European Journal of Operational Research 000 (2018) 1–15

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Innovative Applications of O.R.

Donation management for menu planning at soup kitchens

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A R T I C L E I N F O

Article history:
Received 6 July 2017
Accepted 5 June 2018
Available online xxx

Keywords:
OR in societal problem analysis
Food waste reduction
Food donations
Menu planning
Soup kitchen

A B S T R A C T

The food industry is confronted with a pressure to reduce waste and to make agreements on donating surplus food to charitable organizations. Charitable organizations such as food banks and soup kitchens can use these donations in preparing food parcels or meals for their clients. For soup kitchens, donation management is strongly influencing menu planning, and conversely, menu planning considerations have a strong impact on donation management decisions. To make the best use of (mostly highly perishable) food donations, we develop an MILP model for integrated donation management and menu planning that proposes a menu plan and suggests which (part of the) donations to accept. The combination of menu planning and donation management is essential for soup kitchens, but has not been studied before.

The model is used to assess the impact of contracts on a strategic or tactical level, and captures operational decision making due to the integration of donation management and menu planning. To deal with meal variety considerations and to resemble planning practices, the developed model is solved in a rolling horizon. The results show that (i) the use of donations reduces overall costs for the soup kitchen; (ii) despite the short shelf life of donations, most donations can be used efficiently; and (iii) meal variety can be easily ensured and food donations increase this variety. In addition to the benefits for soup kitchens, the approach has implications for waste reduction in food supply chains, by structural/contractual donations of surplus food by retailers.

1. Introduction

Charitable organizations such as food banks and soup kitchens are important contributors to food and meal provision to socially isolated and poor people. In such organizations, one of the main ways to keep costs low is to use surplus food from retailers or food companies. For instance, supermarkets can have difficulties in aligning supply and demand for perishable products, and often order many products to prevent out-of-stock situations, potentially resulting in surplus food and large waste streams (Monier et al., 2010).

Companies find different solutions to cope with this surplus food, such as donating to soup kitchens or food banks, or conversion to bio gas (Lee & Tongarlak, 2017). Minimizing food waste has recently also been put on the political agenda, for instance demonstrated in the French Government's introduction of a law that forbids supermarkets to waste food, and obliges them to sign contracts with charitable organizations for food donations (Chrisafis, 2016). Another example is a Californian law that limits the amount of organic waste companies can produce yearly (CalRecycle, 2017, (Accessed at 20 March, 2018)).

This paper deals with donation management and menu planning at soup kitchens, which are institutions that mostly rely on donations and provide complete meals for people that require assistance, such as homeless people. One of the best-known charitable organizations providing these services is the Salvation Army. Due to the characteristics of food donations, i.e. varying products with a generally short shelf life, menu planning at soup kitchens is challenging. Products must be used shortly after they are donated, and be integrated in menu plans that aim at a varied diet. For soup kitchens, this implies fast decision making on whether they want to accept a food donation or not, depending on the amount of product, its shelf life, as well as its usefulness in menu planning. The soup kitchen wants to avoid accepting donations it is not able to use, to prevent wasting the donated product, as well as potential costs related to the collection of the donation. From a supply chain perspective, accepting a donation that will eventually still be wasted would just shift the food waste to another party in the food supply chain. Furthermore, it prevents other par-

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https://doi.org/10.1016/j.ejor.2018.06.005

ties from using this donation. Whether products are useful mainly depends on the meal variety a soup kitchen wants to offer. Soup kitchen clients are often highly dependent on the provided meals (Wicks, Trevena, & Quine, 2006) and offering varied meals is a way to improve the nutritional intake of the clients (Wilson, Alexander, & Lumbers, 2004). Furthermore, it is also much more attractive to eat varied meals.

Donations to charitable organizations are usually made on a voluntarily basis. These organizations often do not know when and how much food they will receive. Using contracts between the charitable organization and the donating party, such as recently enforced by a French law, could improve the handling of surplus food. When donations are regulated via contracts, soup kitchens are more aware of the food that will come in, possibly making it easier to use donations efficiently. Furthermore, it helps the donating party (e.g. a retailer) to better make use of the surplus food. Besides, contracts give the opportunity to regulate other factors such as transport, quantities, and shelf life.

Assessing available research on donation management for soup kitchens or food banks shows that the above-mentioned issues have not been addressed in the literature. Most available studies either address the characteristics of the client base relying on charitable organizations for food, or they address the nutritional aspects of the provided meals (Eppich & Fernandez, 2004; Sprake, Russell, & Barker, 2014; Wicks et al., 2006). Research focussing on donation management and menu planning for food banks or soup kitchens is not available.

In this paper, we aim to evaluate the donation management at a soup kitchen on a tactical level. In order to evaluate tactical decisions effectively, an integration of operational decisions is required. Therefore we develop a decision support approach integrating menu planning in decision-making for donation management, to be able to make the best use of food donations in soup kitchens while assuring meal variety for the clients. Applying a rolling horizon approach, we study the impact of contractual and managerial issues and characteristics of fresh food donations on the performance of a soup kitchen in terms of costs, product waste, meal variety, and the donation acceptance rate. The problem and results give rise to some decision rules that are tested. As input to a managerial discussion the effect of different types of contracts, donation characteristics (e.g. shelf life), the preferred meal variety, and several cost parameters are studied.

The remainder of this paper is organized as follows. Section 2 discusses related literature on donation management and menu planning. Section 3 then provides our mathematical modeling approach. The experimental design is subsequently stated in Section 4 and our results are discussed in Section 5. In Section 6 the MILP results are compared with some decision rules for ad hoc donations. Finally, the paper discusses conclusions and managerial insights in Section 7.

2. Related literature

In this section, we give an overview of related literature. In general, two streams of literature are related to our research: menu planning and donation management.

2.1. Menu planning

Studies related to menu planning are widely available. The first study providing decision support in this area is the seminal work by Stigler (1945). When computers came into use, Balintfy (1964) was one of the first who solved menu planning by computer. He developed an integer programming model to determine the optimal menu planning by minimizing costs while considering dietary constraints. Over time, these type of menu planning models have become more advanced, e.g. by including meal production scheduling decisions (Guley & Stinson, 1984). An extended review of menu planning can be found in the research of Lancaster (1992); here, we limit ourselves to briefly outlining some recent developments.

In general, there are three generations of menu planning models (Lancaster, 1992). The first generation of menu planning models focuses on cost minimization, the second generation on consumer preferences, and the third generation on individual consumers. In recent years, the focus of dietary problems is mainly on nutritional recommendations, either for humans or animals. For instance, Oishi, Kumagai, and Hirooka (2011) developed a linear programming model to optimize feed systems for cattle based on minimizing costs, as well as nitrogen and phosphorus intake. Also, Cadenas, Pelta, Pelta, and Verdegay (2004) implemented a modeling approach to solve a diet problem at Argentinian farms to minimize costs, while considering the nutritional recommendations. However, models for animal feed do not include palatability or meal variety constraints as is often the case in menu planning for humans. For instance, Leung, Wanitprapha, and Quinn (1995) developed a mixed integer linear programming (MILP) model to optimize a diet for one week, fulfilling the nutritional recommendations and minimizing costs or cooking time. They reduced complexity by using recipes instead of separate food ingredients. Also, Seljak (2009) introduced the diet problem as a multi-criteria knapsack problem, which she solved with an evolutionary algorithm. More recently, Bas (2014) developed an MILP model to minimize the glycemic load of the daily optimal serving sizes. She used robust optimization to deal with the uncertainty in the measured glycemic index of food items.

Although menu planning can be applied in different settings such as catering services and hospitals, no research dealt with soup kitchens and donation management. Food donations obviously impact menu planning decisions, but including donations will result in a more complex decision problem because of the short shelf life of donated food products. They need to be used soon after donation, limiting the options for menu planning.

2.2. Donation management at soup kitchens or food banks

Previous research on donation management for food banks and soup kitchens is mostly related to (i) planning and scheduling issues such as vehicle routing and allocation problems and (ii) nutritional aspects of food donations and meals provided at soup kitchens.

The planning and scheduling issues mostly focus on the design and operation of efficient transportation networks. Ghoniem, Scherrer, and Solak (2012) solved a vehicle routing problem where a central depot serves several customers while balancing transportation distances for the charitable organization and the travel distances for customers. Davis, Sengul, Ivy, Brock, and Miles (2014) propose a system where all donated products flow through satellite locations (food delivery points), especially dealing with perishability and food safety. Balcik, Iravani, and Smilowitz (2014) describe a multi-vehicle sequential allocation problem for collecting and delivering food donations. Their research is an extension of the model developed by Lien, Iravani, and Smilowitz (2014), which only dealt with single routes, and could be applied to either food banks or soup kitchens. Solak, Scherrer, and Ghoniem (2014) studied a location-routing problem with the determination of delivery sites at which agencies pick up food items. Analyzing the donation patterns offered to a food bank is done by Brock and Davis (2015). They used four different forecasting methods to predict the supply of donation to food banks, concluding that the forecasting methods tend to overestimate the future supply. Finally, Orgut, Ivy, Uzsoy, and Wilson (2015) developed mathematical models to distribute food from a central location of a food bank to different satellite locations based on fairness and effectiveness.

The literature dealing with the nutritional aspects of food bank parcels and soup kitchen meals mostly aim to study the sufficiency of food provision to people in need. Eppich and Fernandez (2004) compared the nutritional content of meals of a soup kitchen based in North Carolina, USA, with dietary reference intakes and daily reference values. They concluded that meals only fall short on some nutrients, even though the soup kitchen was providing three meals a day. Sprake et al. (2014) investigated the food intake of homeless people visiting a soup kitchen in Sheffield, UK, and concluded that the daily nutrient intake turned out to be significantly lower than the recommended intake. In a study on food parcels at a Dutch food bank, Neter, Dijkstra, Visser, and Brouwer (2016) dealt with the nutritional value of parcels that completely consist of donated food. It became clear that the provided food was not meeting the nutritional standards. Total energy supply (in kJ) was sufficient, but the provided amount of fruit and fish was lower than recommended. Comparing the situation of a food bank to a soup kitchen, it should however be noted that food parcels are not necessarily supposed to cover the complete nutritional requirement of the beneficiaries, as the food parcels are often an addition to other sources of food supply. Furthermore, since food delivered by food banks is almost completely based on donated surplus food, it might also be hard to completely fulfil requirements. For soup kitchens, which can often buy additional ingredients to provide meals, the nutritional targets are potentially a more interesting benchmark.

2.3. Research gap

Even though donation management decisions are strongly impacted by menu planning decisions for a soup kitchen, and their menu planning is in turn heavily influenced by donation management, no research has combined these topics yet. Menu planning is only used in settings where food is not donated, and therefore not dealing with the extra complexity of short shelf life products and the menu planning limitations caused by donated products. Studies that do provide decision support for donation management are either vehicle routing or allocation problems, in which the decision to accept the donations is already made. However, whether a donation should be accepted depends on whether an ingredient can be used or not. This decision can be made by including menu planning. Menu planning models are widely available, using different mathematical techniques to solve the diet/menu problem. Research on soup kitchen clients or the soup kitchen meals shows that clients are highly dependent on the meals provided and can suffer from malnutrition. This raises the need to develop models that deal with food donations and can provide healthy meals to fulfil the clients' needs. In this paper, we therefore address the benefits of arranging contracts with donors while providing meals to clients.

3. Modeling approach

A model is developed to answer tactical questions around the impact of different types of donation contracts. Therefore an optimization model is developed that integrates donation management and menu planning to answer questions such as (i) which (part of the) donations to accept, (ii) how to use adjust menu planning to use donations efficiently, (iii) how to deal with the complexity arising from food donations and menu planning, such as shelf life constraints and meal variety. In this section, we formulate the decision problem and the solution approach. First the notations of parameters and variables of the mathematical model will be explained, before we formalize the problem and discuss the rolling planning horizon approach.

3.1. Notation

Sets and indices

$i \in \mathcal{I}$	Ingredients
$\tau \in \mathcal{T}^{SIM}$	Time periods of full time horizon
$t \in \{\tau, \ldots, \tau+\lambda-1\} = \mathcal{T} \subset \mathcal{T}^{SIM}$	Time periods in planning horizon
$r \in \mathcal{R}$	Recipes
$s \in \mathcal{S}$	Storage areas
$m \in \mathcal{M}$	Remaining shelf life

Parameters

c_i^B	Costs of ingredient i per kilogram when bought (€)
g	Discount given on buying price of ingredients when product is donated (proportion)
c_i^D	Costs for ingredient i per kilogram when donated, calculated by: $c_i^D = c_i^B * (1-g)$ (€)
c^T	Fixed transportation costs related to collection of donation (€)
λ	Length of planning horizon (days)
χ	Number of periods it is prohibited to use an ingredient after it has been used (days)
ω	Number of periods it is prohibited to use a recipe after it has been used (days)
ϕ_m	Reward value for holding donation at end of planning period, based on remaining shelf life m
m_i	Maximum shelf life of ingredient i (days)
β_{im}	Binary value indicating that ingredient i has shelf life m
i_{im}^0	Inventory of ingredient i with remaining shelf life m at beginning of planning period (kilogram)
vol_i	Volume of ingredient i in storage (cubic decimetre/kilogram)
$caps_s$	Capacity of storage s (cubic decimetre)
α_{is}	Binary value indicating that ingredient i needs to be stored in storage area s
q_{ir}	Quantity of ingredient i needed for 1 kilogram of recipe r (kilogram)
u_{ti}	Binary value indicating that ingredient i is used in period t
v_{tr}	Binary value indicating that recipe r is used in period t
h	Minimum amount to make of a recipe when included in menu planning (kilogram)
d_t	Meal demand in period t (kilogram)
a_{tim}	Amount of ingredient i offered in period t with shelf life m (kilogram)
f_{tim}	Amount of ingredient i donated under contract with shelf life m to be collected in period t (kilogram)
x_{tim}	Amount of ad hoc donation of ingredient i with shelf life m already accepted and to be collected in period t (kilogram)
tr_{ti}	Number of trips for collecting ingredient i to make in period t
M	Relatively large number

Decision variables

I_{tim}	Inventory at start of period t for ingredient i with remaining shelf life m (kilogram)
X_{tim}	Amount of ad hoc donation of ingredient i with remaining shelf life m to be collected in period t (kilogram)
B_{ti}	Amount of ingredient i bought in period t (kilogram)

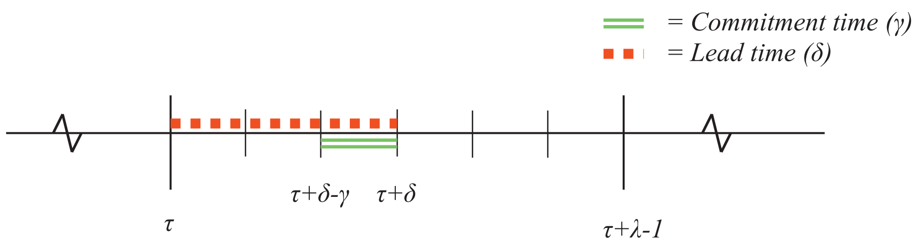

Fig. 1. Planning horizon with length λ. At day τ ad hoc donations available to collect at $\tau+\delta$ are announced and the final decision on acceptance is made at $\tau+\delta-\gamma$.

Y_{tr}	Amount of meal r produced in period t (kilogram)
Z_{tim}	Amount of ingredient i used in period t with remaining shelf life m (kilogram)
W_{ti}	Amount of ingredient i wasted in period t (kilogram)
TR_{ti}	Binary value with value 1 if donation of ingredient i is collected in period t
U_{ti}	Binary value with value 1 if ingredient i is used in period t
V_{tr}	Binary value with value 1 if recipe r is used

3.2. Problem and model description

We consider a soup kitchen that provides d_t kilogram of meals to clients once a day (based on current practice Snels et al., 2012). As only one meal is provided per day, it is not the goal to meet all nutritional recommendations, but by serving different meals throughout the planning horizon the soup kitchen can contribute to a healthy diet. The soup kitchen receives food donations mostly from parties such as warehouses, distribution centres, and retailers that are located in the same geographical area. Costs for collecting donations are thus almost identical, and are dominated by the (fixed) organizational effort of the soup kitchen to arrange the transport oneself (through volunteers) and the depreciation costs of the organization's vehicle(s), or by the fixed transportation costs a logistic service provider accounts. The volume of a donation usually fits well in a car or a mini-van. The transportation or collection costs of collecting a donation is fixed to c^T. In other settings a variable component can be added to the transportation costs, which we neglect here.

The planning horizon starts at day τ, where a menu plan is developed for day τ until $\tau+\lambda$, based on current inventory levels (i^0_{im}) and available food donations (a_{tim}, x_{tim} and f_{tim}). To obtain a certain level of meal variety, menu planning considers restrictions on how often specific ingredients and recipes can be used. Therefore, the planning model keeps track of a tabu list of ingredients used in the last χ days and recipes used in the last ω days. For every day, decisions are made on the meals to serve, the ingredients to buy and the food donations to accept.

Donations occur ad hoc, and some are offered via contracts. For contractual donations, a soup kitchen is obliged to accept them, whereas the acceptance of ad hoc donations is the main donation management decision. Typically ad hoc donations become known only a few days in advance. Furthermore, ad hoc donations can be rejected or accepted in full or in part. Fig. 1 shows the timing considerations related to ad hoc donations. The lead time (δ) is defined as the number of days between announcing/revealing information about the donation and the moment the donation is available to collect. The commitment time (γ) is defined as the number of days between making a final decision on acceptance or rejection and the moment the donation is available to collect. This means that if we are at day τ, the donation available at day $\tau+\delta$ will be announced. The soup kitchen has until $\tau+\delta-\gamma$ to decide to accept or reject this donation. When the donation is accepted in period $\tau+\delta-\gamma$, it must be collected in period $\tau+\delta$.

The focus of this paper is on investigating tactical issues around contractual donations. A contract with the donor should allow for a more stable donation flow, better quality of the donated product and more useful donations. Therefore we differentiate the donations under contract from the ad hoc donations. We assume that the type of ingredients is fixed (vegetables, meat, or other ingredients) and the full information about the contract donation is revealed two days before the donation must be collected. Furthermore, we assume that the (average) shelf life of the ingredients donated via contracts is 1.5 times longer than the shelf life of the ingredients which are randomly donated, as there is a possibility of discussing shelf life within a contract.

3.3. Rolling horizon

The model is applied in a rolling horizon using simulation to capture the stochastic nature by which ad hoc donations are received. This approach allows us to include every day new donation information, and re-plan the menu for the remainder of the planning horizon. The full time horizon ($\mathcal{T}^{SIM}$) comprises one simulated year, and the planning horizon is λ periods (days). Fig. 2 shows how the problem is solved in the rolling horizon. At the beginning of every period new information is revealed on the starting inventory levels (i^0_{im}), ad hoc donations are offered (a_{tim}) or need to be collected (x_{tim}, f_{tim}), and the recipes (v_{tr}) and ingredients (u_{ti}) that were used in the previous periods (and limit decision making during the planning horizon). Note that donations are only known for a part of the planning horizon meaning that donations available after $\tau+\delta$ are not yet considered. Then the planning horizon for all t, from τ until $\tau+\lambda-1$ is solved by the MILP model. After solving, we fix the menu for day τ, update i^0_{im} by $I_{\tau+1,im-1}$, $v_{\tau r}$ by $V_{\tau r}$, $u_{\tau i}$ by $U_{\tau i}$ and $x_{\tau+\gamma,im}$ by $X_{\tau+\gamma,im}$ and roll the planning horizon one day further to $\tau+1$ and plan again. As the model minimizes costs for the planning horizon, it does not consider the possibility to use donations arriving this planning period in a period beyond the planning horizon. To make sure those useful donations are still accepted, we give a reward towards holding inventory at the end of a planning period, based on the remaining shelf life of the ingredients, calculated by:

$$\phi_m = \begin{cases} \dfrac{m-1}{\max_i\{m_i\}} & m < 7 \\ 1 & m \geq 7 \end{cases} \tag{1}$$

In this formulation, the reward given to products increases with the remaining shelf life. Due to the variety constraints, ingredients with a longer shelf life have a higher probability to be used again before the remaining shelf life becomes zero.

3.4. Mathematical optimization model

The objective function (2) minimizes costs related to buying ingredients (3) and receiving and transporting donations (4) over the planning horizon λ. Remaining products in stock at the end of a period are given a positive value as they can be used in the next

Please cite this article as: M.E. Buisman et al., Donation management for menu planning at soup kitchens, European Journal of Operational Research (2018), https://doi.org/10.1016/j.ejor.2018.06.005

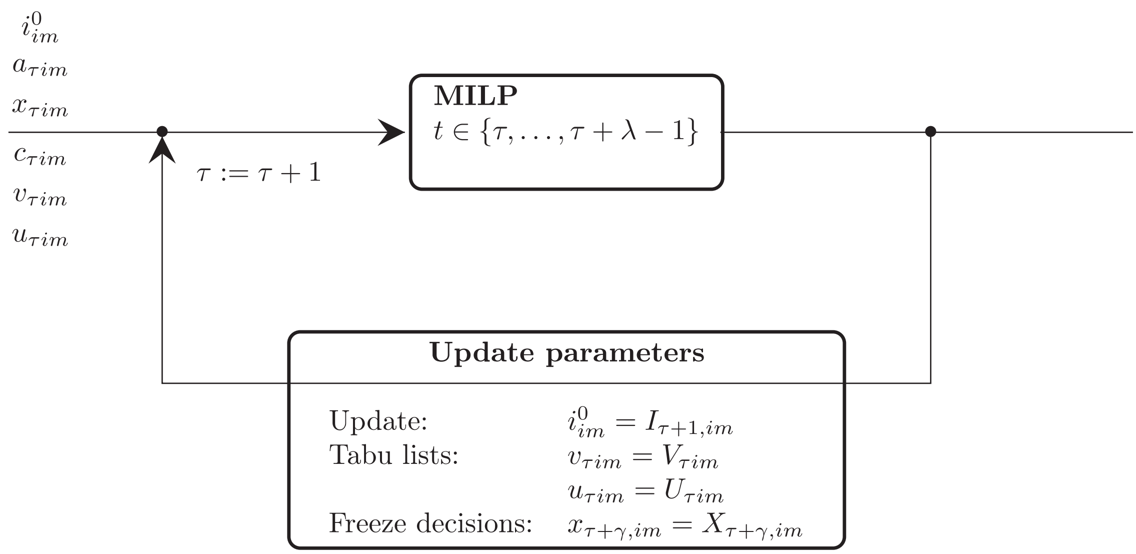

Fig. 2. Rolling horizon algorithm: interactions between MILP and Simulation.

period and are therefore subtracted from the total costs (5).

$$\textit{Minimize} \sum_{t=\tau}^{\tau+\lambda-1} (BC_t + DC_t) - EIR \tag{2}$$

subject to:

$$BC_t = \sum_{i\in\mathcal{I}} B_{ti} \cdot c_i^B \quad \forall t \in \mathcal{T} \tag{3}$$

$$DC_t = \sum_{i\in\mathcal{I}} (TR_{ti} + tr_{ti}) \cdot c^T + \sum_{i\in\mathcal{I}} \sum_{m\in\mathcal{M}} (X_{tim} + f_{tim}) \cdot c_i^D \quad \forall t \in \mathcal{T} \tag{4}$$

$$EIR = \sum_{i\in\mathcal{I}} \sum_{m\in\mathcal{M}} I_{(\tau+\lambda)im} \cdot c_i^B \cdot \phi_m \tag{5}$$

$$\sum_{r\in\mathcal{R}} Y_{tr} = d_t \qquad \forall t \in \mathcal{T} \tag{6}$$

$$\sum_{r\in\mathcal{R}} Y_{tr} \cdot q_{ir} = \sum_{m\in\mathcal{M}} Z_{tim} \qquad \forall t \in \mathcal{T}, i \in \mathcal{I} \tag{7}$$

$$Y_{tr} \geq h \cdot V_{tr} \qquad \forall t \in \mathcal{T}, i \in \mathcal{I} \tag{8}$$

$$I_{tim} + (X_{tim} + f_{tim} + B_{ti} \cdot \beta_{im}) - Z_{tim} = \begin{cases} W_{ti} & , m = 1 \\ I_{t+1,i,m-1} & , m \geq 2 \end{cases} \qquad \forall t \in \mathcal{T}, i \in \mathcal{I} \tag{9}$$

$$\sum_{i\in\mathcal{I}} \sum_{m\in\mathcal{M}} I_{tim} \cdot \alpha_{is} \cdot vol_i \leq cap_s \qquad \forall t \in \mathcal{T}, s \in \mathcal{S} \tag{10}$$

$$X_{tim} \begin{cases} = x_{tim}, & \text{if } t : \tau \leq t \leq \tau + \delta - \gamma \\ \leq a_{tim}, & \text{if } t : t + \delta - \gamma < t \leq t + \delta \\ = 0, & \text{else} \end{cases} \quad \forall t \in \mathcal{T}, \forall i \in \mathcal{I}, m \in \mathcal{M} \tag{11}$$

$$\sum_{m\in\mathcal{M}} X_{tim} \geq M \cdot TR_{ti} \qquad \forall t \in \mathcal{T}, i \in \mathcal{I} \tag{12}$$

$$\sum_{m\in\mathcal{M}} Z_{tim} \leq M \cdot U_{ti} \qquad \forall t \in \mathcal{T}, i \in \mathcal{I} \tag{13}$$

$$\sum_{t'=t-\chi-1}^{\tau-1} u_{t'i} + \sum_{t'=\max\{\tau,\tau-\chi-1\}}^{t} U_{t'i} \leq 1 \qquad \forall t \in \mathcal{T}, i \in \mathcal{I} \tag{14}$$

$$\sum_{r\in\mathcal{R}} Y_{tr} \leq M \cdot V_{tr} \qquad \forall t \in \mathcal{T}, r \in \mathcal{R} \tag{15}$$

$$\sum_{t'=t-\omega-1}^{\tau-1} v_{t'r} + \sum_{t'=\max\{\tau,\tau-\omega-1\}}^{t} V_{t'r} \leq 1 \qquad \forall t \in \mathcal{T}, r \in \mathcal{R} \tag{16}$$

$$I_{tim}, I_{\tau+1,im}, X_{tim}, B_{ti}, Y_{tr}, Z_{tim}, W_{ti} \in \mathbb{R}_{\geq 0} \qquad \forall t \in \mathcal{T}, i \in \mathcal{I}, m \in \mathcal{M}, r \in \mathcal{R} \tag{17}$$

$$TR_{ti}, U_{ti}, V_{tr} \in \{0, 1\} \qquad \forall t \in \mathcal{T}, i \in \mathcal{I}, r \in \mathcal{R} \tag{18}$$

Constraints (6) make sure that demand is met in every period. Constraints (7) make sure that enough ingredients are selected for the meal production. Constraints (8) ensure that when recipe r is served, a minimum amount of h kilogram is produced. Constraints (9) model unused inventory: unused ingredients with remaining shelf life 1 will go to waste, and all other ingredients become inventory for the next period. Constraints (10) ensure that inventory does not exceed the storage capacity at the soup kitchen. Constraints (11) and (12) deal with the available ad hoc donations. As ad hoc donations are only known by the soup kitchen until $\tau + \delta$ and the final decision has to be made at $\tau + \gamma$, no decision can be made for donations available to collect before $\tau + \gamma$. Furthermore, the accepted donations cannot be higher than the amount offered. When donations are accepted, they need to be collected (constraints (12)). Constraints (13)–(16) deal with meal variety. When an ingredient i is used, U_{ti} will get value 1 in constraints (13). Constraints (14) subsequently ensure that an ingredient is only used once every χ days by checking the ingredients used during this planning period (stored in $U_{t'i}$) and ingredients used in the previous period ($u_{t'i}$). Constraints (15) and (16) work similarly, but apply to recipes instead of ingredients. The last constraints, (17) and (18), represent the variable domains.

4. Experimental design

In this section, we formulate scenarios that allow us to analyze the benefits of structuring donations with suppliers via contracts,

Table 1
Design of experiments.

#	Scenario	Contract	Shelf life	γ/δ (days)	g	c^T (€)	ω (days)	χ (days)
1	*Basic*	–	–	–	–	–	7	2
2	*AHD*	-	2 days	2/1	1	3.50	7	2
3	*Contract*	V1	2 days	2/1	1	3.50	7	2
4		V3						
5		V5						
6		VM1						
7		VM3						
8		VM5						
9		VMO1						
10		VMO3						
11		VMO5						
12	*Shelf life*	VM3	1 day	2/1	1	3.50	7	2
13			$0.3^{*}m_i$					
14	*Time*	VM3	2 days	1/1	1	3.50	7	2
15				2/2				
16				7/1				
17				7/2				
18	*Donation cost*	VM3	2 days	2/1	0.2	3.50	7	2
19					0.4			
20					0.6			
21	*Transport cost*	VM3	2 days	2/1	1	0.00	7	2
22						7.00		
23	*Meal variety*	VM3	2 days	2/1	1	3.5	1	2
24							4	2
25							7	1

Table 2
List of contracts.

Contract	Product category	Donation days	Boxes/week
V1	Vegetable	1	1
V3	Vegetable	3	3
V5	Vegetable	5	5
VM1	Vegetable, Meat/Fish	1	2
VM3	Vegetable, Meat/Fish	3	6
VM5	Vegetable, Meat/Fish	5	10
VMO1	Vegetable, Meat/Fish, Other	1	3
VMO3	Vegetable, Meat/Fish, Other	3	9
VMO5	Vegetable, Meat/Fish, Other	5	15

the influence of costs related to donations, the importance of timing aspects such as shelf life and moment of donation announcement and the costs related to meal variety. Table 1 provides an overview of the 25 experiments we study in this section.

4.1. Scenarios

Scenario *Basic* is used as a reference scenario, in which we do not consider any donations, such that all ingredients have to be bought. In the second scenario, *AHD*, we include ad hoc donations. Scenario *Contract* deals with receiving donations via contracts on top of the ad hoc donations. In experiments 3–11, we formulated 9 different contracts, varying in number of suppliers and donation moments (shown in Table 2). The acronyms, V1–VMO5, indicate the type of product(s) involved and the frequency of donations. Donations either occur one, three, or five times per week. Suppliers are either delivering a box of vegetable products (V), meat or fish products (M), or other food products (O). For example, with contract VM3, the soup kitchen receives 6 boxes per week: 3 times per week a donation of 1 box of vegetable (e.g. from a green grocery), and 1 box of meat/fish. The weight (in kilogram) per box depends on the type of product.

The shelf life of donated ingredients can vary. Therefore, we also increase and decrease the remaining shelf life in scenario *Shelf life*. In the scenario *Time*, we vary the lead time of ad hoc donations (δ) and the commitment time (γ). With a longer lead time, a soup kitchen knows earlier what will be donated by donors which potentially benefits planning. Changing the commitment time influences the flexibility in planning: a longer commitment time is expected to reduce flexibility.

The effects of the cost parameters are tested in scenario *Transport cost* and scenario *Donation cost*, in which we vary the transportation costs and the costs of donations, in cases where less than 100% discount is given. This allows us to evaluate benefits or drawbacks of different cost structures.

In the last scenario (scenario *Meal variety*), we test how the constraints on ingredient and recipe use affect the donation use, costs, and menu selection of the soup kitchen.

4.2. Parameter settings and assumptions

The model deals with 40 ingredients ($\mathcal{I}$), which can be combined into 89 unique recipes ($\mathcal{R}$), based on a study at the Salvation Army in the Netherlands (Snels et al., 2012). Recipes only consider the main ingredients, minor ingredients such as salt and spices are neglected. 16 ingredients have a maximum shelf life (m_i) of 22 days, 10 ingredients of 14 days and the other ingredients 7 days or less. Ingredients are either stored frozen ($s = 1$), refrigerated ($s = 2$), or ambient ($s = 3$). Demand (d_t) is assumed to be constant and deterministic (30 kilograms/day), and the initial inventory level (i^0_{im}) is assumed to be zero. Initially, every recipe can be used only once in seven days ($\omega = 7$), whereas ingredients can be used every other day ($\chi = 2$). Ingredient costs c^B_i are retail prices of a Dutch retailer. Fixed costs related to buying ingredients are neglected, as are labour costs. Fixed transport costs of € 3.50 are in current when collecting a donation.

To obtain a data set for ad hoc donations we used information received from a Dutch food bank. From this, we created a dataset with donations (a_{tim}) for the full simulation horizon ($\mathcal{T}^{\mathcal{SIM}}$), specifying the ingredient and quantity. The total quantity of the donations are set to be $\frac{3}{7}$ of the total demand (Neter et al., 2016). In our experiment, food donations contain ingredients that are randomly selected from our ingredient list, where ingredients present in the data received from the food bank have a higher chance to get selected. Donation quantities are based on the weight of a full box of the ingredient (and thus vary per ingredient) and the number of boxes donated is determined by a binomial distribution:

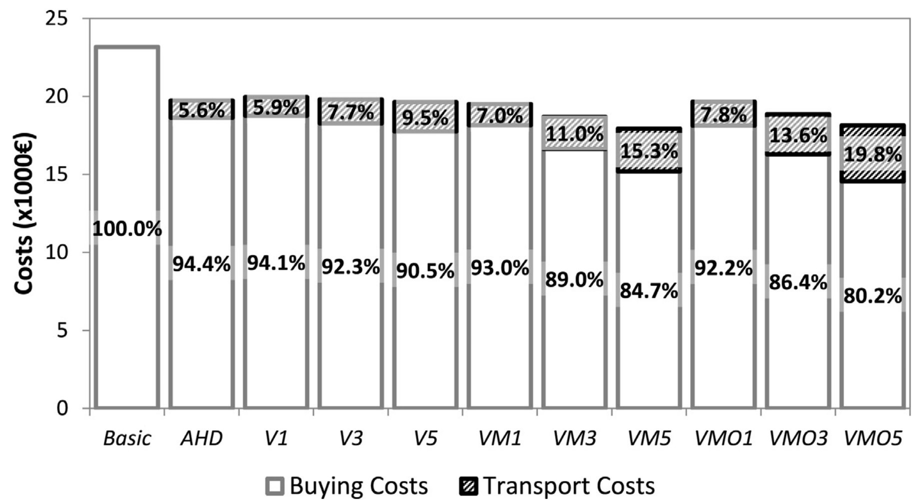

Fig. 3. Total costs for scenario *Basic*, *AHD* and *Contract* divided per cost contribution. Percentages are related to total costs.

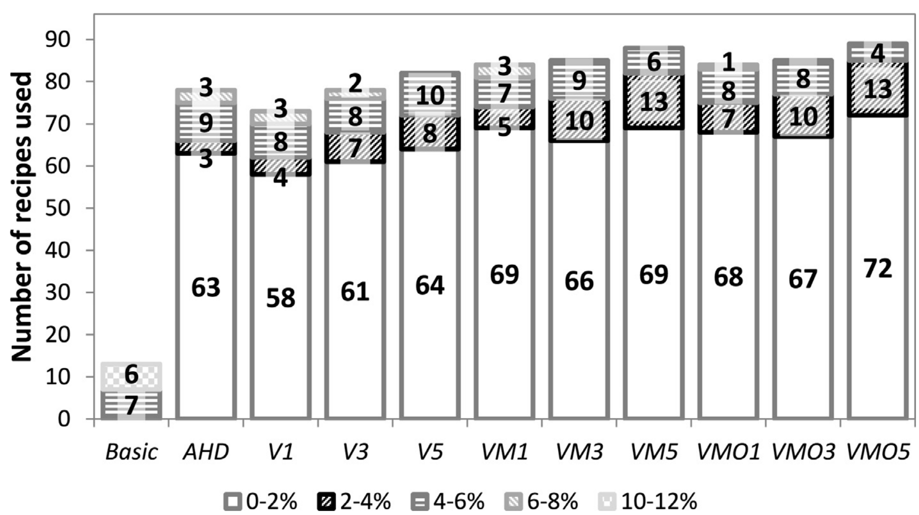

Fig. 4. Menu selection for scenario *Basic*, *AHD* and *Contract*. The numbers above indicate total number of recipes selected.

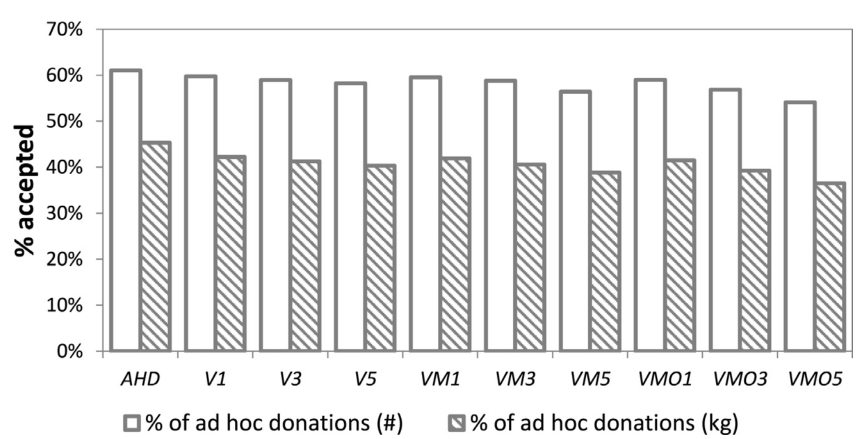

Fig. 5. Acceptance in kilogram and number of offered donation for scenario *AHD* and *Contract*.

$1 + Bin(n, p)$ with $n = 3$ and $p = 0.2$. Donation data for contract donations (f_{tim}) is also generated for the full simulation horizon ($\mathcal{T}^{\mathcal{SIM}}$), where the ingredients are randomly picked.

The problem is solved with a rolling horizon approach for 1 year ($\mathcal{T}^{\mathcal{SIM}}$). Within the rolling horizon approach, each planning problem has a planning horizon of 7 days (λ) and is thus solved 358 times for each experiment. To deal with variation in donations, 10 versions of the datasets a_{tim} and f_{tim} are created. Experiment 2 is executed 10 times with all datasets for a_{tim}, and experiments 3–25 are carried out with 10 versions of dataset f_{tim}. For each experiment, the MILP is thus solved 358*10 times. The model is implemented in Xpress-IVE 7.9 and solved using the Fico Xpress Optimizer. It takes about 1.5 seconds to solve the MILP for one day on a PC with Intel Core i5-5300U CPU 2.3 gigahertz.

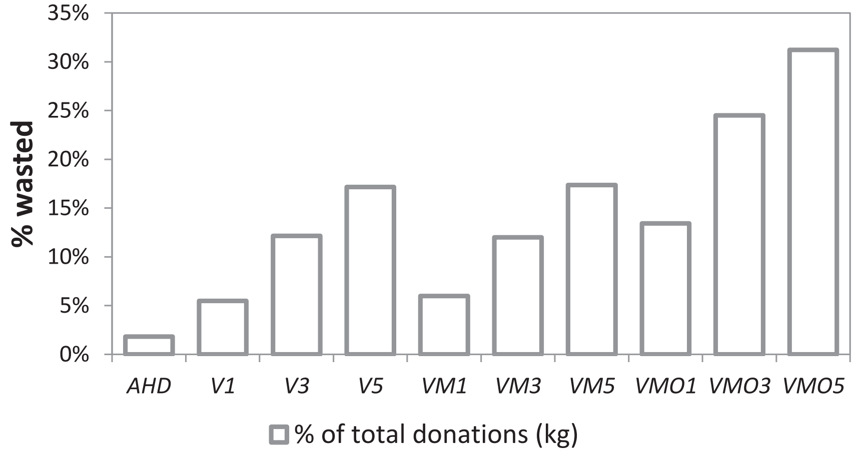

Fig. 6. Food waste in kilogram of incoming donations for scenario *AHD* and *Contract*.

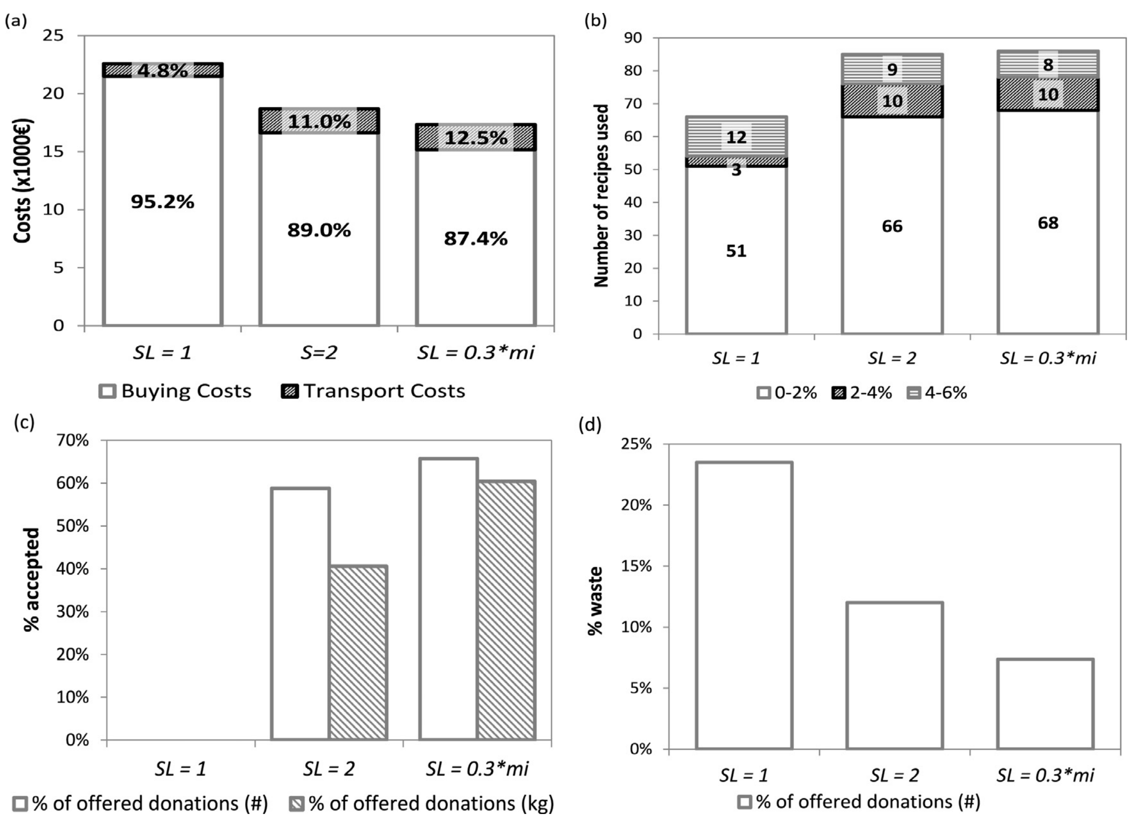

Fig. 7. Results of scenario *Shelf life* (a) Total costs, (b) Menu selection, (c) Donation acceptance, (d) Waste.

5. Results

Evaluation of the scenarios is based on four performance measurements. First, costs are incurred for buying ingredients, transporting donations, and in some cases for buying donations with discounts. The model minimizes total costs over a full planning horizon, which also includes periods for which the planning can still be adjusted. Therefore, the reported costs are obtained by summing up all costs made in the first period of every planning horizon. This ensures we only report the actually incurred costs. Second, we measure meal variety. This measure shows how often recipes are used during the full time horizon. Third, we measure the donation acceptance rate for the ad hoc donations, since we want to evaluate if there are options to increase this rate, and more surplus food can be used. Finally, we measure food waste obtained at the soup kitchen, since donated food might not always be used. Results presented in the following sections are average values over 10 runs, with standard deviations of 1% or less for each experiment.

5.1. Number of donations and contracts

Figs. 3–6 show the main results for the different performance measures for the scenarios *Basic*, *AHD* and *Contract*. These results mainly provide insights in the interaction between ad hoc donations and contract donations based on the number of donations and the contract types.

In scenario *Basic*, where no donations are offered, total costs are the highest, indicating that any kind of food donation reduces overall costs (Fig. 3). Cost reductions lie between 13.9% for contract

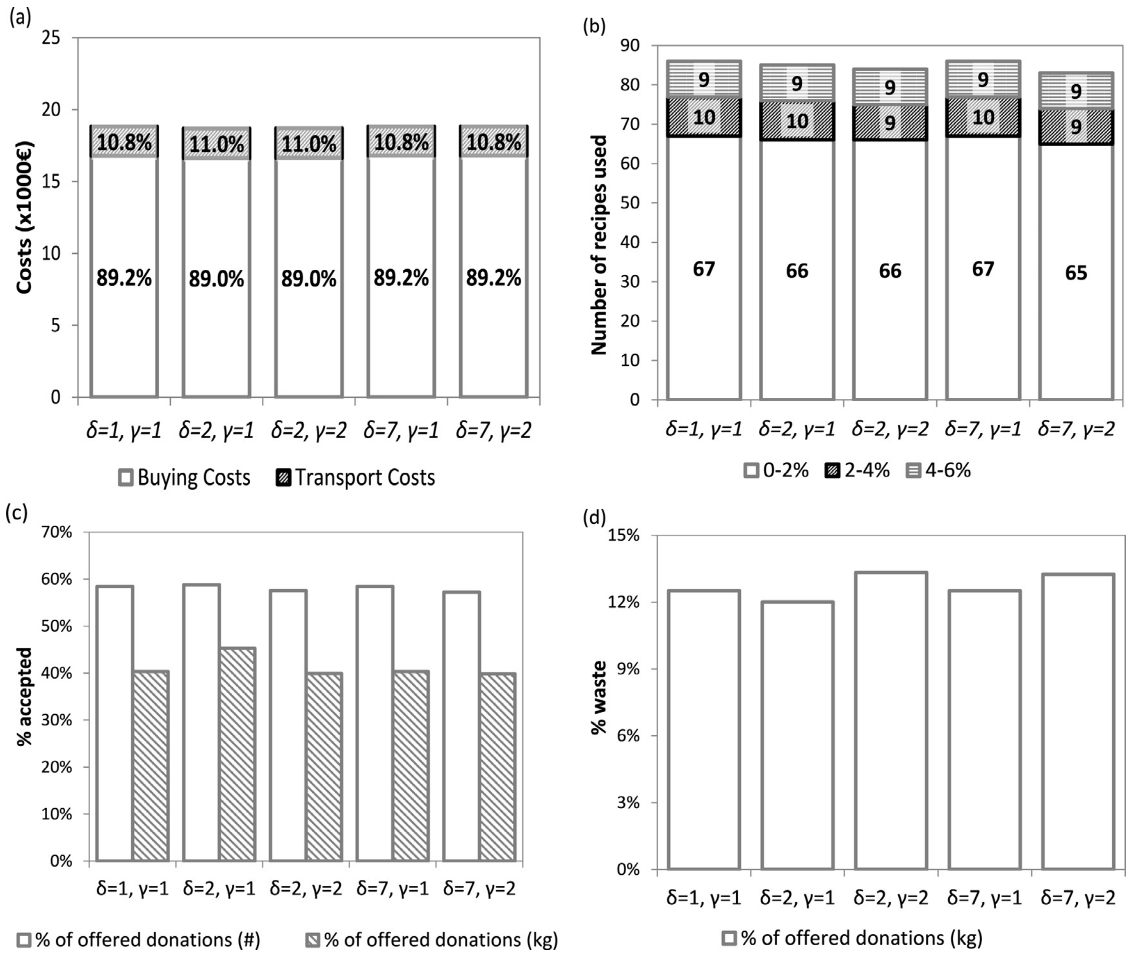

Fig. 8. Results of scenario *Time* (a) Total costs, (b) Menu selection, (c) Donation acceptance, (d) Waste.

V1 and 22.6% for contract VM5 compared to scenario *Basic*. Results show furthermore that the share of transportation costs increases with an increase in donations. However, an increase in contract donations does not necessarily result in lower overall costs, especially when transportation is relatively expensive compared to the buying prices. For instance, the ingredient price of potatoes is € 1.00 per kilogram, whereas transporting a donation is € 3.50. As ingredient prices differ per product, the trade-off between buying an ingredient or collecting it at a donor is different for each product. For contracts *VM1–VM5*, the reduction in buying costs is larger (in number and percentages) than for contracts *V1–V5* as more expensive products are donated.

Fig. 4 shows how often recipes are selected as a percentage of the total meal production over the full horizon. Out of 89 possible recipes, we can for instance see that scenario *Basic* only uses 13 recipes, of which 7 are used 4–6% of the time and 6 recipes 12–14% of the time. This illustrates the variety constraints leading to a minimum level of variety in meals served. Any situation in which donations are offered has significantly more meal variety. For all donation scenarios, most recipes are used only a few times, and none of them more than 8% of the time. Furthermore, the number of recipes that are not selected decreases significantly, from 76 in scenario *Basic* to an average of 6.4 in the donation scenarios, and as low as zero in the scenario where the most donations are offered (VMO5).

The percentage of accepted donations changes if more donations are offered via contracts, even though this is a minor change (see Fig. 5). In scenario *AHD*, 45% of the total amount of offered donations is accepted (in kilogram); as donations can be accepted partly this amount is obtained from 61% of the number of donations offered. If donations are not useful, the soup kitchen will choose not to accept them and avoid the transportation costs resulting from collection. The decrease in donation acceptance, if using contracts compared to only ad hoc donations is relatively small. When contract donations are easy to combine with the ad hoc donations in a menu plan, more donations can be used.

Even though the acceptance rate did not show large changes, when more donations arrive at the soup kitchen, food waste at the soup kitchen does increase significantly (as shown in Fig. 6). Most donations ending in food waste at the soup kitchen are received via a contract as a soup kitchen will not accept ad hoc donations that cannot be used. Making a meal out of donated ingredients usually requires additional ingredients to be bought. When it is then cheaper to make meals that completely consist of bought ingredients, a soup kitchen will waste donated ingredients. However, it is not only the contract donations that end up as waste; some of the accepted ad hoc donations can end up as waste as well. The soup kitchen must decide γ days before collection whether a donation is accepted or not, but the menu planning can still change afterwards based on cost savings resulting from new donation information.

5.2. Shelf life of donations

To evaluate the effect of changes in the remaining shelf life of products donated, we study three alternatives: the 2 days from the basic scenario, an increase to 30% of the maximum shelf life of the

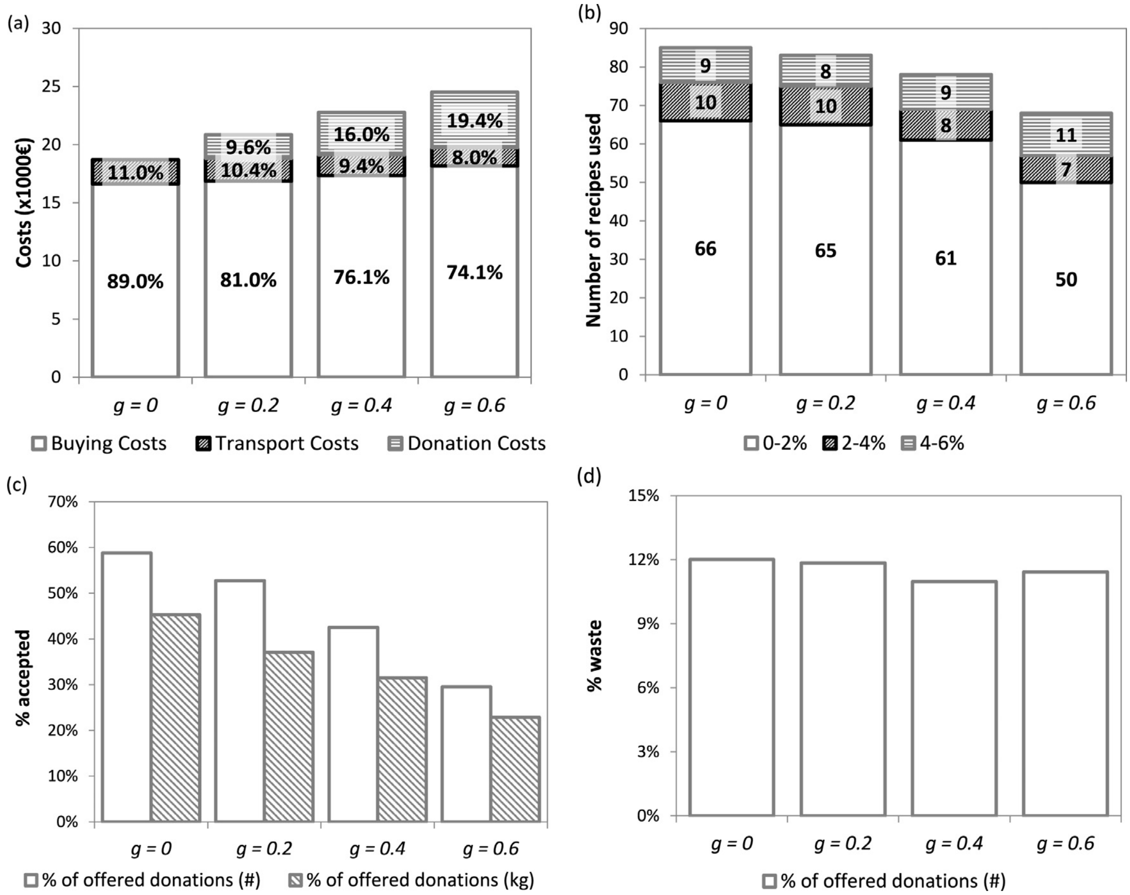

Fig. 9. Results of scenario *Donation cost* (a) Total costs, (b) Menu selection, (c) Donation acceptance, (d) Waste.

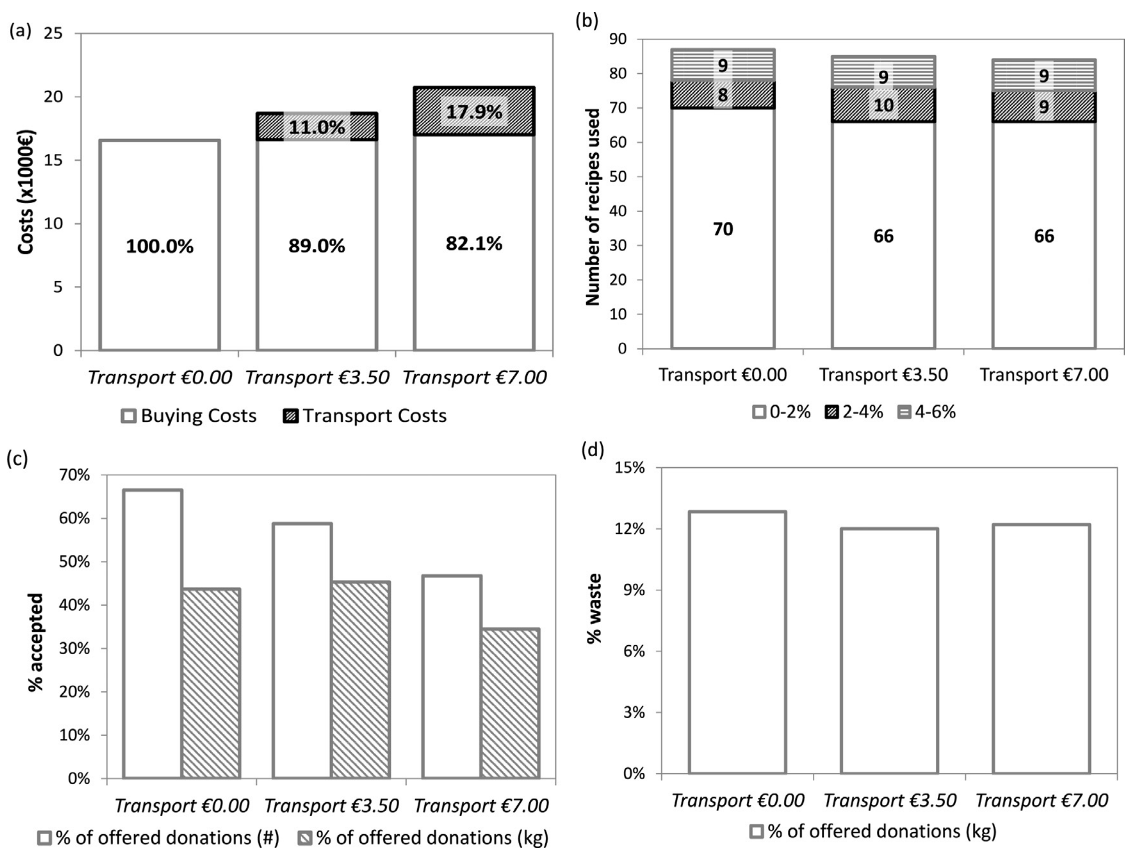

Fig. 10. Results of scenario *Transport cost* (a) Total costs, (b) Menu selection, (c) Donation acceptance, (d) Waste.

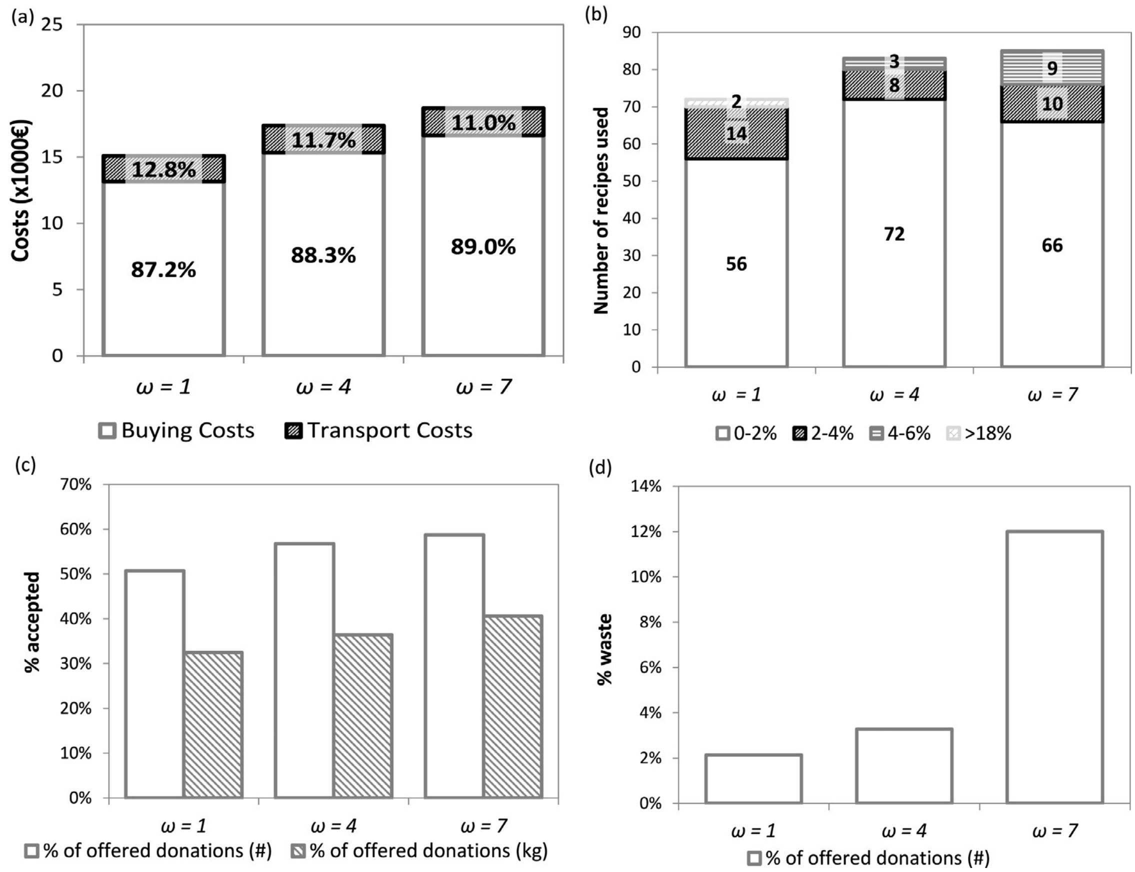

Fig. 11. Results of scenario *Meal Variety* with different ω (a) Total costs, (b) Menu selection, (c) Donation acceptance, (d) Waste.

product m_i, and a decrease to 1 day (note that shelf life of contract donations are 1.5 times longer). Fig. 7(a) shows that, when shelf life is increased, total costs decrease and donation acceptance increases because products can be used for a longer time. The decrease in costs is thus achieved by a decrease in buying costs, since more transportation costs are incurred due to the higher acceptance rate. Total costs increase to almost the level of scenario *Basic* when ad hoc donations only have a shelf life of 1 day. Here, many donations cannot be used efficiently in menu planning and are therefore rejected (Fig. 7(c)), leaving the soup kitchen with only contract donations and a significant decrease in meal variety (as reflected in the recipe use shown in Fig. 7(b)). Fig. 7(c) shows that the percentage of accepted ingredients in kilogram of ingredient offered and the percentage of accepted ingredients in units of offered donations deviate less at a higher remaining shelf life. As there is more time to use the ingredients, larger volumes can be accepted and used. Waste levels shown in Fig. 7(d) are in line with the expectations: when there is more time to use the donations, waste levels will decrease.

5.3. Lead time of donations

The moment ad hoc donations are announced or the time there is to decide to accept or reject a donation can vary. Therefore, we study five cases, in which the lead time varies between 1 or 7 days, and the commitment time is 1 or 2 days for ad hoc donations. Fig. 8(a,b) show that different lead times or different commitment times have a relatively small impact on costs and meal variety, although there are differences in donation acceptance rates and waste. When commitment time (γ) increases with the same lead time (δ), less donations are accepted and waste obtained increases (Fig. 8(c,d)). When decisions must be made longer in advance, there is less information available on upcoming donations. The optimal menu plan can change more easily after making the decision on accepting the donation when more useful donations will be available later. Therefore, the highest donation acceptance rate and the lowest amount of waste is obtained when lead time (δ) is 2 days and commitment time (γ) is 1 day.

5.4. Donation cost and transport cost

In this section, we study the influence of the main cost factors related to donation management. In scenario *Donation cost*, we study the influence of receiving a discount on food ingredients instead of receiving free food donations. In scenario *Transport cost*, we study the influence of transportation costs. As expected, Fig. 9(a) clearly shows that introducing a donation cost leads to an increase in total costs. Furthermore, the meal variety decreases when costs increase (Fig. 9(b)). Also, Fig. 9(c) shows that donation acceptance decreases with higher costs. When donations costs increase, the trade-off between collecting an ingredient as a donation or buying it fresh at the retailers changes. For a decreasing number of ingredients, it will be beneficial to obtain them as a donation. Fig. 9(d) shows a small variation in waste, however this is negligible as it is caused by the stochastic nature of the problem.

Transportation costs have similar effects as costs for donations, as shown in Fig. 10. Even when there are no transportation costs (e.g. the donor brings the donation), part of the donations is still not accepted (Fig. 10(c)). This shows that only donations that can be used by the soup kitchen are accepted. Analyzing the details of donation acceptance decisions show that at most the needed amount for a day is accepted, due to the variety constraints, the total demand, and the limited shelf life. If a larger quantity is offered, the donations will only be partly accepted. Donations are

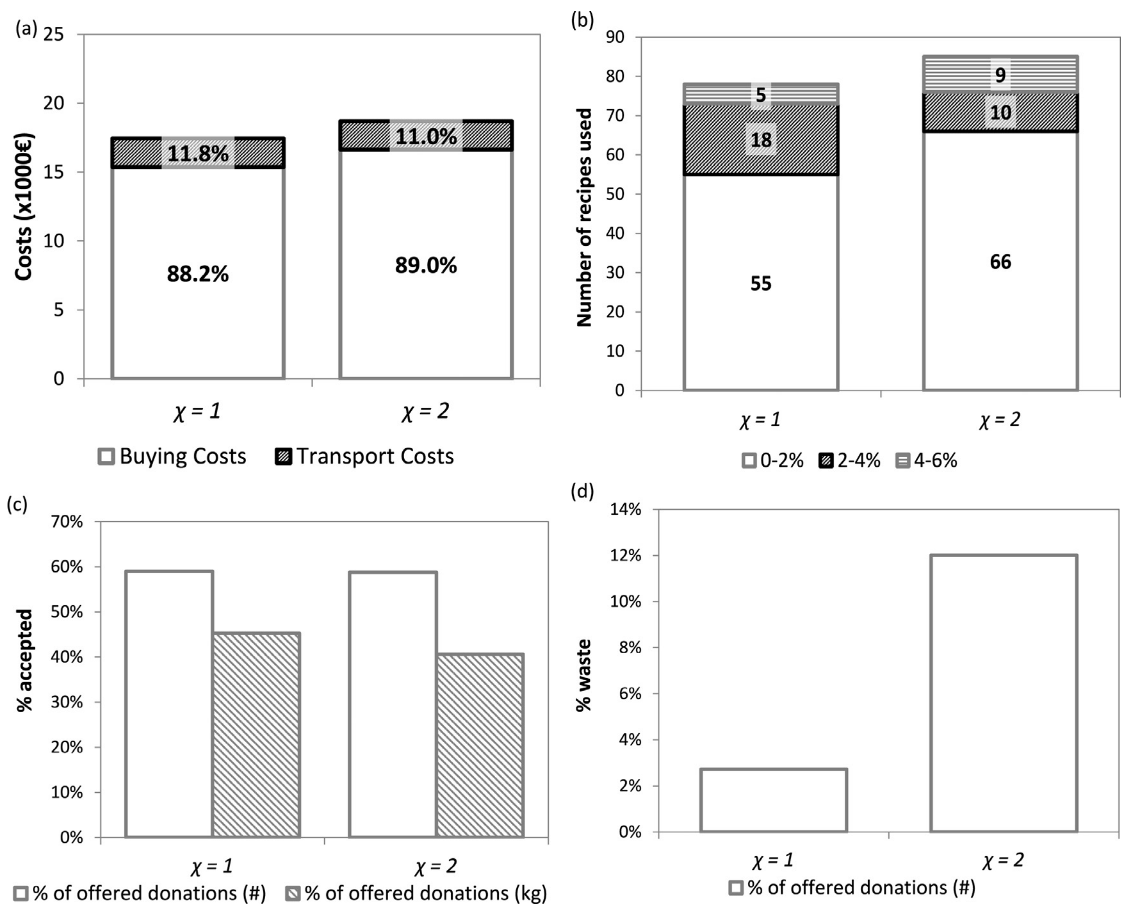

Fig. 12. Results of scenario *Meal Variety* with different χ (a) Total costs, (b) Menu selection, (c) Donation acceptance, (d) Waste.

completely rejected if the ingredient cannot be used the next day due to variety constraints. The meal variety shown in Fig. 10(b) shows the expected trend: more accepted donations will result in a higher number of recipes used throughout the simulation horizon. In line with expectations, the differences in waste obtained (Fig. 10(d)) are small for scenario *Donation cost*. If donations are more expensive, less donations will be accepted and therefore waste will decrease slightly. When transportation costs change, waste levels do not change, although more food donations are accepted. However, it still is not useful to accept donations which cannot be used.

5.5. Meal variety

In the previous scenarios a restriction on the use of ingredients and recipes was used. In the last scenario, these bounds are relaxed. Fig. 11 shows the results of a relaxation of the recipe bound. When recipes can be used every day ($\omega = 1$) total costs are reduced significantly (Fig. 11(a)). This reduction is obtained by an increase in the use of the recipe with the lowest cost. As shown in Fig. 11(b), there are two recipes used more than 18% of the time. Furthermore, the donation acceptance is reduced, and a large decrease in waste levels is obtained, as shown in Fig. 11(c,d). When the restriction on recipes is maintained, but reduced to 4 (i.e. allowing the same recipe to be used every four days), costs still decrease compared to the restriction of 7 days, but the meal variety is not affected. However, the waste levels decrease from 12% to 3%.

When the recipe restriction is maintained, but the ingredient restriction is relaxed, similar results are obtained. Fig. 12(a) shows a small decrease in costs, meal variety, and donation acceptance when ingredients can be used every day (see Fig. 12(b,c)). However, as shown by Fig. 12(d), waste levels are reduced significantly.

6. Decision rules for accepting ad hoc donations

Donation acceptance decisions are difficult to formalize in practice. Decisions on acceptance of fresh produce are between accepting all (to prevent a loss of goodwill by donors), and accepting not too much of each ingredient to enforce meal variety, to meet shelf life constraints, and to reduce waste at soup kitchens. Currently one tends to accept as much as possible and leave the menu planning and prevention of waste to the chefs creativity. If a donation does not fit in the menu plan, the donation is rejected or the menu is adjusted such that the donation can be used. The MILP model includes both options and thus fits to current practice. In case one cannot use a donation in full, in practice the donation may be redirected to other organizations. The scope of this paper is to assess the value of donation contracts for a single organization, thus redirection of donations is beyond the scope. In this section, the performance of the MILP model is compared against the following decision rules that relate to the above considerations on accepting ad hoc donations:

1. All = Accept the full volume of all donations,
2. All-day = Accept all donations but limit the volume to the quantity needed for one day,
3. VMO-day = Accept per category (vegetable products (V), meat or fish products (M), or other food products (O)) only one donation and limit its volume to the requirements for one day.

The idea of limiting the volume to one day in rules All-day and VMO-day, is triggered by the results for MILP and by the meal

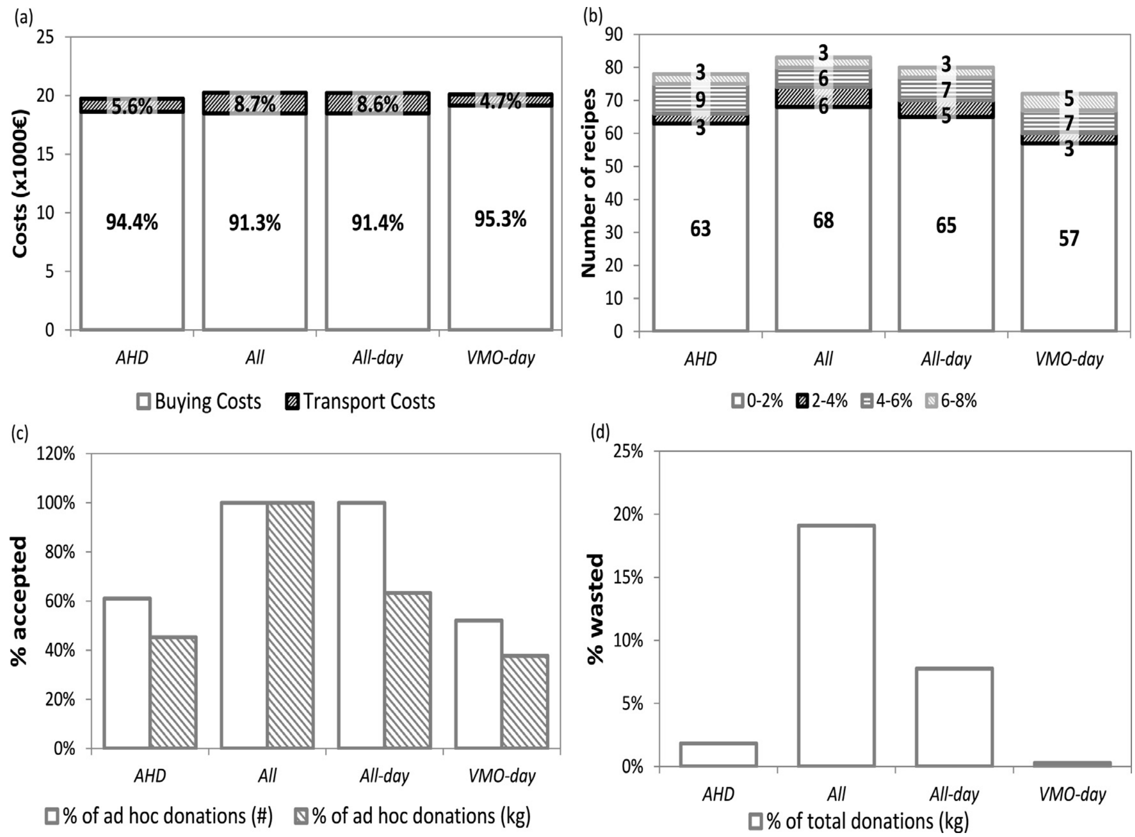

Fig. 13. MILP model vs *decision rules* (a) Total costs, (b) Menu selection, (c) Donation acceptance, (d) Waste.

and ingredient variety constraints and the short remaining shelf life of donated products. Note that these rules are easy to apply in practice, but leave the menu planning and waste reduction to the chef. To evaluate these decision rules, the MILP model is used by restricting the values of the donation acceptance variables (X_{tim}). The restricted MILP model determines a cost-optimal menu planning that makes good use of the accepted donated, and thereby approximates the non-formalized decision of the chef. The results are reported in Fig. 13.

The results of scenario *AHD* are cost-optimal solutions from the previous section. Accepting all ingredients leads to an overall cost increase of 2.6%, which is mostly due to a 60% increase in transportation costs, and a very high percentage of food waste at the soup kitchen. In practice, such a rule is only sustainable if excessive donations are redirected to and used by other organizations, but for products with short shelf lives this might not be possible. Although the cost increase is only 2.6%, this is still an unwanted increase for the soup kitchen, as they are cost driven. Rule All-day still accepts all donations but limits the accepted quantity to the need for a single day. This reduces waste from 19.1% to 7.8%, but some donations do still not fit into a cost-optimal meal plan. Note that even in a cost optimal plan (scenario *AHD*), waste is still 1.8% as some accepted donations become redundant by more favourable donations that occur later. Furthermore a cost increase of 2.5% is obtained for the All-day rule, compared to scenario *AHD*. Finally, the rule VMO-day yields lower waste but higher costs (+ 1.9%) by accepting only one donation per category per day. The overall acceptance rate is slightly lower than scenario *AHD*. Besides higher costs, this rule results in a lower meal variety: 72 vs 78 different recipes are used.

Our results (and decision rules) are relevant for products with relatively short shelf lives. The MILP can easily deal with longer shelf lives (as shown in Section 5.2). However, the decision rules have to become more complex to better assess the value of products with a (much) longer shelf life, i.e. detailed stock keeping administration and meal planning decisions should be included at some level. Both are included in the MILP, which makes the model promising for operational use next to analyzing tactical issues.

7. Conclusion and discussion

In this paper, we combine donation management and menu planning for a soup kitchen, in order to efficiently use food donations and reduce food waste. This integrated planning problem has so far not been addressed in the literature. Menu planning is a planning problem dealing with the selection of recipes, and obviously interacts with decisions on whether donations should be accepted or not. Depending on (variety) constraints introduced in the menu planning model, only a certain share of the offered donations can actually be used efficiently.

International developments regarding food waste reduction (e.g. recently introduced French legislation forcing retailers to donate food surplus to charitable organizations) make it interesting and relevant to not only study donation management, but also to investigate the effect of receiving donations via contracts. Our results show that contracts are a good addition to ad hoc donations, but also show that not all donations arriving at soup kitchens can be used, despite their consideration in menu planning. Costs related to donations, such as transportation or purchasing costs, decrease the attractiveness of donations for soup kitchens. However, one of the benefits of setting up contracts is the possibility for agreements on frequency, quantity, remaining shelf life, and type of ingredient, which all influence the usefulness of donations. Furthermore, restrictions to ensure meal variety are indeed useful in order to serve the clients a varied and arguably healthier meal through-

Please cite this article as: M.E. Buisman et al., Donation management for menu planning at soup kitchens, European Journal of Operational Research (2018), https://doi.org/10.1016/j.ejor.2018.06.005

out the week, even though a higher meal variety cause higher waste levels. From a palatability point of view, ingredient or recipe variety is also preferred, but to what extent this is worth the additional food waste and increased costs is an important managerial discussion that gets input from the results in this paper.

In this paper, we focus on ingredient purchasing and transportation costs. Labour costs are often no economic costs to charitable organizations, since they tend to work with volunteers. Other costs (e.g. overhead costs, meal production costs) are present, and will impact the overall costs, but these costs are not expected to have a significant impact on the trade-offs in the integrated donation management and menu planning problem we considered in this paper.

Furthermore it is assumed that ingredients donated via contracts do have a longer shelf life, as there is a possibility to include a minimum on the shelf life of ingredients within a contract. When the shelf life of contract donations would be similar to the ad hoc donations, the number of donations that can be used will decrease, thus less ad hoc donations will be accepted.

The exclusion of storage capacity and collection truck capacity might influence results if the model is applied to products with a long shelf life. However, if donation quantities are in line with the size of the soup kitchen, the influence of storage capacity is expected to be small. Whether a truck capacity should be included depends on how transportation is organized. Many logistic service providers imply a fixed costs for collecting and delivering products within a certain geographical area. If a (group of) soup kitchen(s) is organizing the transport them selves either (fixed) costs apply for compensating volunteers, or these costs are to be shared if multiple donations are combined in a single trip. In the later case then the collection truck capacity might influence the results, and it is therefore interesting for further research to combine the work in this paper with research on vehicle routing for charitable organizations (see Section 2). This allows the intelligent consideration of truck capacities, both for collecting donations as well as purchasing fresh ingredients.

The proposed optimization model is used in this paper for evaluation on the tactical level. However, soup kitchens could also benefit from such decision support systems to help them make operational decisions. However, in order to implement the developed model in such a way, there would be investments in the soup kitchens IT infrastructure and data management. Charitable organizations usually lack the time and money to fulfil these requirements. We therefore suggest that further research should be undertaken on the practical implication of integrating donation management with menu planning. Besides considering the implementation of an MILP model, this could potentially be done by extending the heuristic decision rules of Section 6. For products with a short shelf life, decision rules may be well structured by the (recipe and ingredient) variety constraints. However, for products with a longer shelf life, decision rules are more complex and the integration of donation and menu planning decisions is even more relevant.

In this research several parameters are used which are stochastic in real life, such as the shelf life of a donation, or the chance that a donation will be available. Due to a scenario based approach and the rolling horizon, these stochastic parameters are integrated in the MILP model. For further research it can be interesting to develop a stochastic MILP to incorporate the stochastic nature of these parameters. Then, the objective function will be a minimization of the expected costs.

Even though we focused on soup kitchens in this paper, more charitable organizations may benefit from similar approaches. Despite some differences between soup kitchens and food banks, our approach could likely be adjusted for a food bank setting in which food donations are used in the construction of food parcels. Deciding on food parcel contents would then replace the menu planning decisions. However, notable differences would likely be that food banks often do not purchase additional products (ingredients), and that transportation costs might be a more important consideration for food banks.

Besides soup kitchens, retailers benefit from donating leftovers by decreasing their food waste levels, and displaying only the freshest items. The greatest reduction in food waste can be obtained when good agreements are made between parties on donation quantities and costs are fairly shared. When costs are too high for either of the parties involved, leftovers will not be used optimally. In further research, we recommend to investigate how costs should be divided among the different parties.

Acknowledgments

This research is partially funded by the REFRESH project, as part of the Horizon 2020 Framework Programme of the European Union under Grant Agreement no. 641933. The content of this document is the sole responsibility of REFRESH and can in no way be taken to reflect the views of the European Union.

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