showing the usefulness of the proposed scenario reduction method to reduce computational times, and how planning decisions change when health and wellbeing benefits are considered.

Keywords: OR in health services; Long-term care planning; multi-objective; stochastic programming; scenario reduction methods

Highlights

- A stochastic multi-objective model is proposed to aid Long Term Care planning.
- Health and wellbeing benefits are modelled within the multi-objective model.
- Alternative scenario reduction methods enabling a faster model resolution are used.
- A novel scenario reduction method accounting for experts' knowledge is proposed.
- The model applicability is shown through a case study in Portugal.

1. Introduction

Healthcare managers are frequently under pressure to control health care expenditure while simultaneously fulfilling the growing demand for services and attempting to deliver equitable, efficient and health and wellbeing centered care. When considering the particular case of the Long-Term Care (LTC) sector, additional challenges are also in place. For instance, in many health systems the provision of LTC is currently low, and dealing with its specificities can be a challenge since LTC is characterized by multiple providers (public and private) delivering both social and health care, ranging from multiple institutional to home-based and ambulatory care services (Brodsky & Clarfield, 2008). Health care managers are thus challenged with improving and planning LTC delivery, this being particularly relevant for National Health Service (NHS)-based countries, in which the State is responsible for financing and/or delivering a growing network of LTC in a context of highly constrained budgets. In order to assist health planners and policy-makers to make informed decisions in such contexts, there is a need to develop planning tools that consider simultaneously the complex delivery of LTC, that pursue a multiplicity of policy objectives, and that anticipate variability in the future demand and supply of LTC.

Mathematical programming models have been widely used to support the location-allocation planning of health care services in general (Brailsford & Vissers, 2011), with recent applications covering the LTC area (e.g., Cardoso et al. (2016) and Song et al. (2015)). Such studies have made a start in addressing key features of healthcare delivery by considering the multi-service nature of health care services (e.g., Cardoso et al. (2016)), the modelling of multiple policy objectives (e.g., Wang and Ma (2018)), and the impact of uncertainty on planning decisions (e.g., Mestre et al. (2015)).

Nevertheless, if these models are to be used to assist planners in practice, they need to be further developed. First, models developed in the last two decades mostly consider a narrow range of equity- and cost-related objectives. In contrast, policy statements indicate that it is central for health care decisions to also pursue other end objectives, such as the maximization of health and wellbeing for patients and society (Ministry of Health, 2006; Kruk & Freedman, 2008). In most developed countries top in-laws recognize the promotion of a healthy population as a key policy objective to be attained by the state, as well as the objective to promote population wellbeing (World Health Organization, 2018). This has also been recognized for public LTC delivery, which is characterized by combining both health and social care services, with policy documents and literature pointing out that an adequate planning implies going beyond health benefits and also capturing benefits in terms of the overall wellbeing of individuals (Flynn et al., 2015). In fact, according to Makai et al. (2014), an health measure alone can be too reductionist and so wellbeing instruments capture broader benefits relevant to the delivery of care. Secondly, health care delivery is known to be critically affected by uncertainties in the future supply and demand of care, and existing planning models that deal with these uncertainties turn out to be difficult to use in practical settings due to prohibitive computational times (Dupačová et al., 2003; Heitsch & Römisch, 2003; Li & Floudas, 2014).

This study tackles the above issues by advancing stochastic multi-objective mixed integer linear programming (MILP) tools to inform health policy-makers on how to build and reorganize a multi-service network of LTC in terms of services location (for existing or for new LTC units), capacity planning and patients allocation, in what we call the *LTCNetPlanner*. The *LTCNetPlanner* allows the exploration of a diversity of policy objectives that are typically relevant for LTC planners. It considers the minimization of costs and the maximization of equity, in terms of equity of access, socioeconomic equity, geographical equity and equity of utilization, as well as the maximization of health and of wellbeing benefits, which require specific modelling. While equity and cost objectives have been previously explored in health literature (see, for instance, Mestre et al. (2015), Cardoso et al. (2015, 2016), Khodaparasti et al. (2017) and Wang and Ma (2018)), to the best of our knowledge health and wellbeing objectives have not been previously incorporated into location-allocation literature. Furthermore, the *LTCNetPlanner* addresses the modelling of demand uncertainty in a reasonable computational time: a scenario-based stochastic multi-objective approach is first developed, resulting in the generation of a high number of scenarios; faster solution methods are afterwards explored by using alternative scenario reduction methods with distinct reduction criteria. Accordingly, two scenario reduction methods available in the literature (methods not commonly used in the health context) are used and compared with a novel approach herein proposed – the *Morphol-KMG method*. The *Morphol-KMG method* differs from the existing methods by allowing the reduction of a number of scenarios by using experts' knowledge to identify plausible, contrasting and relevant scenarios, being inspired by concepts from the foresight literature. Although having a potential role in the scenarios' selection process, experts' involvement has not been common in healthcare planning studies. To illustrate the applicability of the *LTCNetPlanner*, a Portuguese case study is studied.

The remainder of this article is organized as follows. Section 2 presents a brief literature review. Main features of the problem are explored in Section 3. Section 4 presents the mathematical details of the *LTCNetPlanner*, also describing the scenario reduction methods. The results obtained are explored in Section 5, and key conclusions and future research are presented in Section 6.

2. Literature Review

A vast body of literature exists on location-allocation health care planning (see the reviews by Rahman and Smith (2000), Rais and Viana (2010) and Güneş and Nickel (2015)) with mathematical programming models playing a key role (Brailsford & Vissers, 2011). This section focuses on location-allocation mathematical programming models developed for health care planning purposes that account for multiple objectives and address the uncertain nature of health care delivery, with a special focus on LTC literature. Scenario reduction methods and scenario planning concepts and approaches are also reviewed.

2.1. Location-allocation mathematical programming models for health care planning

2.1.1. Accounting for multiple objectives

Health care planning literature clearly recognizes that an adequate planning of health care delivery should account for multiple policy objectives (Stummer et al., 2004). Nevertheless, existing location-allocation studies are still dominated by single-objective mathematical programming models (Rahman & Smith, 2000). And even when considering the small but growing body of research exploring the multi-objective nature of health care planning during the last decade (e.g., Smith et al. (2012), Mestre et al. (2015), Cardoso et al. (2016), Wang and Ma (2018) and Nasrabadi et al. (2020)), most of these studies still consider a small number of objectives. Within these objectives, equity- and cost-related objectives play a key role. In particular, several studies have developed location-allocation models aiming at minimizing total costs (e.g., Syam and Côté (2010), Mahar et al. (2011), Benneyan et al. (2012) and Ghaderi and Jabalameli (2013)). In what concerns equity-related objectives, different authors have considered several dimensions of equity, namely, equity of access [EA] (e.g., Oliveira and Bevan (2006), Mitropoulos et al. (2006), Mestre et al. (2012, 2015), Khodaparasti et al. (2017), Wang and Ma (2018) and Nasrabadi et al. (2020)), geographical equity [GE] (e.g., Zhang et al. (2016), Luo et al. (2017) and Mousazadeh et al. (2018)), socioeconomic equity [SE] (e.g., Drezner and Drezner (2011)) and equity of utilization [EU] (e.g., Oliveira and Bevan (2006)). Recently, Cardoso et al. (2015, 2016) recognized the multidimensionality of the equity concept.

In addition to equity and cost objectives, health policy literature stresses the relevance of considering other policy objectives, such as the maximization of health benefits (Kruk & Freedman, 2008; Santinha, 2016), which is at the heart of health policy (Baker, 2000). Nevertheless, to the best of authors' knowledge, no location-allocation study considers this objective, and only a few allocation models have explored its impact on allocation decisions (e.g., Chalabi et al. (2008) and Knight et al. (2012)). In addition, there is also the recognition that it is relevant to pursue in LTC delivery and in other service areas not only health benefits but more holistic benefits, as captured by overall wellbeing of individuals (Flynn et al., 2015). To the best of authors' knowledge, no location-allocation study in health has included wellbeing–related objectives.

The special case of health benefits

Although not typically used in existing location-allocation studies, several metrics can be used to capture health benefits in health economics, in health policy, and in health technology assessment literatures. These metrics include the Quality Adjusted Life Years (QALYs), the Healthy Years Equivalents (HYEs), the Disability Adjusted Life Years (DALYs) and the Willingness-to-Pay (WTP) approach (Whitehead & Ali, 2010; Drummond et al., 2015). Still, the majority of recent research still recommends the use of QALYs

(Drummond et al., 2015; Augustovski et al., 2017), which is a health measure combining both quality of life (as a morbidity proxy) and quantity of life (as a mortality proxy) into a single metric. Nevertheless, although being the most commonly used and the golden standard in much health technology assessment literature, the use of QALYs entails multiple challenges (Whitehead & Ali, 2010). One of such challenges is related to its estimation, with a wide variety of direct or indirect methods being available for that purpose (Whitehead & Ali, 2010). The direct methods more commonly applied to build QALYs utility scores are the Visual Analogue Scale, the Time Trade-Off and the Standard Gamble for a specific set of health states (Whitehead & Ali, 2010), with other methods emerging (Oliveira et al., 2018; Gansen et al., 2019). Indirect methods have usually involved the application of generic preference-based measures that can characterize the full range of hypothetical health states (commonly referred as *questionnaires*) and are also available. Two of the most commonly used questionnaires are the EuroQol 5D (with two different versions available, the EQ-5D-3L and the EQ-5D-5L) and the Short Form 6D (SF-6D) (Drummond et al., 2015). By combining the health states characterized in questionnaires with the utility scores (corresponding to these states) produced for several countries/contexts, health gains can be estimated in a straightforward way.

The special case of wellbeing benefits

A variety of wellbeing instruments have also been developed for economic evaluation purposes and have potential to be used for measuring general wellbeing (Makai et al., 2014). This is the case of the WHO-Qol, ICECAP (ICEpop CAPability measure) and ASCOT (Adult Social Care Outcomes Toolkit). Among these, the ICECAP is the one that has been the most widely validated in the health economics evaluation literature (Al-Janabi et al., 2012; Makai et al., 2014; Flynn et al., 2015), with different versions being available: ICECAP-A for adults and ICECAP-O for older people. Similarly to the measurement of health benefits, wellbeing benefits are also estimated by combining these instruments with a value set of capability scores specific per country/context, with estimations entailing multiple theoretical and practical challenges.

2.1.2. Accounting for uncertainty

Accounting for uncertainty is crucial for adequate planning in health, especially for long-term planning (Owen & Daskin, 1998). When it comes to account for uncertainty within location-allocation mathematical programming models in health settings, three main options have been followed. The simplest and most widely used approach relies on sensitivity analyses (see, for instance, Bruni et al. (2006), Santibáñez et al. (2009), Mestre et al. (2012) and Cardoso et al. (2016)). Robust approaches represent a second possible approach (see, for instance, Nasrabadi et al. (2020)), but often appear to be seen as conservative (Owen & Daskin, 1998). Alternatively, stochastic models based on scenario planning have been used in a few studies: Mestre et al. (2015) for health care planning in general; Ghane and Tavakkoli-Moghaddam (2018) for location-allocation decisions related to organ transplant centers; Boujemaa et al. (2018) for emergency medical services; and Cardoso et al. (2015) for LTC planning. These are two-stage stochastic approaches, with location and allocation decisions being decided in the first- and second-stages, respectively. While sensitivity analyses allow for exploring the optimal solution only for a controlled variation in model input parameters, stochastic approaches allow for identifying the solution that performs best under a complete set of scenarios (Owen & Daskin, 1998; Verderame et al., 2010). For this reason, and due to the location-allocation nature of LTC planning, a two-stage stochastic approach is adopted in this study.

A key issue in the development of stochastic models is the definition of a finite set of scenarios that depict uncertainty in an adequate form. Typically, a high number of scenarios are generated, which may result in numerically intractable problems (Dupačová et al., 2003; Heitsch & Römisch, 2003; Li & Floudas, 2014). Under these circumstances, different decomposition techniques (e.g., L-shaped method and Lagrangean decomposition) have been proposed (Kall & Wallace, 1994; Grossmann et al., 2016), although not always with satisfactory results (Feng & Ryan, 2013). As an alternative to these techniques, scenario reduction techniques have been explored, allowing a reduced set of scenarios to be obtained so that stochastic models become less complex to solve while maintaining the problem representation (Li & Floudas, 2014; Löhndorf, 2016). The application of these techniques and inherent challenges are described in detail in Section 2.2.

2.1.3. LTC models

Few location-allocation studies have been devoted to LTC planning, and most of it are single-objective (Lin et al., 2012). For instance, Greene et al. (1998) and Song et al. (2015) aim at planning LTC delivery while minimizing costs, and Kim and Kim (2010) and Marić et al. (2015) aim at locating LTC facilities while minimizing the maximum facilities' load. To the best of authors' knowledge, only Shroff et al. (1998) and Cardoso et al. (2016) have proposed multi-objective LTC planning models. The former used Data Envelopment Analysis for that purpose, while the later used a MILP model. When it comes to account for the impact of uncertainty, only Cardoso et al. (2015) have explored that topic.

Table 1 provides an overview of location-allocation health studies from 2000 onwards, and shows that: a) health and wellbeing benefits have not been considered in location-allocation literature, and no study proposed the joint attainment of all the reviewed objectives; b) few studies have modeled uncertainty through stochastic modelling; and c) within stochastic modelling, no study has employed scenario reduction to enable a faster resolution of models. Accordingly, there is scope to develop more comprehensive location-allocation planning models that jointly advance in these dimensions. This paper aims to fill this gap.

2.2. Scenario reduction methods and scenario planning

2.2.1. Scenario reduction methods for stochastic models

Scenario reduction methods have been shown to make stochastic models less complex to solve while retaining the quality of the stochastic solution (Löhndorf, 2016). Alternative scenario reduction methods have been proposed within the stochastic programming literature, with different methods being used for two-stage and multi-stage stochastic models (Høyland & Wallace, 2001).

Table 1. Key policy objectives and uncertainty modelling within health care planning studies in general, and LTC planning studies in particular (grey cells depict cases of features considered in a study)

Study	**Policy objectives**							**Uncertainty modelling**		**LTC studies**
	Cost	**Equity**				**Health benefits**	**Wellbeing benefits**	**Stochastic modelling**	**Scenario reduction**	
		EA	**GE**	**SE**	**EU**					
M. Oliveira and Bevan (2006)		■			■					
Bruni et al. (2006)		■								
Mitropoulos et al. (2006)	■	■								
Syam and Côté (2010)	■									
Drezner and Drezner (2011)				■						
Mahar et al. (2011)	■									
Smith et al. (2012)		■								
Benneyan et al. (2012)	■									
Ghaderi and Jabalameli (2013)	■									
Mestre et al. (2015)	■	■						■		
Song et al. (2015)	■									■
Marić et al. (2015)										■
Cardoso et al. (2015)	■	■	■	■	■			■		■
Cardoso et al. (2016)	■	■	■	■	■					■
Zhang et al. (2016)	■		■							
Khodaparasti et al. (2017)	■	■								
Luo et al. (2017)			■							
Ghane and Tavakkoli-Moghaddam (2018)								■		
Wang and Ma (2018)	■	■								
Mousazadeh et al. (2018)			■							
Boujemaa et al. (2018)	■							■		
Nasrabadi et al. (2020)	■	■								
LTCNetPlanner	■	■	■	■	■	■	■	■	■	■

Existing scenario reduction methods used for two-stage stochastic models are based on mathematical programming and can be distinguished according to their mathematical features and data requirements (Dupačová et al., 2003; Gröwe-Kuska et al., 2003). One can find methods that rely on the minimization of the distance between the original and the reduced tree, which is the case of the so-called *Backward reduction/Forward selection* method proposed by Dupačová et al. (2003) and Gröwe-Kuska et al. (2003). And one can also find methods that rely on the minimization of the number of scenarios in the reduced tree, as is the case of the method proposed by Karuppiah et al. (2010) (hereafter called *KMG method*, with K, M and G being related to the authors' names). Regarding data requirements, there are methods that do not require any information from experts (*KMG method*) or that depend on experts views to define the number of reduced scenarios to be used (*Backward reduction/Forward selection* method).

Several authors have extensively used the *Backward reduction/Forward selection* method (e.g., Zeballos et al. (2014)) which was updated by Heitsch and Römisch (2003, 2007). This method has been implemented in the library SCENRED of GAMS (GAMS/SCENRED Documentation, 2003). Li and Floudas (2014, 2016) and Chen and Yan (2018) further developed these algorithms by proposing adapted versions of the reduction criterion.

Although scenario reduction techniques are recognized as key to the use of models in real decision-making processes (for instance, by Karuppiah et al. (2010), Govindan and Fattahi (2017) and Paulo et al. (2017)), to the best of authors' knowledge, only Leaven and Qu (2014) have applied the scenario reduction algorithms available in GAMS, in a health context, to schedule phlebotomists in a hospital laboratory.

With the exception of Karuppiah et al. (2010), all these studies require input only regarding the desired dimension of reduction, thereby adopting technocratic ways to decrease the number of scenarios. If these studies are followed, neither the meaning of the scenarios to be eliminated nor other considerations are accounted for when building the reduced set of scenarios. Nevertheless, when reducing scenarios, identifying plausible and relevant scenarios is recognized to be powerful information in scenario planning literature, and experts' involvement commonly play a key role in this area (Amer et al., 2013). We thus explore this research line. Accordingly, in the following section we explore how expert judgments as used in the scenario planning and foresight literature can be used to enhance existing scenario reduction methods.

2.2.2. Scenario planning and foresight concepts

A definition of scenario planning compatible with the nature of scenarios used within stochastic models is provided by Amer et al. (2013), who state that scenario planning starts from the current reality to explore multiple paths to possible and plausible futures (i.e., scenarios), and these multiple futures, rather than forecasts, make explicit the future uncertainties. Three schools of techniques are recognized in scenario planning literature (also called foresight), requiring different levels of interaction with experts and a distinct information basis (Amer et al., 2013): Intuitive Logics, *La Prospective* and Probabilistic Modified Trends.

La Prospective and Probabilistic Modified Trends are characterized by a high level of involvement with experts when building scenarios. In the former, experts are expected to identify and evaluate an exhaustive list of variables which impact on the system under study, and to evaluate the plausibility of generated scenarios (either quantitatively or qualitatively). The latter asks experts to build quantitative scenarios departing from modified time series forecasts. The Intuitive Logics approach has been the most common approach to build scenarios in health contexts, usually being implemented without expert involvement (see recent examples in Gregório et al. (2014) and Willis et al. (2018)).

One can thus argue that exploring plausible scenarios with experts has the potential to reduce scenarios and the consequent complexity in stochastic approaches. Different scenario planning approaches may be selected for that purpose, depending upon the type of information that is relevant to capture from experts. And depending on the selected approach, different techniques and tools may be employed (Amer et al., 2013): STEEP analysis and stakeholder analysis are typically used with Intuitive Logics; Morphol Software and Scenaring Tools are used for performing Morphological Analysis with *La Prospective*; and trend impact analysis and cross impact analysis are employed with Probabilistic Modified Trends. As explained in Section 4.2.2, in this article we make use of the *La Prospective* Approach and Morphol Software. The Morphol Software is used for the Morphological Analysis, which is a systematic approach that allows for a visual exploration and analysis of the complete set of scenarios and assisting the selection of plausible scenarios, with such selection being achieved with the involvement of experts in the area (Godet, 2016).

Fig. 1 summarizes key conclusions from this review, showing that there is no study exploring scenario reduction methods in health planning models when uncertain conditions or multiple objectives are pursued.

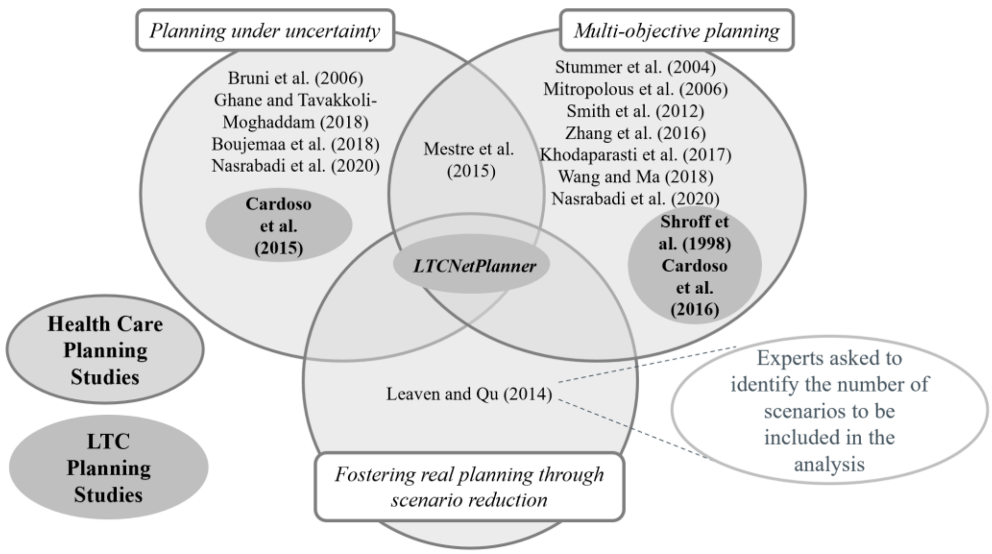


Figure 1. Key features considered in existing health and LTC planning studies

3. LTC Problem Main Features

This study proposes the *LTCNetPlanner* that is designed to support the planning of an LTC network in NHS-based countries, such as Portugal (Simões et al., 2017) and UK (Cylus et al., 2015), with the Portuguese National Network of Long-Term Care (*Rede Nacional de Cuidados Continuados Integrados*, RNCCI) being taken as a reference. The RNCCI was implemented in Portugal in 2006 within the scope of the Ministry of Health and the Ministry of Labor and Social Solidarity, and integrates a mix of public and private providers within a multi-service network of care (Simões et al., 2017). It is targeted to dependent individuals with chronic illnesses and/or disability or to frail elderly individuals. The RNCCI comprises institutional (IC), home-based (HBC) and ambulatory (AC) care (Ministry of Health, 2006) and has features similar to the LTC networks operating in several other countries. IC comprises a variety of services with different resource requirements and length of stay (LOS), including convalescence care (CC), medium-term and rehabilitation care (MTRC), long-term and maintenance care (LTMC) and palliative care (PC) (Ministry of Health, 2006):

a. CC is provided to individuals requiring short-term and intensive rehabilitation services;
b. MTRC is provided to individuals requiring longer periods of institutionalizations and no technological differentiated care;
c. LTMC allows for longer admissions and aims at preventing the worsening of the dependency;
d. PC is focused on people suffering from serious or incurable diseases.

HBC is delivered at patients' homes for those that are able to perform their daily activities independently. AC is provided for those not warranting the provision of either IC or HBC.

Beginning with this network, the planning approach proposed in this study aims to inform on: i) where and when to open/close IC services; ii) the bed capacity that should be available in each IC service over time, including investments in new beds; iii) the redistribution of bed capacity across IC services and locations over time; and iv) on the allocation of patients across IC, HBC and AC services over time. These decisions should be considered within a context of multiple objectives and of an uncertain environment. In addition, planning decisions should been done within the context of budget constraints, meaning that the existing low supply very hardly will be able to fully satisfy demand for care.

Based on the conclusions from Section 2.1.1, the *LTCNetPlanner* adds the maximization of health and wellbeing benefits to the minimization of costs and to the maximization of equity (as captured by the above defined EA, GE, SE and EU dimensions). While the costs and equity objectives are modelled as suggested by Cardoso et al. (2015), the modelling of health and wellbeing benefits is worth further description. A key challenge related to such modeling relies on the selection of metrics that should be used for that purpose (bearing in mind that all metrics entail conceptual and practical issues in their definition and estimation). In this study, and following the literature described in Section 2.1.1, QALYs are proposed as a metric to estimate health benefits, and these are estimated by combining the EQ-5D-3L questionnaire – the one most commonly used for economic evaluation purposes (Drummond et al., 2015) – with the utility scores built for the Portuguese population by Ferreira et al. (2014). The ICECAP-A instrument is used for measuring wellbeing benefits, and the reference utility score developed for the UK by Flynn et al. (2015) is used since no such value set exists for Portugal. The details related to this modeling are presented in Section 5.1.

Concerning the modelling of uncertainty, since it is not possible to foresee with total confidence how LTC demand and delivery will evolve (Pickard et al., 2011), it is critical to address uncertainty related with the number of individuals in need of LTC and the LOS (Birge & Louveaux, 1997). These parameters have been shown to have a key impact in planning results (Cardoso et al., 2015).

Within this setting, we depart from the two-stage stochastic model of Cardoso et al. (2015) and enhance it in several ways: by bringing to location-allocation literature key concepts from health economics for the measurement of health and wellbeing; and by further developing scenario reduction approaches in stochastic location-allocation literature, so that models can be used in practice with low computational times and incorporate experts' knowledge. We not only test existing scenario reduction approaches used in other areas of literature, but also explore how these approaches can be enhanced with expert judgments as used in the scenario planning and foresight literature.

The location-allocation mathematical model on the basis of the *LTCNetPlanner* and that reflects all these features is formulated and described in detail in the next section, which also incorporates the description of the different scenario reduction methods used to foster its use in practice.

4. Methodology

4.1. Stochastic multi-objective MILP model

4.1.1. Mathematical formulation of the model

A stochastic location-allocation planning model is developed with a level of detail that recognizes that:

i. People living in different areas may face different levels of need (index d);
ii. People with different levels of income require different levels of support (index g);
iii. Different types of LTC services are usually associated with different levels of care (indices s,p);
iv. Different levels of demand typically arise as the time passes (indices t,w);
v. The impact of uncertainty on the demand for and supply of LTC is accounted for (indices n,k).

Notation

Sets

D	Demand points
$F = \{(d,l): d \in D, l \in L\}$	Demand points d that can receive LTC in locations l
$G = G_P \cup G_{NP}$	Socioeconomic groups, divided into subsets G_P (individuals with priority as a result of having lower levels of income) and G_{NP} (other individuals).
$L = L_I \cup L_O$	Locations for services, divided into subsets L_I (locations for IC services) and L_O (locations for HBC and AC services).
N	Scenario tree nodes
$Q = \{(t,n): t \in T, n \in N\}$	Time periods t associated with scenario tree nodes n
$S = S_I \cup S_O$	LTC services, divided into subsets S_I (IC services) and S_O (HBC and AC services)
T	Time periods
$U = \{(s,l): s \in S, l \in L\}$	Services s that can be provided in locations l

Indices

$d \in D$	Demand points	$n,k \in N$	Scenario tree nodes
$g \in G$	Socioeconomic groups	$s,p \in S$	LTC services
$l,j \in L$	Locations for services	$t,w \in T$	Time periods

Parameters

c_{st}^{inv}	Investment cost per new bed installed in IC service s ($s \in S_I \subseteq S$) at $t \in T$
c_{st}^{op}	Operational cost per service s per period $t \in T$
$c_{st}^{RealocOut}$ / $c_{st}^{RealocIn}$	Cost of reallocating a bed to IC service s ($s \in S_I \subseteq S$) from a service delivered in a different location/from another service delivered in the same location at $t \in T$
EA_t / EU_t / GE_t / SE_t	Target defined for EA/EU/GE/SE at $t \in T$
hb_s / wb_s	Health/wellbeing benefits per service $s \in S$
ind_{dgstn}	Number of individuals from demand point $d \in D$ and socioeconomic group $g \in G$ requiring service $s \in S$ at $t \in T$ in scenario tree node $n \in N$
ind_{tn}	Number of individuals from lower income groups ($g \in G_P \subseteq G$) requiring LTC at $t \in T$ in scenario tree node $n \in N$
ind_{dtn}	Number of individuals from demand point $d \in D$ requiring LTC at $t \in T$ in scenario tree node $n \in N$
ind_{stn}	Number of individuals requiring service $s \in S$ at $t \in T$ in scenario tree node $n \in N$
tt^{max}	Maximum travel time allowed for patients accessing IC services (in minutes)
tt_{dl}	Travel time between demand point $d \in D$ and service location $l \in L_I \subseteq L$ (in minutes)
ρ_n	Probability of scenario tree node $n \in N$

First-Stage Variables

Δ_{slt}^{bed}	Number of additional beds required for IC service s ($s \in S_I \subseteq S$) located in l ($l \in L_I \subseteq L$) at $t \in T$
X_{slt}	Equal to 1 if service $s \in S$ is located in $l \in L$ at $t \in T$; and 0 otherwise

Second-Stage Variables

B_{slpjtn}^{Realoc}	Number of beds reallocated to IC service s ($s \in S_I \subseteq S$) located in l ($l \in L_I \subseteq L$) from IC service p ($p \in S_I \subseteq S$) located in j ($j \in L_I \subseteq L$) at $t \in T$ in scenario tree node $n \in N$
B_{dgsltn}^{req}	Number of beds required for individuals from demand point $d \in D$ belonging to socioeconomic group $g \in G$ and receiving IC service s ($s \in S_I \subseteq S$) located in l ($l \in L_I \subseteq L$) at $t \in T$ in scenario tree node $n \in N$
IND_{dgsltn}^{prop}	Proportion of individuals from demand point $d \in D$ and socioeconomic group $g \in G$ receiving service $s \in S$ in location $l \in L$ at $t \in T$ in scenario tree node $n \in N$
IND_{dtn}	Number of individuals from demand point $d \in D$ receiving LTC at $t \in T$ in scenario tree node $n \in N$
IND_{tn}	Number of individuals belonging to the lower income groups receiving LTC at $t \in T$ in scenario tree node $n \in N$
IND_{stn}	Number of individuals receiving service $s \in S$ at $t \in T$ in scenario tree node $n \in N$
P_{tn}	Penalty (in minutes) attributed to individuals not receiving IC at $t \in T$ in scenario tree node $n \in N$
TC_{tn}^{inv} / TC_{tn}^{op}	Total investment/operational cost at $t \in T$ for scenario tree node $n \in N$
TT_{tn}	Total travel time (in minutes) at $t \in T$ for scenario tree node $n \in N$

Defining objectives

The *LTCNetPlanner* considers the minimization of expected costs (f_1, Eqs.(1-3)), as well as the maximization of a range of equity objectives: expected equity of access to services [EA] (f_2, Eqs.(4-6)); expected geographic equity across regions [GE] (f_3, Eqs.(7-8)); expected socioeconomic equity across income groups [SE] (f_4, Eqs.(9-10)); and expected equity of utilization across LTC services [EU] (f_5, Eqs.(11-12)). Additionally it considers the maximization of expected health (f_6, Eq.(13)) and wellbeing (f_7, Eq.(14)) benefits promoted through LTC delivery.

The minimization of expected costs (Eq. (1)) includes costs related to the investment in new beds (c^{inv}_{st}) and to the reallocation of beds between services ($c^{RealocOut}_{st}$, $c^{RealocIn}_{st}$) (Eq. (2)), as well as operational costs (c^{op}_{st}) associated with the operation of beds in IC services and with the delivery of HBC and AC (Eq. (3)).

$$Min\ f_1 = \sum_{n \in N} \sum_{t:(t,n) \in Q} \rho_n \times \left(TC^{inv}_{tn} + TC^{op}_{tn} \right) \tag{1}$$

$$TC^{inv}_{tn} = \sum_{s \in S_I} \sum_{\substack{l \in L_I \\ l:(s,l) \in U}} \left(\Delta^{bed}_{slt} \times c^{inv}_{st} + \sum_{p \in S_I} \sum_{\substack{j \in L_I \\ j:(p,j) \in U \\ j \neq l}} B^{realoc}_{slpjtn} \times c^{RealocOut}_{st} + \sum_{\substack{p \in S_I \\ p:(p,l) \in U}} B^{realoc}_{slpltn} \times c^{RealocIn}_{st} \right) \forall (t,n) \in Q \tag{2}$$

$$TC^{op}_{tn} = \sum_{d \in D} \sum_{g \in G} \left(\sum_{s \in S_I} \sum_{\substack{l \in L_I \\ l:(s,l) \in U \\ l:(d,l) \in F}} B^{req}_{dgsltn} \times c^{op}_{st} + \sum_{s \in S_O} \sum_{\substack{l \in L_O \\ l:(s,l) \in U \\ l:(d,l) \in F}} ind_{dgstn} \times IND^{prop}_{dgsltn} \times c^{op}_{st} \right) \forall (t,n) \in Q \tag{3}$$

The maximization of *expected* equity is ensured through the minimization of four different equity measures – the smaller the value of these equity measures, the better the provision of LTC. Eqs. (4-6) aim at maximizing expected EA by minimizing total travel time for individuals accessing institutional services – TT_{tn} (Eq. (5)) captures the total travel time for patients receiving LTC, while P_{tn} (Eq. (6)) is used to penalize individuals without access to LTC by assuming that individuals not receiving the care they need incur the maximum travel time. Eq. (7) aims at maximizing expected GE by minimizing unmet need in the geographical area with lowest level of supply, using as a basis the number of patients receiving LTC per geographical area as given in Eq. (8). Eq. (9) aims at maximizing expected SE by minimizing unmet need for the lower income groups, departing from the number of patients belonging to the lower income groups ($g \in G_p$) and receiving LTC as given in Eq. (10). Eq. (11) aims at maximizing expected EU by minimizing unmet need for the LTC service with the lowest provision of care, using as a basis the number of patients receiving each type of LTC service as given in Eq. (12). All these objectives are evaluated at the end of the planning horizon, with the probabilities of different scenarios (ρ_n) being accounted for.

$$Min\ f_2 = \sum_{t:(t,n) \in Q} \rho_n \times \left(\frac{TT_{(t=|T|)n} + P_{(t=|T|)n}}{\sum_{s \in S_I} ind_{s(t=|T|)n}} \right) \tag{4}$$

$$TT_{tn} = \sum_{d \in D} \sum_{g \in G} \sum_{s \in S_I} \sum_{\substack{l \in L_I \\ l:(s,l) \in U \\ l:(d,l) \in F}} ind_{dgstn} \times IND^{prop}_{dgsltn} \times tt_{dt} \quad \forall (t,n) \in Q \tag{5}$$

$$P_{tn} = \sum_{d \in D} \sum_{g \in G} \sum_{s \in S_I} tt^{max} \left(ind_{dgstn} - \sum_{\substack{l \in L_I \\ l:(s,l) \in U \\ l:(d,l) \in F}} ind_{dgstn} \times IND_{dgsltn}^{prop} \right) \quad \forall (t,n) \in Q \tag{6}$$

$$Min\ f_3 \geq \sum_{t:(t,n) \in Q} \rho_n \times \left(1 - \frac{IND_{d(t=|T|)n}}{ind_{d(t=|T|)n}} \right) \quad \forall d \in D \tag{7}$$

$$IND_{dtn} = \sum_{g \in G} \sum_{s \in S} \sum_{\substack{l \in L \\ l:(s,l) \in U \\ l:(d,l) \in F}} ind_{dgstn} \times IND_{dgsltn}^{prop} \quad \forall d \in D, (t,n) \in Q \tag{8}$$

$$Min\ f_4 = \sum_{t:(t,n) \in Q} \rho_n \times \left(1 - \frac{IND_{(t=|T|)n}}{ind_{(t=|T|)n}} \right) \tag{9}$$

$$IND_{tn} = \sum_{d \in D} \sum_{g \in G_P} \sum_{s \in S} \sum_{\substack{l \in L \\ l:(s,l) \in U \\ l:(d,l) \in F}} ind_{dgstn} \times IND_{dgsltn}^{prop} \quad \forall (t,n) \in Q \tag{10}$$

$$Min\ f_5 \geq \sum_{t:(t,n) \in Q} \rho_n \times \left(1 - \frac{IND_{s(t=|T|)n}}{ind_{s(t=|T|)n}} \right) \quad \forall s \in S \tag{11}$$

$$IND_{stn} = \sum_{d \in D} \sum_{g \in G} \sum_{\substack{l \in L \\ l:(s,l) \in U \\ l:(d,l) \in F}} ind_{dgstn} \times IND_{dgsltn}^{prop} \quad \forall s \in S, (t,n) \in Q \tag{12}$$

In addition, expected health and wellbeing benefits are maximized according to Eq. (13) and Eq. (14), respectively. According to Eq. (13) the maximization of health benefits is defined as the sum of the individual health benefits (hb_s) obtained by all the patients receiving each type of LTC service $s \in S$. A similar condition is defined in Eq. (14) for the maximization of wellbeing benefits. These individual benefits (hb_s and wb_s) vary with the type of service and can be modelled as described in Section 5.1.

$$Max\ f_6 = \sum_{n \in N} \rho_n \left[\sum_{s \in S} \sum_{t:(t,n) \in Q} hb_s \sum_{d \in D} \sum_{g \in G} \sum_{\substack{l \in L \\ l:(s,l) \in U \\ l:(d,l) \in F}} ind_{dgstn} \times IND_{dgsltn}^{prop} \right] \tag{13}$$

$$Max\ f_7 = \sum_{n \in N} \rho_n \left[\sum_{s \in S} \sum_{t:(t,n) \in Q} wb_s \sum_{d \in D} \sum_{g \in G} \sum_{\substack{l \in L \\ l:(s,l) \in U \\ l:(d,l) \in F}} ind_{dgstn} \times IND_{dgsltn}^{prop} \right] \tag{14}$$

Defining the model constraints

The model makes use of a set of constraints that are detailed in Appendix A [Eqs. (A1-A15)]: i) opening/closing a service is not possible after its previous closure/opening; ii) minimum level of demand satisfaction; iii) care should be delivered in the closest available service, when considering the residence of patients as reference (own home or institution), and cannot be delivered by providers located at a distance greater than a maximum distance; iv) maximum/minimum number of beds and patients are set per service; and v) reallocating beds between services in different locations can take place only in the first time period.

4.1.2. Solution approach: dealing with multiple objectives

In order to deal with the multiple policy objectives defined above, one can i) identify compromise solutions, i.e., the so-called Pareto optimal or non-dominated solutions; or ii) model preferences from relevant stakeholders and/or from policy-makers and planners so as to identify the solution (Cohon, 1978). We follow the first of these approaches in this study. Two methods have been widely used in the literature for that purpose: the weighting method and the ε-constraint method (Mavrotas, 2009). According to Mavrotas (2009), some advantages of the ε-constraint method over the weighting method are:

a. The ε-constraint method allows to obtain a rich representation of the efficient set – it generally allows producing a different efficient solution every run;
b. As a consequence of a., with the ε-constraint method it is possible to control the number of efficient solutions of the Pareto set;
c. The ε-constraint method does not require the use of a scaling procedure, leaving to the decision-maker the analysis of the Pareto frontier.

For these reasons, the ε-constraint method is selected for this study. Particularly, the augmented ε-constraint method proposed by Mavrotas (2009) as an alternative to the original ε-constraint method is used – this alternative method solves the well-known pitfalls of the original ε-constraint method, particularly, the calculation of the range of each objective over the efficient set, and the guarantee of an efficient solution. Using this method, one of the multiple policy objectives is used as the objective to be optimized (minimized in the case of costs), whereas the remaining are imposed as constraints.

4.2. Scenario reduction

4.2.1. Overview of scenario reduction methods

As mentioned above, stochastic models typically lead to complex problems in computational terms, caused by the number of scenarios defined. However, some of these scenarios may not be relevant, and so may be excluded. To do so, a set of scenario reduction methods available from literature is here explored to be applied within the *LTCNetPlanner*, as described in Table 2. Two main scenario reduction methods exist in the literature (see Section 2): the *Backward reduction/Forward selection method* (Dupačová et al., 2003;

Gröwe-Kuska et al., 2003; Heitsch & Römisch, 2003, 2007) and the *KMG method* (Karuppiah et al., 2010). These methods can be distinguished according to their mathematical features and data requirements related to the desired dimension of reduction (Dupačová et al., 2003; Gröwe-Kuska et al., 2003):

i. *Backward reduction/Forward selection method:*
   a. Data requirements: Method relying on experts' opinion on the desired dimension of reduction, i.e., experts are asked to identify the number or percentage of scenarios to be eliminated from the original tree, without considering the nature and meaning of scenarios;
   b. Mathematical features: Scenarios are eliminated based on the minimization of the probability distance between the original set and the reduced set of scenarios – scenarios are thus deleted when they are close or when they have small probabilities of occurrence.

ii. *KMG method*:
   a. Data requirements: no information related to the dimension of reduction is asked to experts;
   b. Mathematical features: method that allows determining the minimum number of scenarios to be preserved in the reduced sub-tree such that the optimal objective obtained with the full scenario tree is closely approximated by the optimal objective of the reduced problem.

Since using experts' knowledge can help in depicting relevant and meaningful scenarios within scenario reduction (as noted in Section 2.2.1), a new method combining existing scenario reduction methods with a scenario planning approach – the *Morphol-KMG method* – is also proposed. This new method differs from the existing ones by exploring the reduction of a number of scenarios by using experts' knowledge to identify the set of plausible and relevant scenarios. Instead of simply asking experts for the dimension of reduction, this method relies on the minimization of the number of scenarios (similarly to the *KMG method*) while simultaneously avoiding the elimination of scenarios that are considered as relevant by experts. This new method accounts for both the probabilities and values/meaning of scenarios for reduction purposes.

Table 2. Comparison of key scenario reduction methods features (features in grey cells)

	Backward reduction/Forward selection method	***KMG method***	***Morphol-KMG method***
Accounts for probabilities of scenarios			
Accounts for values/meaning of scenarios			
Makes use of experts' knowledge on relevant and meaningful scenarios			
Experts not asked to identify the dimension of reduction			

4.2.2. The *Morphol-KMG method*

A key contribution of this study is the development of a novel and generic method to deal with uncertainty – the *Morphol-KMG method.* It combines an adapted version of the *KMG method* (detailed later on) with a scenario planning approach that fits *La Prospective* Approach – the Morphological Analysis (briefly described in Section 2.2.2). The reasoning for combining an adapted *KMG method* with a Morphological

Analysis is two-fold. First, the approach of *La Prospective* in general, and Morphological Analysis in particular, allow for expert involvement and are compatible with the type of scenarios under analysis in this work (i.e., different quantitative scenarios defined via specific parameter uncertainties). Secondly, by using an adapted version of the *KMG method*, the minimum number of scenarios to be included in the reduced scenario tree is computed, thus avoiding asking experts for the dimension of reduction. This minimum number includes the set of plausible scenarios first selected by experts in the Morphological Analysis.

Fig. 2 gives an overview of the *Morphol-KMG method* and can be read as follows. Beginning with historical information on the uncertain parameters and associated trends and probabilities, the proposed method makes use of a Morphological Analysis (Godet, 2016) that explores a set of Morphol Software tools (Stage 1) and of a MILP model (Stage 2) to generate a reduced scenario tree.

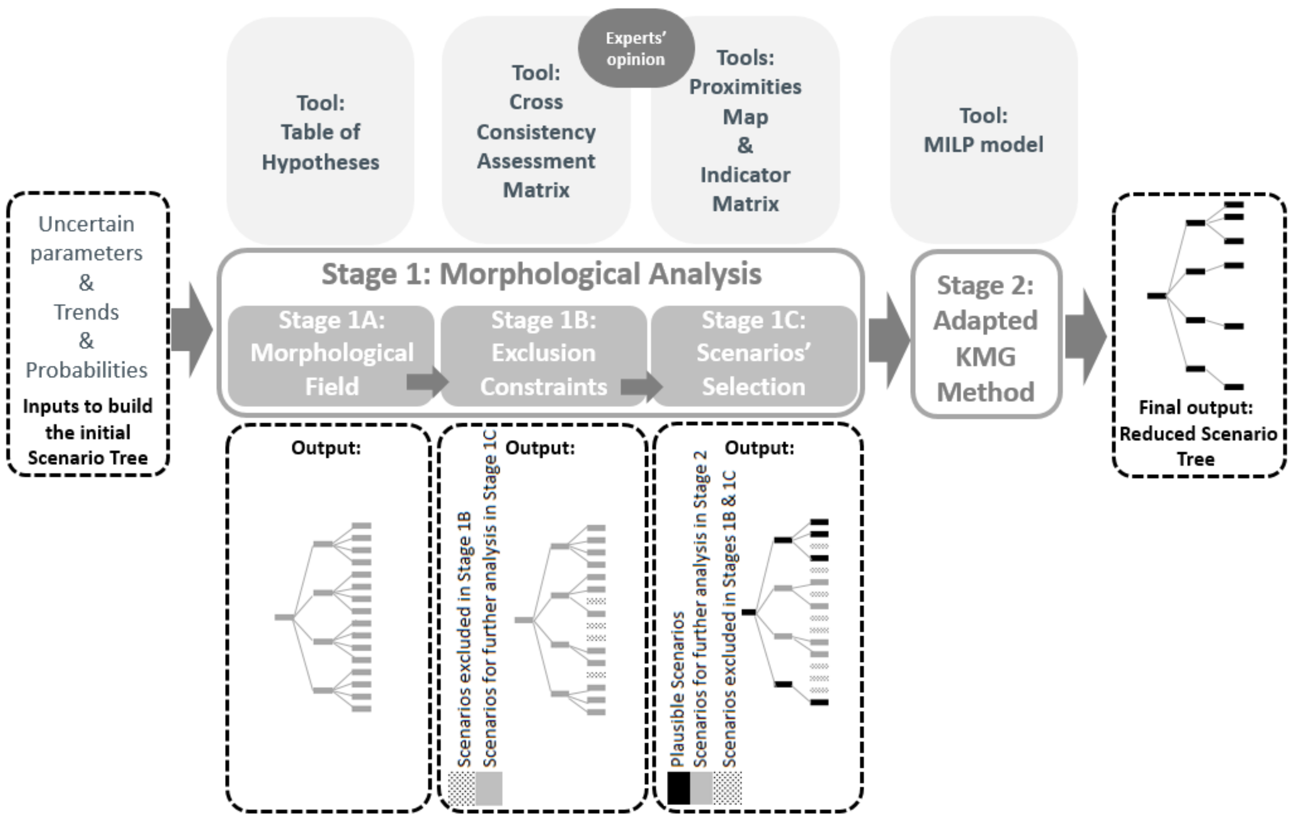


Figure 2. Key stages and tools of the *Morphol-KMG method*

The key stages involved in the *Morphol-KMG method* are described below using an application in the LTC sector for illustrative purposes, and considering the two parameters earlier recognized as key for LTC planning: LOS and demand. The number of individuals in need of LTC for a three-year period and their LOS are considered uncertain parameters (also referred as key variables or drivers in the scenario literature). And for these uncertain parameters it is considered that: a low initial number of individuals in need and a low LOS are found in the first year (t=0); and there are three trends (low, average and high) in the following years (t=1, t=2) for both the demand and the LOS. These three trends for t=1 and t=2 are usually called hypotheses in the scenario literature. Although the proposed method is presented for the health context, it can be applied within any other two-stage stochastic model, and also with any given number of scenarios.

4.2.2.1. Stage 1: Morphological Analysis

La Prospective approach

Building scenarios under *La Prospective* approach implies a proper involvement with experts, and the scenario building process should uptake the following steps:

a. Identification and assessment of a list of key variables (n; also called drivers) that may have impact in the system under analysis – taking the illustrative example as reference, these key variables correspond to the individuals in need of LTC and the LOS at t=1 and t=2 (uncertain parameters);
b. For each key variable in a., there is a need to involve the group of experts in the discussion to identify future trends (m; representing the hypotheses) – low, average and high in the illustrative example (for both the individuals in need and LOS);
c. The Morphological analysis is then used to identify scenarios that come up from the combination of variables and trends as identified in a. and b., respectively.

The key stages of the Morphological Analysis are described in detail below.

Morphological Analysis - Key stages

Fig. 3 depicts the stages of the Morphological Analysis (Stages 1A to 1C).

Morphological Field (Fig. 3, Stage 1A): The Morphological Analysis starts with the definition of the initial scenario tree (morphological field definition). The first step builds a Table of Hypotheses with information on key variables (the uncertain parameters in our context) and hypotheses (future trends). By combining all the key variables and hypotheses, the initial scenario tree is defined, including m^n scenarios. Considering our illustrative example, the dimension of the initial scenario tree is 81 scenarios (3^4 – 3 hypotheses [low, average and high] and 4 key variables [number of individuals in need and LOS at t=1 and t=2]).

Exclusion Constraints (Fig. 3, Stage 1B): Once the initial scenario tree is built, scenarios that result from incompatible hypotheses are identified by experts through the use of a Cross Consistency Assessment Matrix. This matrix enables the comparison of all the combinations of key variables and hypotheses, and for each pair a judgement is made on whether it represents, or not, a compatible combination (Ritchey, 2006). The output of this stage is a reduced morphological field characterized by a scenario tree with a typically lower number of internally compatible scenarios. Fig. 3 (Stage 1B) illustrates this stage in which an expert judges as incompatible all the scenarios characterized by a low demand at t=2 and a decreasing number of individuals in need. In this case the initial scenario tree is reduced from 81 to 46 scenarios.

Scenarios Selection (Fig. 3, Stage 1C): This stage requires experts to identify the combination of plausible scenarios, using as a basis numerical and visual outputs provided by the Morphol Software (Godet, 2016):

a. The Proximities Map helps with visualizing the scenarios that share a high number of common hypotheses and the most remote scenarios. E.g., scenarios represented by 2232[1] and 2222 in Fig. 3 (Stage 1C) are close to each other since they share three hypotheses out of four, namely, average demand at t=1 (2232 and 2222) and at t=2 (2232 and 2222) and average LOS at t=2 (2232 and 2222). One should consider that each scenario is represented by a four-digit number in the Morphol Software, since each digit represents one out of four variables, and each digit/variable can assume the value 1, 2 or 3, depending on which hypotheses (low, average or high, respectively) is selected;
b. The Indicator Matrix presents a summary of key proximity indicators whose purpose is to evaluate the general compatibility between scenarios, with a particular proximity indicator playing a key role in this analysis (Computer Innovation Institute, 2006) – the CT indicator. For each scenario, the CT indicator represents the sum of common hypotheses with the remaining scenarios, meaning that a scenario with a high CT value plays a key role in the set and should be considered for selection.

Accordingly, within Stage 1C, experts are expected to select one plausible scenario per set of closest scenarios in the Proximities Map, and this selection should be based on the Proximities Map and on (high) CT values. Considering the illustrative example depicted in Fig. 3, five sets of closest scenarios can be distinguished (see the five sets of scenarios in different shades of gray in Fig. 3, Stage 1C), and so a combination of five plausible scenarios is selected. After this selection, there is a need to exclude scenarios that are close to each selected plausible scenario, and this exclusion should be simply based on the list of closest scenarios provided in the Indicator Matrix (see Fig. 3, Stage 1C).

Within this setting, three sets of scenarios can be distinguished at this point (associated probabilities are determined under Stage 2, as detailed in section 4.2.2.2):

a. Plausible scenarios selected by experts to integrate the final reduced scenario tree;
b. Excluded scenarios that are dismissed due to closeness to plausible scenarios;
c. Non-plausible and non-excluded scenarios, representing the ones neither selected as plausible nor excluded from analysis; these should be further analyzed within Stage 2, so that it is decided whether they should be integrated in the final reduced tree. As asking experts for a deep analysis of all these scenarios may be time consuming, the adapted *KMG method* is proposed in Stage 2.

[1] Average demand at *t=1* (2232), average demand at *t=2* (2232), high LOS at *t=1* (2232) and average LOS at *t=2* (2232).

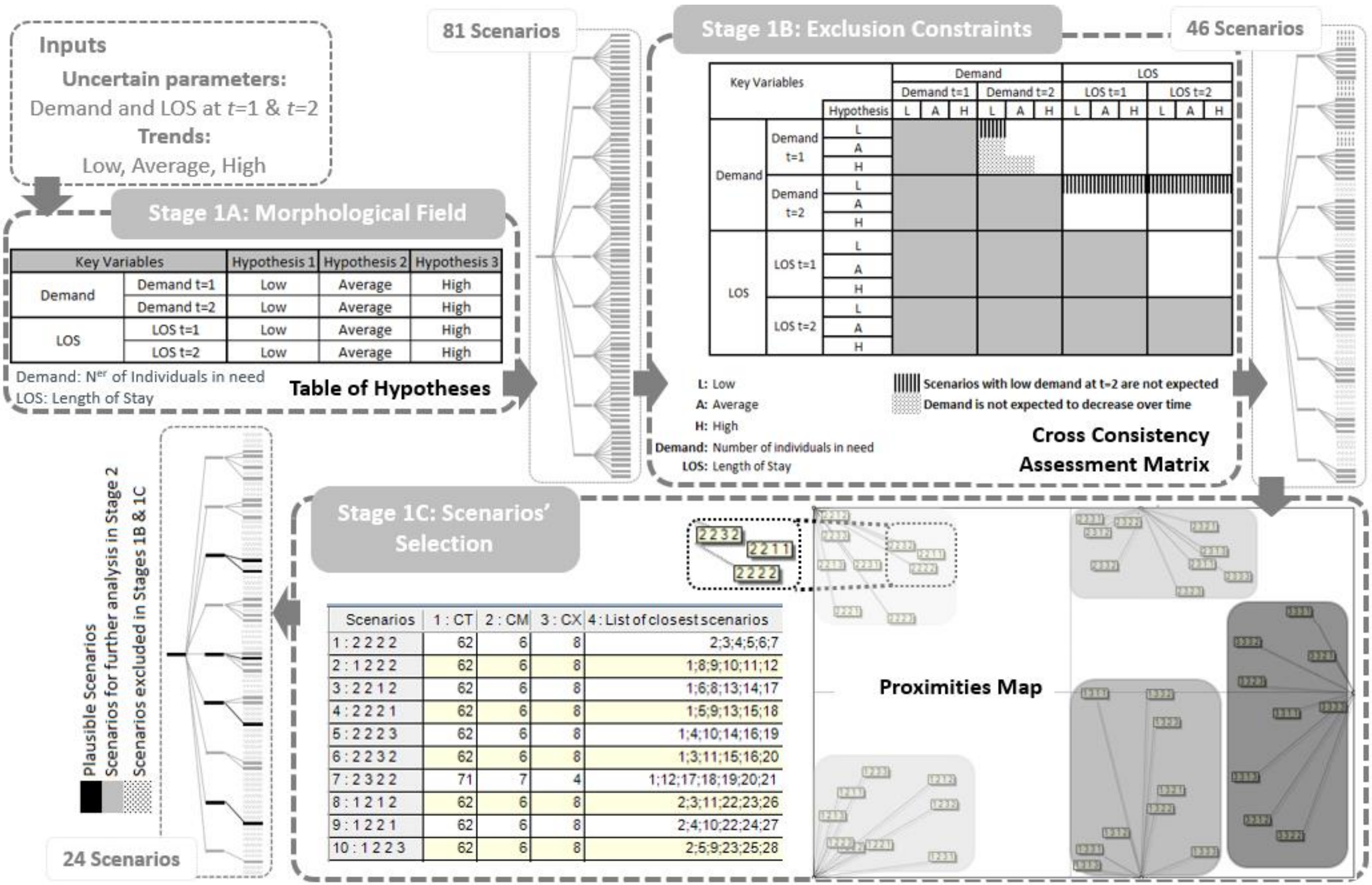


Figure 3. Key stages of the Morphological Analysis (Stage 1) in the *Morphol-KMG method* – inputs, outputs and tool

In our illustrative example, a scenario tree with 46 scenarios (output from Stage 1B) was reduced to 24, from which five (black scenarios in Fig. 3, Stage 1C) are selected by experts as the most plausible.

The interaction with experts in the Morphological Analysis follows the protocols described below.

Protocol with experts

Two protocols are developed to guide the interaction with experts under Stages 1B and 1C: Protocol I for Stage 1B, and Protocol II for Stage 1C (Appendix B, Table B1). Considering again the illustrative example in the LTC sector, is it possible to observe the results obtained by following Protocol I (Fig. 3, Stage 1B; and Appendix B, Table B2) and Protocol II (Appendix B, Figure B1 and Table B2).

The application of these protocols should consider the number of experts to be involved and the procedures adopted to promote a consensus. Hence, depending upon the number of experts to be involved, adequate group participatory (and interactive) processes should be carefully designed. When a large group of experts with diverse and possibly divergent points of view is to be included in the study, the interaction can be guided through a workshop or decision conferencing setting in a face-to-face environment, with the assistance of an impartial facilitator and with the support of computer-aided tools (Phillips & Phillips, 1993; Phillips & Bana e Costa, 2007), or possibly through combined face-to-face and non-face-to-face processes fit for the context (see examples in Alvarenga et al. (2019) and Vieira et al. (2020)). Such processes promote the generation of constructive knowledge, with the discussion between experts fostering the achievement of a compromise in the scenario building process (Keeney, 1992; Bana e Costa et al., 2014; Franco et al., 2016). Voting procedures and tools can be also used to promote convergence and a compromise (Bana e Costa et al., 2014) and to avoid group problems, such as interpersonal conflicts (Vieira et al., 2020). In fact, participatory processes are of utmost importance when large and diverse groups of experts are involved, with group heterogeneity (e.g. a diverse composition in terms of demography or level of expertise) being considered key to increase the quality of the decisions (Franco et al., 2016).

4.2.2.2. Stage 2: *Adapted KMG method*

The scenario tree obtained as output from Stage 1C not only includes the selected plausible scenarios, but also scenarios not selected as plausible nor excluded by experts, and that still need to be analysed to understand if they should be included in the final reduced scenario tree. To support this process, an adapted version of the *KMG method* proposed by Karuppiah et al. (2010) is proposed. In particular, the *adapted KMG method* used in the *Morphol-KMG method* only differs from the *KMG* (which is a MILP model) by requiring two additional constraints: imposing the inclusion of the plausible scenarios previously selected under Stage 1 in the final reduced tree; and imposing the exclusion of the scenarios excluded under the same stage. Eqs. (15-16) represent these constraints:

$$w_{1k_1,2k_2,...,Ik_I}=\begin{cases}1 & \forall k_1\in K_1^{PS}, k_2\in K_2^{PS} ..., k_I\in K_I^{PS}\\ 0 & \forall k_1\in K_1^{ES}, k_2\in K_2^{ES},..., k_I\in K_I^{ES}\end{cases} \tag{15}$$

$$p_i^{k_i}=0 \quad \forall k_i\in K_i^{ES} \tag{16}$$

in which $i \in I$ represents the set of uncertain parameters with possible values $k_i \in K_I$ and probabilities $p_i^{k_i}$ (single probability of uncertain parameter i assuming the value k_i), and $w_{1k_1,2k_2,...,Ik_I}$ is equal to one if a scenario characterized by uncertain parameter i taking the value k_i is selected for the reduced scenario tree. Particularly, Eq. (15) imposes that plausible scenarios selected under Stage 1C ($k_i \in K_i^{PS}$; with PS standing for *Plausible Scenarios)* should be maintained in the final reduced tree (and for these scenarios, new probabilities $p_i^{k_i}$ are determined, similarly to the proposal of Karuppiah et al. (2010)), whereas scenarios that are close to these plausible scenarios ($k_i \in K_i^{ES}$; with ES standing for *Excluded Scenarios*) should be excluded. For those scenarios that should be excluded, there is also the need to set their probabilities to zero (according to Eq. (16)).

Fig. 4 shows the results obtained when considering the illustrative example in the LTC sector – a final reduced tree of 13 scenarios is obtained, including the five plausible scenarios selected by experts under Stage 1C.

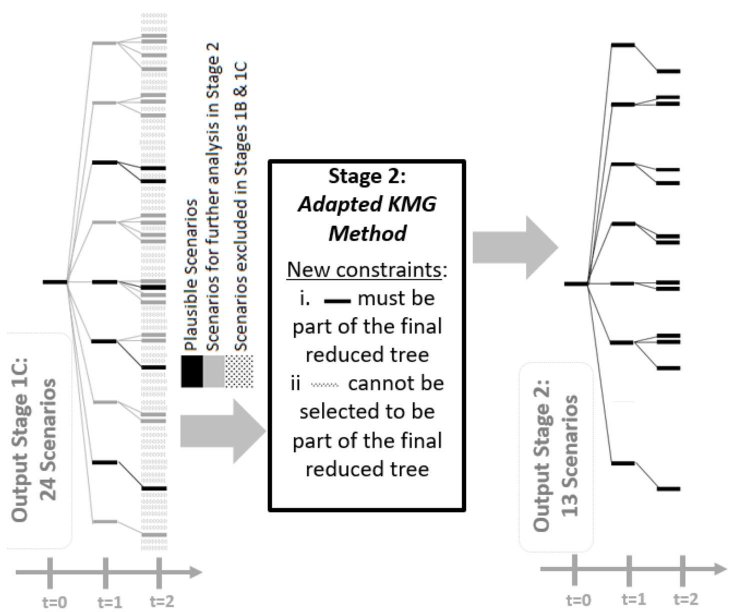


Figure 4. *Adapted-KMG method* (Stage 2) in the *Morphol-KMG method* – inputs and outputs

5. Case study

We herein apply the *LTCNetPlanner* at the county level in the Great Lisbon region in Portugal over the 2018-2020 period. This small geographic unit is considered appropriate to capture geographic access and travelling times, and is a meaningful unit for LTC planning purposes. The LTC network in the Great Lisbon region delivers IC, HBC and AC, with different levels of provision being available across the nine counties of the region (with these representing the nine demand points - *Amadora*, *Cascais*, Lisbon, *Loures*, *Mafra*, *Odivelas*, *Oeiras*, *Sintra* and *Vila Franca de Xira*). IC is currently provided in 13 different units, with 5 CC units, 7 MTRC units, 8 LTMC units and 6 PC units. Part of these units provides more than one typology of LTC. HBC and AC are provided by the PHCC belonging to each of the nine counties. The population in the region is divided between low- and high-income groups, with around 55% of the people having lower incomes. And around 35% of the total demand for LTC is found in the county of Lisbon, whereas the lower number belongs to *Mafra* (Ministry of Health, 2006; Cardoso et al., 2012).

The model was implemented in the General Algebraic Modeling System (GAMS) 23.7 and was solved with CPLEX 12.0 on a Two Intel Xeon X5680, 3.33 Gigahertz computer with 12 Gigabyte RAM. This section describes the dataset in use and explores the results obtained.

5.1. Dataset for applying the stochastic multi-objective MILP model

The dataset used includes both deterministic and uncertain data. Deterministic data includes the current supply of LTC, costs, budget, travel times, and maximum travel time allowed per patient requiring IC. Uncertain data related to the number of individuals in need of LTC and LOS for the 2018-2020 period was used to build a scenario tree with 81 scenarios:

i. The number of individuals requiring LTC was obtained as a probability distribution predicted using a Markov simulation model (Cardoso et al., 2012). This probability distribution was afterwards converted into three (parameter) values based on the extended Pearson-Tuckey method[2] (Clemen and Reilly, 2003);
ii. The LOS was obtained with data from the Central Administration of the Health System (2019). Three (parameter) values were also considered, representing the minimum, average and maximum LOS per typology of LTC in Portugal.

Further details on these data are available upon request to the authors. Further data is required for modelling health (hb_s) and wellbeing (wb_s) benefits associated with LTC provision as detailed below.

Modelling health benefits

QALYs gained with the delivery of each LTC service are used as a proxy to health benefits (hb_s) and are estimated using the EQ-5D-3L self-report questionnaire, as follows:

[2] The extended Pearson-Tuckey method replaces a continuous probability distribution by a three branch uncertainty node, including the 5th quantile, the median and the 95th quantile.

I. Make use of the EQ-5D-3L self-report questionnaire using information from Rato et al. (2009). This questionnaire allows to characterize patients' health states (before and after receiving LTC) according to five dimensions – mobility, self-care, usual activities, pain/discomfort and anxiety/depression – and within each dimension three possible levels are available – no problems [coded as 1], some problems [coded as 2] and extreme problems [coded as 3];
II. Determine the 5-digit numbers describing these EQ-5D-3L states before and after receiving each type of LTC service – for instance, the health state 11233 means that such a patient has no problems with mobility and self-care (<u>11</u>233), some problems with usual activities (11<u>2</u>33) and extreme problems with pain/discomfort and anxiety/depression (112<u>33</u>);
III. Determine the value of the EQ-5D-3L states before and after receiving LTC within the RNCCI using the EQ-5D-3L value set built by Ferreira et al. (2014) for Portugal;
IV. Calculate the QALYs gained per type of LTC service based on the difference between the values of the EQ-5D-3L states after and before receiving LTC.

Modelling wellbeing benefits

The ICECAP-A measure is used to estimate wellbeing improvements (wb_s). The adopted procedure is similar to the procedure presented for health gains, with the following differences:

a. In Step I, information on disabilities is used to complete the ICECAP-A instrument. This instrument captures individuals' capability to function (before and after receiving LTC) in five areas – stability, attachment, autonomy, achievement and enjoyment – and four levels are available to assess these dimensions. Accordingly, a 5-digit number is also obtained under Step II to represent the state of each patient – for instance, 44444 indicates full capability on all dimensions, whereas 11111 indicates an absence of capability;
b. In Step III, the value of the states before and after receiving LTC within the RNCCI is determined using the UK ICECAP-A value set built by Flynn et al. (2015).

One should however note that these estimates on health and wellbeing benefits represent average values per typology of LTC service as obtained for a sample of patients (1145 patients used as a basis in Rato et al. (2009)) and do not vary across time, being crude (proxy) estimates.

5.2. Scenario reduction approaches in use

In the case study the initial scenario tree entailed 81 scenarios (full tree), obtained by crossing the uncertainty regarding the number of individuals in need and regarding the LOS; the scenario tree was afterwards reduced using the *KMG method*, the *Backward reduction/Forward selection method* and the proposed *Morphol-KMG method.* Accordingly, three reduced trees were then obtained:

a) *Reduced Scenario Tree A*: obtained using the *KMG method* proposed by Karuppiah et al. (2010) and characterized by having the minimum possible number of scenarios (see Section 4.2.2.1);

b) *Reduced Scenario Tree B:* obtained using the *Backward reduction/Forward selection method* proposed by Dupacová et al. (2013) and Gröwe-Kuska et al. (2003); this method is run by imposing the minimum number of scenarios obtained as output with the *KMG method*, which is information that is not always easy to identify*;*

c) *Reduced Scenario Tree C*: obtained using the proposed *Morphol-KMG method*:

   i. Stage 1A: the number of individuals in need and LOS for the 2018-2020 period are used as uncertain parameters, and with three possible trends – low, average and high (with each trend being obtained as described earlier in section 5.1);

   ii. Stages 1B and 1C: stages applied together with two researchers with expertise in LTC planning in Portugal that assumed the role of experts in this study, and who decided which scenarios should be excluded (Stage 1B, following Protocol I) and which scenarios should be kept it the final tree (Stage 1C, following Protocol II);

   iii. Stage 2: the *KMG method* proposed by Karuppiah et al. (2010) is adapted by including Eqs. (15-16), and is used to obtain the final reduced tree.

It should be highlighted that for the particular case of the *Morphol-KMG method*, the implementation of scenario reduction in the case study depends on information which was gathered through two face-to-face meetings with the two experts:

i. The first meeting was focused on gathering information to fill the Cross Consistency Assessment Matrix (using Protocol I), and then to select plausible scenarios from the Proximities Map (using Protocol II);

ii. The second meeting took place to validate the reduced scenario tree obtained after applying Stage 2 of the method (as described below in section 5.3).

5.3. Validation of the *LTCNetPlanner*

When applying the *LTCNetPlanner,* it is essential to consider which validation procedures should be adopted. We herein describe how a two-phase validation procedure has been (and can be) used:

i. Validation Phase I: A validation with experimental data was first performed so as to confirm if the proposed model is able to reproduce expected results. Particularly, the MILP model was validated by solving it for several small instances and by comparing the obtained results with the expected results. These small instances were defined by the authors, representing hypothetical and small LTC networks whose expected results represent planning decisions under different planning objectives that are easily obtained without any optimization model;

ii. Validation Phase II: The *Morphol-KMG method* was afterwards validated together with the two experts. Particularly, after being involved in Stages 1B and 1C of the *Morphol-KMG method*, the experts are again called upon to participate after Stage 2 – the final reduced scenario tree is obtained after Stage 2, and the experts are asked to validate this tree, i.e., to verify if the tree reflects their views and opinions about the reality of the LTC sector in Portugal.

Validation Phase I allowed to confirm the validity of the proposed MILP model, and Validation Phase II allowed to confirm that the scenarios selected for the analysis based on the *Morphol-KMG method* reflect both experts' views about the LTC sector in Portugal.

One should however note that these validation procedures could be improved – in line with motivating its use in real settings – by involving a larger and more diverse group of LTC policy-makers and experts (through a specifically designed participatory process) in the construction and selection of scenarios. This would increase the legitimacy of the approach, as well as would promote model adoption (White & Bourne, 2007; Franco et al., 2016).

5.4. Results

The results obtained by applying the *LTCNetPlanner* to the county level in the Great Lisbon region in Portugal, for the 2018-2020 period, were set to respond to the following Research Questions [RQ]:

i. RQ1: What is the impact of accounting for multiple policy objectives, particularly health and wellbeing benefits, when planning the delivery of LTC?
ii. RQ2: What is the impact of scenario reduction methods in planning results?
iii. RQ3: What is the impact of scenario reduction methods on the computational performance of the planning model?

The *LTCNetPlanner* is then run under seven different planning cases shown in Fig. 5 – these cases differ in terms of the planning objectives to be optimized, as well as in terms of the scenario reduction approaches that are employed. Firstly, RQ1 is explored by comparing the results obtained under Cases 0, I, II and III – the difference between these cases relies on the planning objectives in use, and not on the scenario reduction approaches, as in here the same reduction approach is used in all these cases (the *Morphol-KMG method*). Secondly, RQ2 and RQ3 are analyzed based on the comparison of Cases II, IV, V and VI. These cases rely on the same planning objectives (costs and health benefits), being thus possible to explore which is the impact of running the model with the full scenario tree (Case VI) or with the reduced scenario trees (*Reduced Scenario Tree A* for Case V, *Reduced Scenario Tree B* for Case IV *and Reduced Scenario Tree C* for Case II). Particularly, while RQ2 allows exploring the impact on planning results for the 2018-2020 period, RQ3 allows analyzing impacts on the computational performance of the model for different planning periods – a shorter period, 2018-2020, and a longer one, 2018-2021.

All cases were run by imposing all the constraints defined in the Appendix A [Eqs. (A1-A15)], with objectives functions EA [Eqs.(4-6)], GE [Eqs.(7-8)], SE [Eqs.(9-10)] and EU [Eqs.(11-12)] being adapted as constraints by imposing equity satisficing levels to be attained over time: $f_2 < 0.85$, $f_3 < 0.5$, $f_4 < 0.25$, $f_5 < 0.8$.

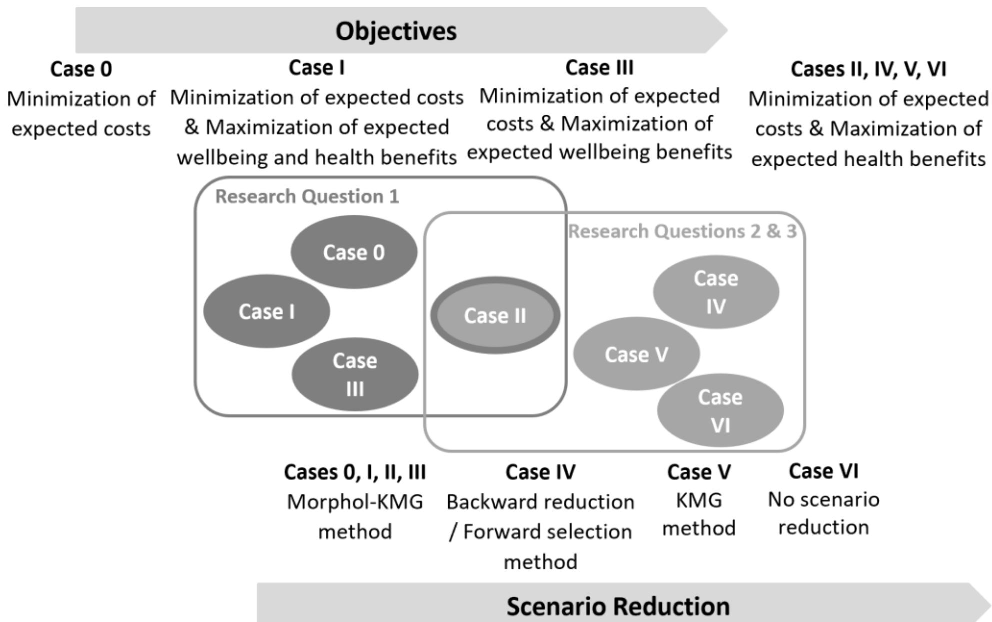


Figure 5. Planning cases considered for analysis

5.4.1. Planning results

RQ1: Impact of accounting for health and wellbeing benefits

Two analyses were carried out to explore the impact of accounting for health and wellbeing gains:

i. Research Question 1A: Decisions arising when none of these objectives is imposed (i.e., when only a cost objective is pursued, Case 0) are compared with those arising when each of these objectives is considered separately (Cases II and III);
ii. Research Question 1B: Then, results obtained under Cases II and III are compared with the case in which health and wellbeing objectives are considered together with the cost objective (Case I).

Research Question 1A: Fig. 6 depicts the Pareto frontiers obtained when running the multi-objective stochastic model under Cases II (Fig. 6a)) and III (Fig. 6b)), i.e., when accounting for cost-related objectives together with health and wellbeing benefits, respectively – cost is used as the main objective function while health and wellbeing objectives are replaced as constraints for the augmented ε-constraint method. Solutions A and A' represent the solutions with the minimum expected cost and with the minimum health and wellbeing benefits, respectively. These solutions are characterized by the lowest levels of LTC provision, i.e., with the minimum equity satisficing levels. On the opposite end of the Pareto frontiers one can find solutions J and J', which are characterized, respectively, by the maximum expected health and wellbeing benefits. These are the highest cost solutions and are characterized by full LTC provision (i.e., with 100880, 104837 and 108706 individuals in the Great Lisbon region receiving LTC in 2018, 2019 and 2020, respectively).

Since health policy literature points out the need for maximizing health and wellbeing benefits for the whole population (Baker, 2000), benefits in Fig. 6 are shown as cumulative benefits for the whole population in need of LTC. However, it is also relevant to analyze these benefits as benefits per capita (considering as reference the population in the Great Lisbon region) or as benefits per individual in need. These analyses show that health/wellbeing benefits per capita would range between 23 QALYs and 5 wellbeing units per 1000 inhabitants (solution A/A') and 54 QALYs and 14 wellbeing units per 1000 inhabitants (solution J/J'), whereas health/wellbeing benefits per individual in need would range from 0,168 QALYs and 0,039 wellbeing units (solution A/A') up to 0,423 QALYs and 0,296 wellbeing units per individual in need (solution J/J'). Note that individual health and wellbeing benefits are considered to vary between 0,214 and 0,861 QALYs and 0,056 and 0,296 wellbeing units, depending on the typology of LTC service.

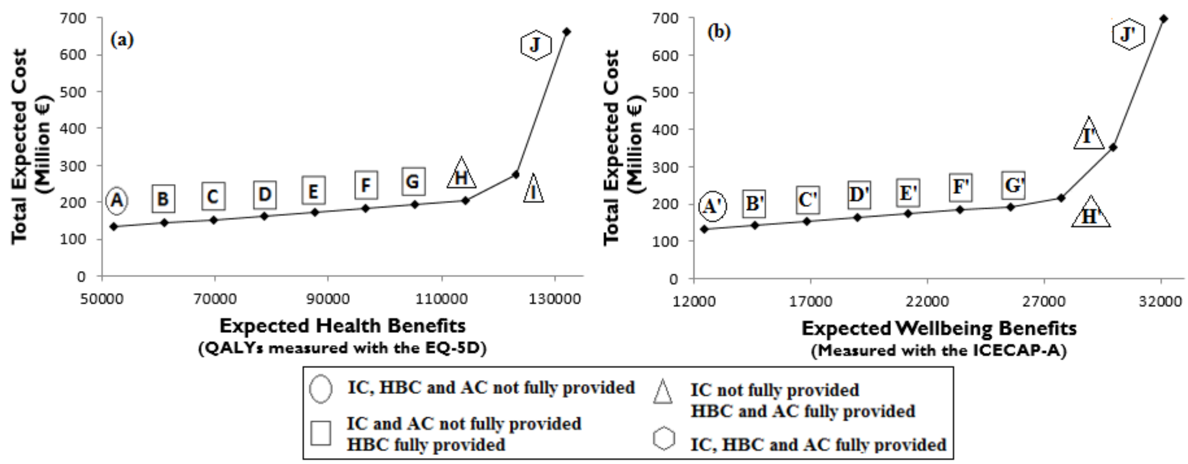


Figure 6. Pareto frontiers obtained when running the multi-objective stochastic model under (a) Case II (with cost- and health-related objectives) and (b) Case III (with cost and wellbeing-related objectives)

It becomes clear from Fig. 6 that any improvement in benefits (health or wellbeing) would require an extra investment. Taking Fig. 6(a) as example, if the aim is to further improve LTC delivery so as to move from a network characterized by solution A to a network with the characteristics of solution B, this development would bring an improvement of around 9000 units in QALYs (representing an increase of around 17% in benefits) with a required investment of 10 million €: this represents a cost per QALY of around 1111€. The same level of investment would be required to move between consecutive (lower-cost) solutions, until reaching a network with the characteristics of solution H. All these investments are focused on improvements in the delivery of HBC and AC. On the other hand, improving the delivery of LTC so as to move from solution H to solution I and from solution I to solution J, although being both also associated with improvements of around 9000 units in QALYs, would require investments of around 70 and 430 million €, respectively – these represent a cost per QALY of 7778€ and 47778€, respectively. These higher investments are mainly related to the higher costs of IC, which are required for attaining those solutions.

Similar level of investments would be required to improve wellbeing benefits – investments of around 10 million € to achieve an improvement of around 2200 units in wellbeing benefits for lower cost solutions (i.e., until having a LTC network with the features of solution H); whereas improving the LTC delivery so as to move from solution H to solution I and from solution I to solution J would involve higher investments of around 140 and 350 million €, respectively.

These results make clear that planning priorities should be defined with caution, especially when a limited budget is available. Particularly, if the achievement of health/wellbeing benefits is considered as a policy priority, investments should be first focused on AC and HBC, and only afterwards in IC. Also, if one compares the cost per QALY associated with improvements in LTC delivery for the lower cost-solutions with the cost-efficiency threshold of around 33000€ (30000£) per QALY that has been suggested as reference by the National Institute for Health and Care Excellence (NICE, 2018), it can be argued that improving the delivery of both HBC and AC provides good value for money.

Further to the trade-off shown in Fig. 6, the impact of further improvements on equity on both costs and benefits is also explored – Fig. 7 takes the Pareto frontier obtained under Case II as example. Fig. 7 shows that the same trade-off between cost and health benefits is achieved when improvements of around 15% (when compared to Case II) are imposed for each level of equity individually – i.e., when minimum equity satisficing levels for EA, GE, SE and EU are imposed as $f_2 < 0.70$, $f_3 < 0.40$, $f_4 < 0.20$, $f_5 < 0.65$ (instead of $f_2 < 0.85$, $f_3 < 0.5$, $f_4 < 0.25$, $f_5 < 0.8$). Nevertheless, further improvements on EU and EA would require higher costs for the same level of benefits, when compared to the level of costs obtained under Case II. Particularly, 15% improvements on EU and EA would require investments 20% and 10% higher, respectively, for the lower-cost solutions (when compared to the investments required under Case II). These higher investments are mainly due to improvements in the delivery of LTC in typologies of care leading to smaller health benefits – for instance, a higher improvement on EU requires extra investments in LTMC, and since LTMC is the typology of LTC with the lower health benefits, it means that the same level of benefits will be achieved with higher investments. A similar behavior was found for Case III.

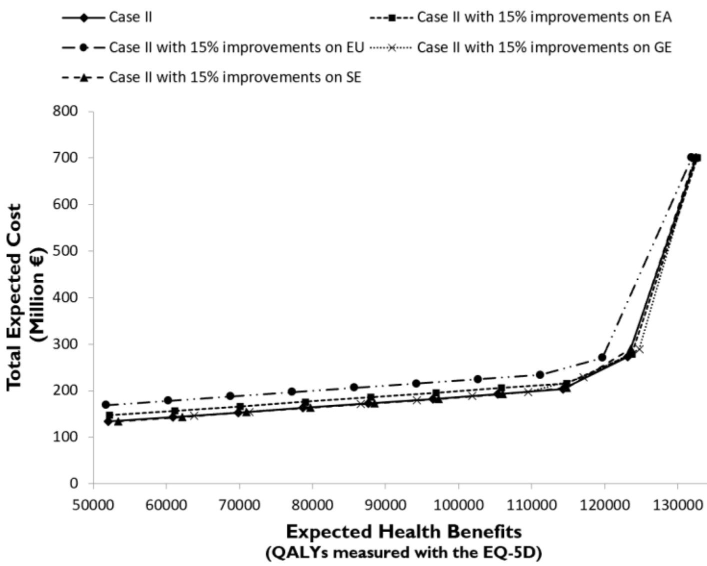


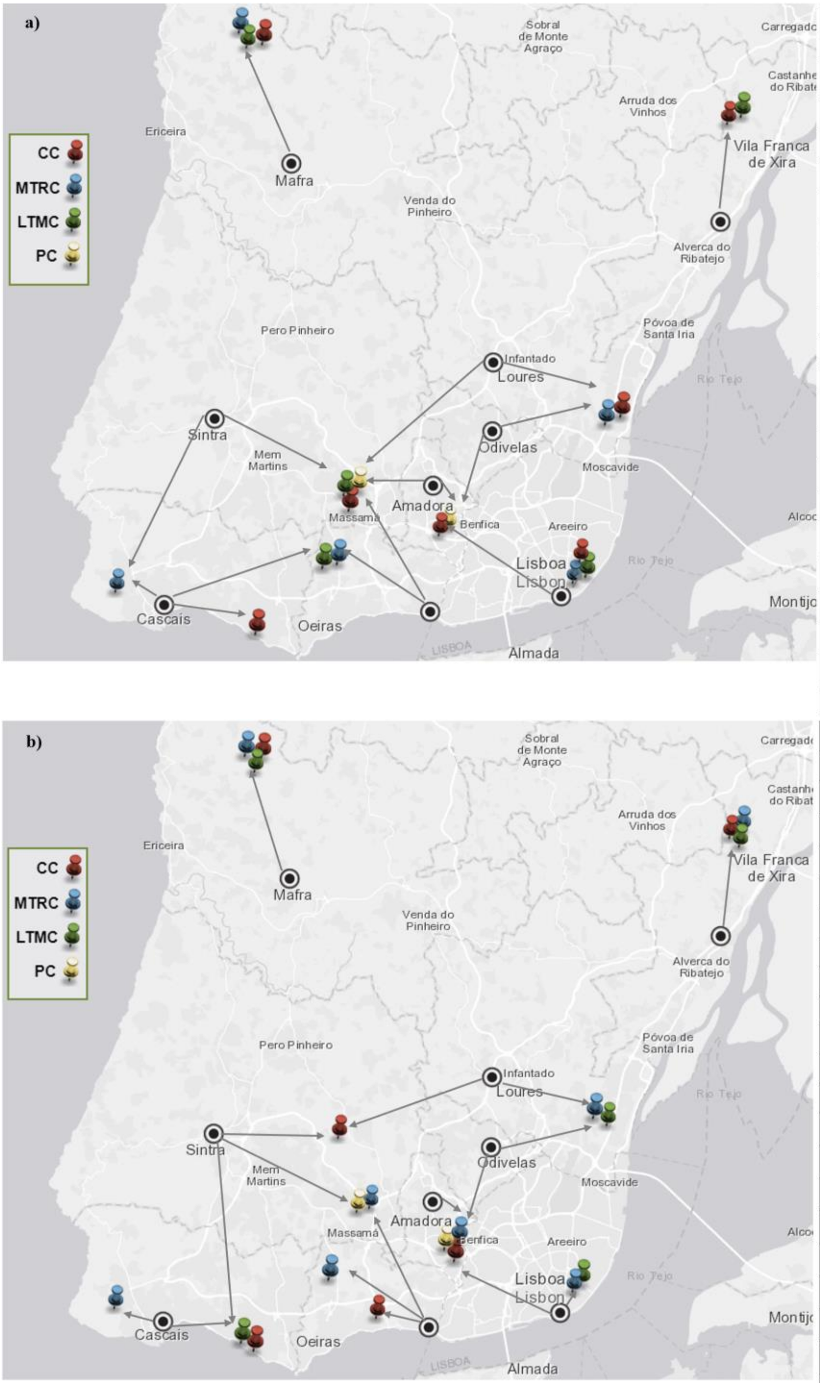
Figure 7. Pareto frontiers obtained when running the multi-objective stochastic model under Case II (with cost- and health-related objectives) and when higher improvements are imposed for each equity level (improvements of around 15% when compared to Case II - f_2<0.70, f_3<0.40, f_4<0.20, f_5<0.65)

Table 3 now compares solutions A (Case II) and A' (Case III) with the solution of Case 0, where the only objective is the minimization of expected cost. According to these results, higher costs and higher investments in new beds arise when health or wellbeing-related objectives are imposed. Nevertheless, these higher investments are dependent on the desired benefits – if LTC planners aim to improve health benefits, CC, LTMC and PC should be targeted for investments, whereas MTRC should be further developed when the aim is to improve wellbeing benefits.

Table 3. Total costs of reorganizing the LTC network and additional beds in which there is need to invest over the 2018-2020 period under cases 0, II and III

		Case 0	Case II (solution A)	Case III (solution A')
Total expected costs (Million €)		132.1	133.3	132.9
Additional beds	CC	51	49	40
	MTRC	195	101	115
	LTMC	206	329	310
	PC	2	33	14
	Total	454	512	479

Fig. 8 also shows that significant differences in location-allocation decisions arise when health (Case II) and wellbeing (Case III) benefits are separately accounted for.



c)	CC	MTRC	LTMC	PC
Opening of services				
Amadora	⊕			⊕
Odivelas				
Cascais				
Lisbon		⊕	⊕	
Loures		⊕		
Mafra				
Oeiras				
Sintra	⊕		⊕	
Vila Franca de Xira	⊕			
Total	3	2	2	1
Closure of services				
Amadora			⊗	
Odivelas				
Cascais				
Lisbon				⊗
Loures				⊗
Mafra				⊗
Oeiras		⊗		⊗
Sintra		⊗	⊗	
Vila Franca de Xira				
Total	0	2	2	4

d)	CC	MTRC	LTMC	PC
Opening of services				
Amadora	⊕	⊕		⊕
Odivelas				
Cascais			⊕	
Lisbon		⊕	⊕	
Loures		⊕	⊕	
Mafra				
Oeiras	⊕	⊕		
Sintra	⊕			
Vila Franca de Xira	⊕	⊕		
Total	4	5	3	1
Closure of services				
Amadora			⊗	
Odivelas				
Cascais				
Lisbon	⊗			⊗
Loures	⊗			⊗
Mafra				⊗
Oeiras	⊗		⊗	⊗
Sintra	⊗		⊗	
Vila Franca de Xira				
Total	4	0	3	4

Figure 8. Geographical location of IC services and allocation of patients to existing services under a) Case II and b) Case III; and opening (⊕) and closure (⊗) of IC services under c) Case II and d) Case III (solution A and A' taken as reference)

Differences are found: on the number of services that should be operating (e.g., seven CC services should be operating under Case II, whereas only six CC services are needed under Case III); on the geographical distribution of services (e.g., no MTRC service should be located in *Amadora* under Case II, whereas one MTRC service should be operating in that area according to Case III); and on the allocation of patients across services (e.g., under Case II patients from *Cascais* should receive LTC both in their area of residence but also in *Oeiras*, whereas according to Case III they should receive care only in their area of residence). These differences are mainly related to the pursuit of health and wellbeing objectives. For instance, when compared to Case II, a lower number of CC services are operating under Case III, mainly because CC is characterized by higher health benefits.

Research Question 1B: Considering now the cost objective together with health and wellbeing benefits (Case I), it is possible to verify that when higher investments are carried out, both health and wellbeing benefits are obtained (see Fig. 9).

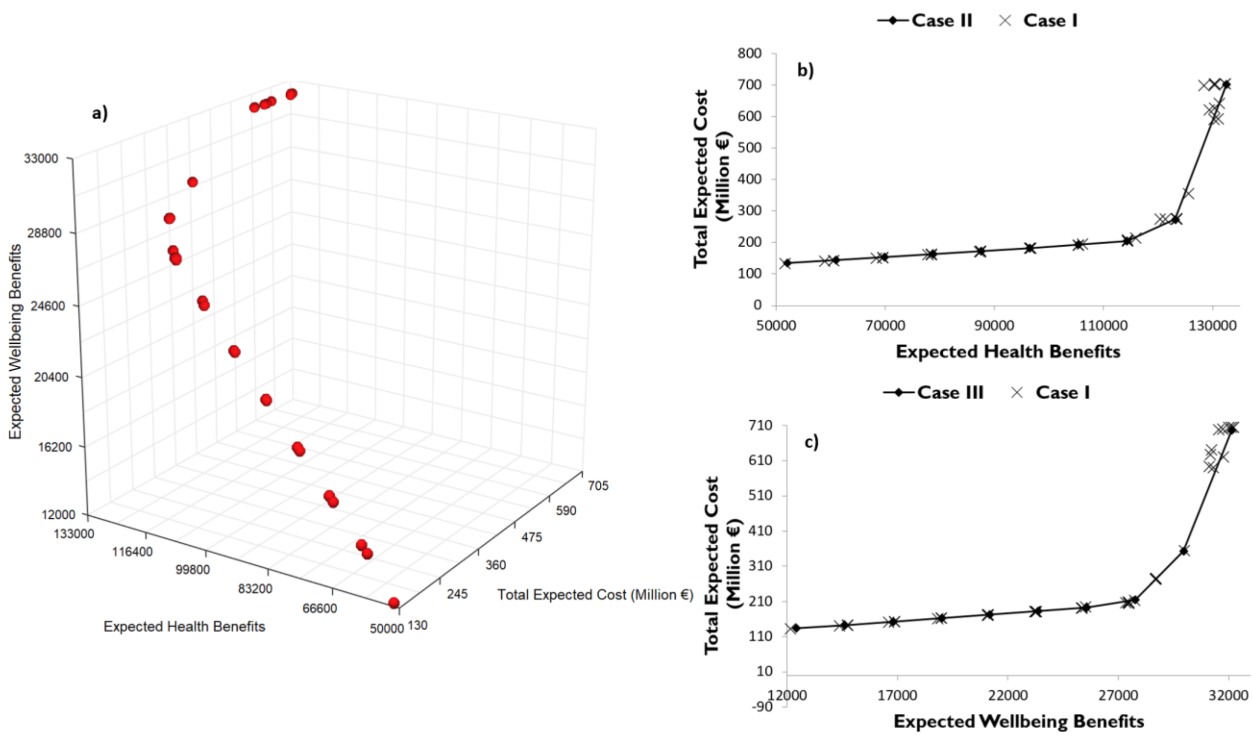


Figure 9. a) Pareto frontier obtained when running the multi-objective stochastic model under Case I, i.e., with health-, wellbeing- and cost-related objectives; and comparison of these Pareto-optimal solutions with b) Case II (when only cost and health benefits are considered), and c) Case III (when only cost and wellbeing benefits are considered).

These higher benefits are obtained because extra investments in any of the typologies of LTC bring both health and wellbeing improvements. Furthermore, when comparing the Pareto-optimal solutions obtained under Case I (i.e., when considering the three objectives) with the Pareto frontiers obtained under Cases II and III (when considering only two objectives, i.e., the cost objective together with health or wellbeing benefits, respectively), it becomes clear that the Pareto-optimal solutions obtained for Cases II and III represent the best solutions of Case I – according to Fig. 9(b) and Fig. 9(c), the two-objective frontiers lie on the outer edge of the three-objective solutions. In fact, the Pareto-optimal solutions lying on the left of the two-objective frontiers are justified because a third objective is also considered for optimization, thus resulting in the sacrifice of the other objectives.

To conclude, accounting for health and wellbeing-related objectives has an impact on planning, with health planners needing to reflect on whether they want to pursue one or both of these objectives (please note that the same sample of patients was used to calculate health and wellbeing gains).

RQ2: Impact of scenario reduction methods on planning decisions

The reduced scenario trees obtained with the three reduction methods are presented in Fig. 10. Fig. 10 should be read as follows: considering Case II as example, and considering that at $t=0$ (i.e., in 2018) both the demand and the LOS are low (LL), the first scenario is characterized by low demand at $t=1$ (<u>L</u>HLH), high demand at $t=2$ (L<u>H</u>LH), low LOS at $t=1$ (LH<u>L</u>H) and high LOS at $t=2$ (LHL<u>H</u>).

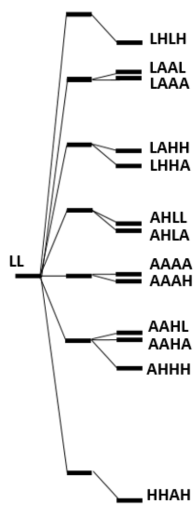
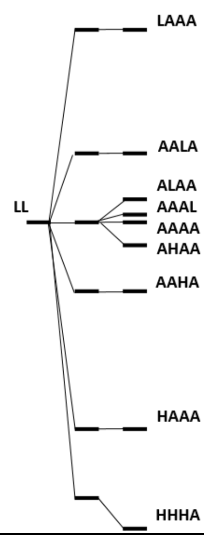
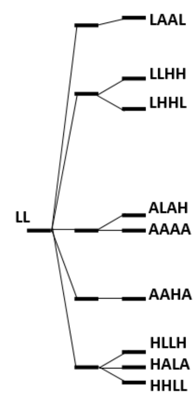
	Case II	Case IV	Case V
Number of scenarios	13 scenarios	9 scenarios	9 scenarios
Reduced tree			

Figure 10. Reduced trees obtained under different scenario reduction methods. Legend: L – Low; A – Average; H – High

Fig. 11 shows the impact on planning decisions when using the above-mentioned scenario trees, as well as the full scenario tree (81 scenarios, Case VI). Particularly, it shows the Pareto frontiers obtained when applying the model using each of those trees for the case in which the aim is to minimize total expected cost and maximize expected health gains. As shown in Fig. 11, lower-cost solutions, which arise from a planning priority on improving HBC and AC, are not associated with significant differences in health benefits. Nevertheless, for higher-cost solutions (solutions in the right side of Fig. 11), in which IC turns to be the planning priority, different and more costly planning decisions arise – under these solutions, decisions vary in terms of costs, health gains and services organization. A similar behavior has been found when expected cost is minimized and expected wellbeing gains maximized.

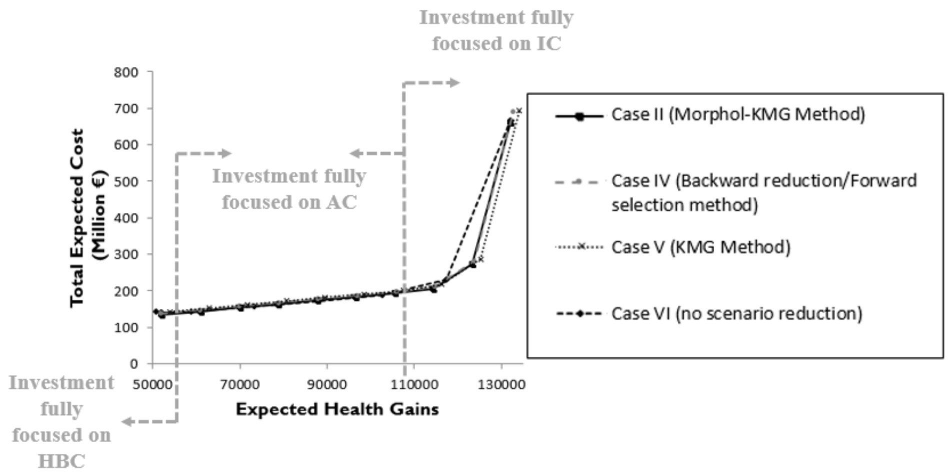
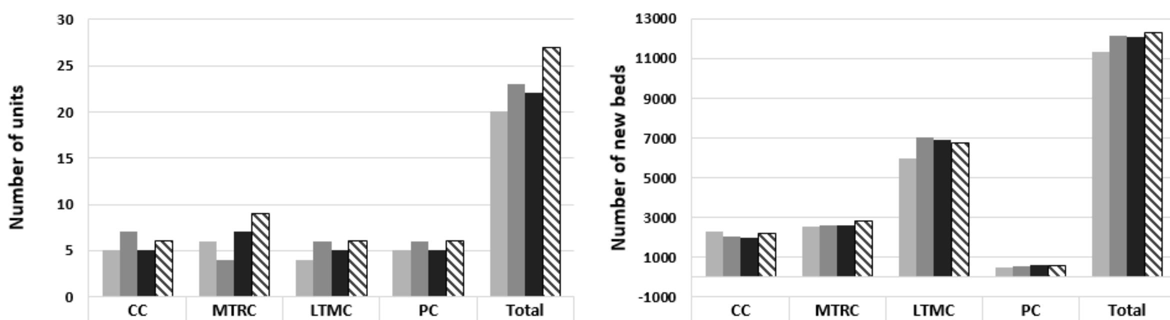


Figure 11. Pareto frontiers obtained when running the multi-objective stochastic model with no scenario reduction (Case VI) and when using the reduced scenario trees obtained under Cases II, IV and V

A more detailed analysis is presented in Fig. 12 (highest-cost solution in Fig. 11 used as reference).



	CC	MTRC	LTMC	PC	Total
Case II	5	6	4	5	20
Case IV	7	4	6	6	23
Case V	5	7	5	5	22
Case VI	6	9	6	6	27

	CC	MTRC	LTMC	PC	Total
Case II	2310	2550	5981	497	11338
Case IV	2044	2595	7014	511	12164
Case V	1998	2619	6873	569	12059
Case VI	2191	2823	6763	535	12311

Figure 12. Number of units and new beds characterizing the highest-cost solutions obtained when applying the stochastic model with no scenario reduction (Case VI) and with the reduced scenario trees characterizing Cases II (*Morphol-KMG method*), IV (*Backward reduction / Forward selection method*) and V (*KMG method*)

According to this figure, if planning decisions are based on the complete set of scenarios (81 scenarios) a higher number of units and new beds should be ensured when compared with planning decisions based on a reduced set of scenarios. On the other hand, different planning results arise when using alternative scenario reduction methods. In particular, it can be observed that the solution obtained under Case II represents the one with the lowest investment, requiring the operation of the lowest number of units and new beds. These results are mainly related with the nature of the scenarios selected for the reduced scenario set (validated by the experts as capturing their views after following the different steps of the *Morphol-KMG method*). This set of scenarios differs from the ones selected with the *Backward reduction/Forward selection* and the *KMG methods,* because part of these scenarios were explicitly selected by the two LTC experts who collaborated in this study.

Planning decisions thus prove to be sensitive to the selection of scenarios, with the *Morphol-KMG method* being a relevant alternative for building this scenario set. Some thinking thus needs to be dedicated on which experts to involve and how to involve them, as scenario selection is influenced by experts' inputs.

RQ3: Impact of scenario reduction methods on the computational performance

Table 4 shows the impact of scenario reduction methods on the computational performance of the model for different planning periods - a shorter period, 2018-2020, and a longer one, 2018-2021. These results not only show significant reductions in the computational time required to run the model (with these being achieved when any of the scenario reduction methods is used) but also highlight that this reduction is of utmost importance for longer planning horizons. Particularly, it can be seen that extending the planning horizon by only one year (considering a 4-year period instead of a 3-year period) makes it extremely time costly to obtain a solution when using the full tree – in this case, it resulted in an increase from 81 to 729 scenarios, taking almost 4 days to achieve a (high-gap) solution.

It should be noted that these results were obtained when using two stopping criteria: i) a minimum gap criterion, namely, a gap of at least 1% should be achieved; and ii) a maximum execution time criterion, namely, 8 hours (28 800 seconds) when applying the model for a 3-year period, and 4 days (345 600 seconds) when applying the model for a 4-year period. As a result, low-gap results (lower than 1%) are obtained within the time limit imposed under Cases II, IV and V; and the execution time imposed as maximum was achieved when running the model under no scenario reduction (Case VI), thus explaining the higher gaps obtained under this case.

Table 4. Computational results obtained when running the stochastic planning model under different scenario reduction methods and for different planning horizons – solution A is used as reference

Planning horizon	**2018-2020 (3 Time Periods)**			**2018-2021 (4 Time Periods)**		
Scenario Reduction Method	**# Scenarios**	**Computational time (sec)**	**GAP (%)**	**# Scenarios**	**Computational time (sec)**	**GAP (%)**
No scenario reduction (Case VI)	81	28800	2.92	729	345600	92.4
Morphol-KMG Method **(Case II)**	13	3463	0.39	54	12246	0.89
Backward reduction/Forward selection method **(Case IV)**	9	794	0.26	36	2206	0.73
KMG method **(Case V)**	9	2457	0.49	36	3285	0.83

5.4.2. Computational results

Computational results are shown in Table 5, confirming that combining stochastic planning models with scenario reduction methods (Cases 0, I, II, III, IV and V) allows better (i.e., with lower gaps) and faster results to be obtained when compared to stochastic models with no scenario reduction (VI). The stopping criteria described above also impacted the presented computational results.

Table 5. Computational results obtained when running the stochastic planning model under different cases (Cases 0, I, II, III: *Morphol-KMG Method*; Case IV: *Backward reduction/Forward selection method*; Case V: *KMG method*; Case VI: No scenario reduction) – solution A is taken as reference

	Total variables	Integer variables	Total constraints	Iterations	CPU (sec.)	Gap (%)	Objective (€)
Case 0	316730	1404	336150	2711880	3539	0.37	132096554
Case I	316731	1404	336151	1960190	4321	1.10	132573144
Case II	316732	1404	336152	2511743	3463	0.39	133291746
Case III	316731	1404	336151	5618179	5543	0.43	132925871
Case IV	241462	1144	256282	970669	794	0.26	134901086
Case V	266390	1248	288230	1925215	2457	0.49	134121255
Case VI	1370512	5044	1454332	2465515	28800	2.92	135211802

6. Conclusions

This study fills a gap in the health care planning literature by proposing a novel approach based on a stochastic multi-objective MILP model – the *LTCNetPlanner* – that plans a multi-service network of LTC within a reasonable computational time. The contribute of this study is twofold: it introduces the modelling of health and wellbeing benefits in location-allocation literature, which are objectives not commonly considered in the area and are recognized as key by policy-makers; and it develops research on scenario reduction methods to improve models' computational time, by proposing a new scenario reduction approach – the *Morphol-KMG method* – that makes use of experts' knowledge.

The proposed approach is generic and can be used in any country in which national or local governments wish to plan a network of interrelated services (this is typical in countries with a health system based on a NHS structure), or in countries in which cost, equity, health and/or wellbeing are fundamental objectives to be accounted for in LTC delivery. The application of the proposed approach requires the collection of the data needed to apply the MILP model, including information on current supply and future demand of LTC. For the uncertain information regarding input parameters, when such information is not available, it is possible to use the approach proposed by Cardoso et al. (2012) to build such forecasts. Concerning the scenario reduction process, it requires the involvement of LTC stakeholders or expert(s).

The usefulness of the proposed model is illustrated by applying the *LTCNetPlanner* at the county level in the Great Lisbon region in Portugal for the 2018–2020 period. This application has confirmed that both health and wellbeing benefits impact LTC planning, and that combining scenario reduction methods with stochastic planning models can speed up the running of location-allocation models. The *Morphol-KMG method* proved to have potential in the reduction of scenarios through experts' input.

As further research, several topics may be pursued. First, one may use multiple criteria decision analysis methods and involve policy-makers if a single solution is sought. Secondly, alternative scenario reduction methods and other methods to build comprehensive scenarios, also inspired by the foresight literature, could be developed so as to allow for a higher level of involvement with experts in the selection of scenarios. Also, applying the proposed approach together with real key planners and decision-makers in the LTC sector should also be considered, both at regional and national level. Furthermore, in order to potentiate the use of these methods in practice, an easy-to-use tool integrating the *LTCNetPlanner* and the *Morphol-KMG method* with Geographic Information Systems and user-friendly interfaces could be developed. This would not only facilitate the use of the proposed methods by experts in the area without specific knowledge about the methods, but it will also enable an easy visualization of planning results. Also, being recognized in the health services research literature that personal health and wellbeing benefits per LTC service may greatly differ across patients and along time of treatment, further studies should be pursued to generate more precise estimates of these benefits. Furthermore, the multi-objective model herein presented could be extended to include several other policy objectives – such as other equity objectives that are meaningful within the context of NHS countries, as well as wellbeing-related objectives that accounts for both the patient and the caregiver wellbeing. Finally, a more extensive analysis on the space of solutions could be performed: a higher number of cases could be explored and cluster analysis could be performed to identify solutions that allow obtaining better performances across a higher number of objectives.

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