Food Waste Reduction in Switzerland: A Control Approach

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Abstract— **Food waste is a severe local and global environmental issue. Sadly, or maybe luckily, producers and consumers are a main cause for this issue through their role in the market and their preferences. In the following, we analyze this issue from a control systems point of view, using a mass-flow network model with interconnected discrete time systems. Various concepts and control approaches, including linear programming (LP), model predictive control (MPC), greedy control and PID feedback control, aiming to represent real life scenarios, are evaluated. Findings conclude that the amount of food waste is strongly determined by consumers' behavior and the adaptation of producers to changing food demands. Applying feedback mechanisms can help producers to adjust food supply in response to changes in demand, contributing to a more sustainable supply chain and ultimately reduced amounts of food waste.**

I. Introduction

The public awareness of food waste and the associated negative environmental impact has been increased in recent years all over the world, especially in Western European countries. Governments but also international organizations have formulated ambitious strategies and launched numerous campaigns which aim to reduce the amount of food waste caused by society [1], [2]. According to the Swiss Federal Office for Environment, approximately one third of all edible food products is lost or wasted along the journey from production to end consumers [3]. A study conducted by ETH Zurich revealed that Switzerland produces approximately 2.8 million tons of food waste every single year, which corresponds to about 330kg of food loss per person per year [4]. Although it is difficult to precisely quantify the environmental impact of food waste, experts agree upon on the fact that food waste is a non-neglectful contributor to global CO2-emissions. In the case of Switzerland, estimates suggest that the environmental burden caused by food waste corresponds to almost half the environmental impact of motorized individual transport [3]. These figures highlight the importance of implementing effective measures to reduce food waste, not only to conserve resources but also to decrease the carbon footprint and mitigate climate change.

A common approach to investigate and analyze the behavior of systems that are characterized by multiple agents or compartments and include network flows which fulfill conservation laws, is to model them as dynamical flow systems. Examples for dynamical flow systems can be found in various fields such as environmental and ecological networks, transportation systems, communication networks as well as models describing pandemic spreading [5], [6]. As the production, distribution, and consumption of food products in general follows the simple concept of a supply chain model that involves multiple agents, it can be considered as dynamical flow system as well. Prior work has already made and in-depth analysis on what levels food waste occurs and also proposed different measurements that can help in reducing the amount wasted food [4], [7]. However, up until now, only little efforts were made to quantitatively model the dynamics of the system and apply control principles for optimization purposes.

To address this shortcoming, this paper introduces a network model which can be used to describe the flow of food products from producers to consumers. Moreover, different control approaches that aim to minimize the amounts of food waste are presented and their respective results discussed. First, a graph representation of the network model is derived such that it can be regarded as a minimum-cost flow problem (MCFP) that can be solved by using well-established optimization algorithms. Many publications already showed that linear programming (LP) techniques can be applied to efficiently solve network flow problems and find optimal solutions [8]. Then, a decentralized model predictive control (MPC) approach is implemented since the system contains multiple constraints and other papers already showed that this method can be used for similar network optimizations [9]. Next, a greedy control approach is implemented to investigate the effect on food waste. Finally, proportional feedback control is applied in a distributed way because we assume that food waste can be partly attributed to the imbalance between food demand and supply. Implementing a feedback mechanism can thus help the system in achieving an equilibrium where supply is adjusted in response to changes in demand and thereby food waste in minimized. Also here, prior work and examples from other fields (e.g., supply chain management) have confirmed the appropriateness of this control method for this type of problem [10], [11].

The remainder of this paper is organized as follows: Section II formulates the time-discrete network model as well as the optimization and control techniques applied. Section III presents the results of the base case simulation and control techniques. Finally, in section IV we summarize the results and make suggestions for future work on this topic.

II. Model setup

The model we have developed for analyzing the occurrence of food waste consists of a network system with multiple agents. In this network model, we distinguish between three different types of agents: producers (Ps), social-charity organizations (SCs) and consumers (Cs). As illustrated in Figure 1, each agent of the system is represented by a node while food flows from one agent to another are indicated by directed edges. The state of every agent i in the network is expressed by its vector $x^i \in \mathcal{R}^T$. The state vector x^i comprises multiple variables $x^i_t \in \mathcal{R}$ which refer to the stored food items of age $t \in \{0, ..., T-1\}$. In general, the internal state dynamics of each agent have the form:

$$x^i(k+1) = A^i x^i(k) + B^i u^i(k) \tag{1}$$
$$y^i(k) = C^i x^i(k) \tag{2}$$

where $x^i(k)$ is the state of node i at time k and $u^i(k)$ refers to the respective food inflow at node i. The matrix A^i describes the update function of the current food stock of node i from time k to $k+1$. Specifically, $x^i(k)$ can be self-consumed, flow out of the node, contribute to food waste or stored in x^i_{k+1}. Assuming non-negativity, A^i has the following form:

$$A^i = \begin{bmatrix} 0 & 0 & ... & 0 \\ 1-\alpha^i_1 & 0 & ... & 0 \\ \vdots & \ddots & \dots & 0 \\ 0 & ... & 1-\alpha^i_{T-1} & 0 \end{bmatrix}$$

where $0 \leq \alpha^i_t \leq 1$ defines the fraction of food items in state $x^i_t(k)$ that leaves the node. To capture the food flow dynamics, we suppose that food can enter node i via the matrix B^i and the input vector u^i and exit node i via the matrix C^i and resulting output vector y^i. In particular, the flow of food products between n nodes at iteration time k is given by $\mathcal{F}_k(i,j,t) \in \mathcal{R}^{n \times n \times T}$ where i, j, t represent the outflow node, inflow node and food age respectively. Here, positive entries represent outflows from a node whereas negative entries correspond to inflows. Due to the network design and symmetry of network flows, the following conditions must hold for all states and all iteration steps k:

$$\mathcal{F}_k(i,j,t) = -\mathcal{F}_k(j,i,t) \quad \forall i \neq j$$
$$\mathcal{F}_k(i,i,t) = 0 \quad \forall i \forall t$$

However, the directions of food flows within our network model are not completely arbitrary as indicated by the directed graph. In general, we assume that fresh food enters the system via the producers. Therefore, producer nodes have an external inflow $u^i(k)$ where all food products enter the producer's first state $x^i_0(k)$. Producers can distribute their food stock either by selling their food products to consumers or by giving food items to social charity organizations. Thereby, consumer and social charity nodes receive inflows from producer nodes as described by $\mathcal{F}$. Here, we assume that social charity organizations tend to receive only older food items from producers since producers try to sell fresh food products to consumers before giving them to social charity organizations. For our model setup, this means that only entries in $\mathcal{F}$ referring to higher states are non-zero. Because social charity charities do not consume food themselves but redistribute the obtained food products among consumers, they also feature outflows to consumers that are again expressed by the entries in $\mathcal{F}$.

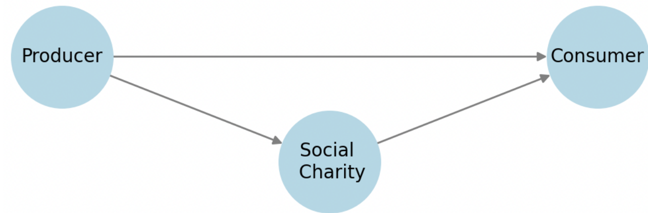

Fig. 1. Graph representation of a simple system featuring only one producer, one social charity organization and one consumer

Apart from food flows within the network, we consider that every agent also encounters some food loss due to food waste that is denoted by the output variable y^i_{fw}. In general, all states can contribute to food waste. However, we assume that older food items are more likely to cause food waste, since fresh food products normally have a certain storage life before becoming food waste. Therefore, the food waste factor γ^i_t that is comprised in the matrix C^i increases for larger t. Moreover, food items that have reached the final state x^i_T can no longer be consumed and are thus considered as food waste (i.e., x^i_T is contributing 100% to food waste y^i_{fw}).

Finally, we account for the self-consumption of consumers by introducing the output state variable y^i_{sc}. Based on their individual consumption behavior, consumers can use food products of different states t to meet their daily food demand. It is important to highlight that the food demand of consumers has to be satisfied for all iteration steps k because otherwise consumers would start to starve. By incorporating the self-consumption factor θ^i_t, which describes the amount of food with age t that is used for consumption, the matrix C^i is given by:

$$C^i = \begin{bmatrix} f^i_{11} & f^i_{12} & ... & f^i_{1T} \\ \vdots & \vdots & \vdots & \vdots \\ f^i_{n1} & f^i_{n2} & ... & f^i_{nT} \\ \gamma^i_1 & \gamma^i_2 & \dots & \gamma^i_T \\ \theta^i_1 & \theta^i_2 & \dots & \theta^i_T \end{bmatrix}$$

where f^i_{jt} denotes the flow factor that describes the flow of food with age t from node i to node j.

Because we require food flow conservation for all nodes i and every time step k, we can derive the following relationship between the matrix entries of A^i and C^i:

$$\sum_i c_{ij} = \alpha^i_j \quad \forall j \in \{1, ..., T\}$$

This means that the column sum of matrix C^i must be equal to the factor α^i that is deducted from the off diagonal of matrix A^i. Thereby, we ensure that food is neither created nor destroyed within our system.

Note that the A^i and C^i matrices may change with simulation steps k depending on the algorithm used but the mass conservation condition always has to be fulfilled. For the base case, greedy and feedback control, A^i and C^i are considered to be constant for all k whereas for the decentralized MPC, we actually compute the optimal A^i and C^i at every time step.

Using this model, we want to answer the following questions: How much food waste can be reduced *within* the current state of the system, by optimizing flows and consumption patterns (via decentralized MPC)? How big is the impact of adjusting the total food supply (via proportional feedback)? What if consumers are very cautious about food waste (via greedy method)?

A. Parameters

The choice of suitable parameters is ground-laying for a meaningful model. Therefore, the assumptions previously presented have to be implemented based on a set of parameters. The details can be found in the code on GitHub and the a full list of parameters is listed in the appendix. A limited amount of the main parameters are discussed here. Firstly, the simulation horizon in this paper was chosen to be 20 steps for simplicity but 100 steps results where also executed, yielding similar results. The number of food states was chosen to be ten, meaning after nine time steps the food was considered as wasted. The number of producers, social-charities and consumers were set to one, one and ten respectively for a concise analysis. Same as for to the time horizon, greater amounts of nodes resulted in similar findings but made the large network less readable. The results of an extended network model including more network agents are listed in the appendix section. For the food flow between producers and consumers, a default value of the current situation (3.55 MCal per consumer per day [4]) was chosen. The stored amount of food at the producers level was set to 73% to yield near-realistic results. For the initial states, the base case simulation was first executed to find a steady-state food store content at the producers, social-charities and consumers level. The idea behind this is: we want to start the simulation at steady-state realistic values and not arbitrary ones, for example $x(k = 0) = 0$. Also, initially consumers use up food products of all states, meaning food age, in their store at the same proportion.

B. Base cases

In order to compare the results, there needs to be a base case as a reference. This base case tries to replicate the current state of food waste in the real world in a very reduced model:

1) Simple model - base case (BC)

In 2021, an average person in Switzerland consumed 12.7 MJ per day or roughly 850kg per year [12], [4]. The current nutritional value of food waste losses are estimated at 33% or 1160 kcal/person/day [4]. Details of the BC model parameters can be found in the appendix.

C. Linear Programming Approach

A possible way to analyze the dynamics of the previously introduced model and optimize for minimal food waste is to consider it as a network flow problem. In particular, the idea is to reformulate the food waste reduction problem as a minimum-cost flow problem which can be solved by using linear programming techniques.

As depicted in Figure 2, each state variable of every agent in our system is now represented by a node whereas potential food flows between producers, consumers and social charity organizations are represented by edges f_{ij}. In our simplified model, every edge is characterized by a certain capacity u_{ij} and weight function c_{ij}. Moreover we can set the demand of every node i to a certain value b_i, ensuring that this node either receives (b_i<0) or provides (b_i>0) a certain net flow from or to the system. Assuming the graph $G(N, E)$ where N is the set of nodes and E is the set of edges, the optimization problem is as follows:

$$\min \sum_{(i,j)\in E} c_{ij} f_{ij}$$

with the constraints:

$$f_{ij} \leq u_{ij}, \forall (i,j) \in E$$

$$\sum_{j:(i,j)\in E} f_{ij} - \sum_{j:(j,i)\in E} f_{ji} = b_i, \forall i \in N$$

Since our aim is to minimize food waste, we attribute a positive weight to all edges that are pointing towards the food waste node, all other weights are set to zero. Food enters our system via the producers, therefore a source node is connected to the node representing the first state of the producer only. To ensure that every consumer receives enough food for every time step of our simulation, we set the demand variable of every consumption node in our network to the daily intake (flow from consumer to consumption). The remaining flows can be optimized.

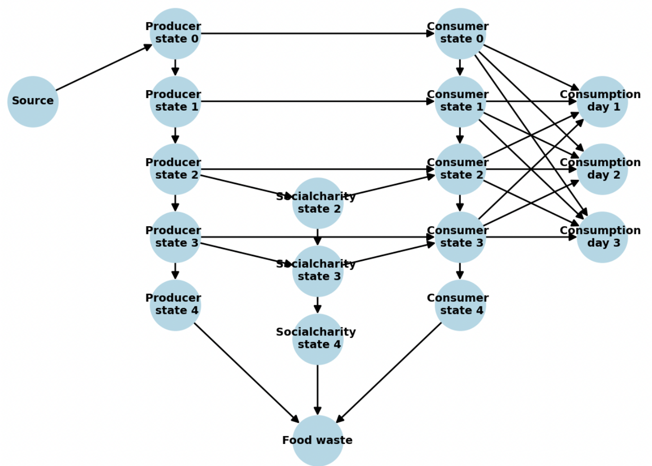

Fig. 2. Network representation for linear programming approach including one producer, one consumer, one social charity organization, five food states and a simulation horizon of three days

D. Decentralized MPC

Model predictive control (MPC) is a common control approach for process optimization and can be used for various problems. Descriptively, MPC is a static, nonlinear, time-invariant feedback control law.

There are multiple reasons for using MPC in this context: a) there are a many constraints that may be exploited, b) MPC may represent realistic scenarios and c) it has yielded superior results in previous network flow systems such as energy hubs [16].

For our dynamical network flow system we can make use of the MPC in a decentralized approach: a local MPC with an objective at every node. This, obviously, does not guarantee any global goals but is actually a realistic scenario for our model: Every actor (node) tries to reduce their own food waste given its constraints and control variables (inputs). In real life, there does not exist a central authority ordering everyone from producers to consumers how to behave in order to reduce food waste, but every actor chooses their action individually.

We can define the linear cost function $\ell^i\left(x_k^i, u_k^i\right) = q^\top x_k^i + r u_k^i$ and an apply economic MPC at every node:

$$\begin{aligned} &\min_{u,x} \sum_{k=0}^{K-1} \ell_i(x_k^i, u_k^i) \\ &\text{s.t. } x_{k+1}^i = A x_k^i + B u_k^i \\ &\qquad y_k^i = C x_k^i + D u_k^i \end{aligned} \tag{3}$$

With the decentralized MPC, we implement a *limited action scenario*: For the producers, we assume that that they can decide when to produce food, i.e. choose when to increase or decrease u_i. However, the total input has to equal the constant number food input to comply with the current state of the production. Another reasoning for this assumption is that producers and food retailers should not under-supply consumers, for example by producing or buying nothing in order to reduce food waste leading to the starvation of consumers. Mathematically:

$$\begin{aligned} \ell^{Pi}(k) &= \begin{bmatrix} 0 & \dots & 1 \end{bmatrix} x_k^{Pi} = x_{k,N}^{Pi} \\ \text{food input} &= \sum_{k=0}^{K-1} u_k^i \quad \in \mathcal{R}^+ \end{aligned} \tag{4}$$

Now onto the social charities: These actors cannot control any input as they are only given what is left from the producers (provided that it is not already regarded uneatable) and pass it on to the consumers with some fraction also contributing to food waste. Therefore no MPC formulation is needed.

The consumers however have a choice on their personal time-dependent consumption behavior: they can choose to eat fresh or older, but still edible, food products, while meeting their daily nutritional intake (i.e., daily intake). In this limited action scenario we assume that consumers still pose the same demand but can only change the time component. Therefore the formulation is as follows:

$$\begin{aligned} &\ell^{Ci}(k) = \begin{bmatrix} \gamma_1^{Ci} & \dots & \gamma_N^{Ci} \end{bmatrix} x_k^{Ci} \\ &\quad = \begin{bmatrix} 1 & \dots & 1 \end{bmatrix} x_{k,fw}^{Ci} \\ &\text{s.t. } \forall k \\ &\quad x_k^{Ci} = x_{k,store}^{Ci} + x_{k,sc}^{Ci} + x_{k,fw}^{Ci} \\ &\quad x_k^{Ci}, x_{k,store}^{Ci}, x_{k,sc}^{Ci}, x_{k,fw}^{Ci} \geq 0 \\ &\quad x_k^{Ci} \geq x_{k,store}^{Ci}, x_{k,sc}^{Ci}, x_{k,fw}^{Ci} \\ &\quad x_{k+1}^{Ci} = \begin{bmatrix} 0 & 0 & \dots & 0 \\ 1 & 0 & \dots & 0 \\ \vdots & \ddots & \dots & 0 \\ 0 & \dots & 1 & 0 \end{bmatrix} x_{k,store}^{Ci} + B^{Ci} u_k^{Ci} \\ &\quad \text{daily intake} = \begin{bmatrix} 1 & \dots & 1 \end{bmatrix} x_{k,sc}^{Ci} \quad \in \mathcal{R}^+ \end{aligned} \tag{5}$$

E. Greedy Method

The greedy method is a simple and straightforward way to solve control problems. We choose a locally optimal choice at each stage with the intention to reach a global optimum.

In our case, the greedy approach represents *super sustainable consumers*, as they eat all old food items first before consuming more recent ones. This choice was made to model the impact of consumers best impact with respect to food waste. With D being the daily intake, every consumer at every iteration does the following:

$$\begin{aligned} &\forall k,\ \tau = T - 1 : \\ &\qquad D = D - x^{Ci}(\tau) \\ &\qquad \tau = \tau - 1 \\ &\qquad\quad \text{while } D > 0 \\ &\qquad\qquad \text{if } D \geq x^{Ci}(\tau) \\ &\qquad\qquad\quad D = D - x^{Ci}(\tau) \\ &\qquad\qquad\quad x^{Ci}(\tau) = 0 \\ &\qquad\qquad \text{else} \\ &\qquad\qquad\quad D = 0 \\ &\qquad\qquad\quad x^{Ci}(\tau) = x^{Ci}(\tau) - D \\ &\qquad\qquad \tau = \tau - 1 \end{aligned} \tag{6}$$

F. Proportional Feedback Control

PID feedback control is a well known, standard feedback control method. It can also be applied in network flow systems yielding good performance [17]. Further, it is suitable to be applied in this problem as we have perfect information on input/output and we can tune the parameters of the controller.

Making use of this control method, we are trying to represent a different scenario to the distributed MPC case. While the distributed MPC is intended to represent a system where the overall flows are constant (state-of-the art), the P-feedback control enables a more radical shift in food production and consumption patterns. In this scenario the producers can decide to adapt their input flow. Nevertheless, we have to be aware of not under-supplying the consumers. Therefore, we implement a feedback law from consumers to producers: if the inventory of the consumers is higher then the required food intake, we reduce the planned food input by a factor K.

$$u_k^{Pi} = f_{base,k} - K\left(\sum_i \left[x_{store}^{Ci} - f_{intake}\right]\right) \tag{7}$$

(8)

The next feedback mechanism determines the food demand of consumers from the producers: They start buying less if they have stocked up their inventory, similarly to the rational of the producers. So the flow is adapted according to:

$$\mathcal{F}_k(C_i, P_i) = \min\left(\frac{x_{store,k}^{Pi}}{n_{Ci}}, K_c\left[x_{store,k}^{Ci} - f_{intake}\right]\right) \tag{9}$$

with the $\min$ function as a fuzzy logic element to split the food amount of the producer fairly, not exceeding the stored amount.

III. Results

The numerical evaluation of the food waste model is presented here. The plots can be used interactively by cloning the GitHub repository [14]. Parameters such as simulation horizon can be viewed in the appendix.

A. Results of Base Case Simulation

As a reference, the base case results depicted in Figure 3 have to comply approximately with real world consumption and food waste data. This was achieved as roughly 1/3 of calories are wasted, with a higher proportion contributed by consumers, and consumers fulfilling their daily food demand.

B. Results of Linear Programming Approach

Although the amount of food waste is basically determined by the amount of food being supplied by the producers and the amount of food being consumed by consumers, the linear programming approach allows to analyze how food flows are efficiently distributed within the network. Assuming food products cannot flow completely freely within the network, one can derive a connected graph model such that edge capacities correspond to real-life constraints. For example, it is a highly unrealistic scenario, that producers supply consumers just at the very beginning of the simulation with fresh food, causing consumers' stocks to increase rapidly, and then they do not receive any products anymore. A relatively realistic scenario that goes in line with the assumptions made for our base case simulation is depicted in Figure 4.

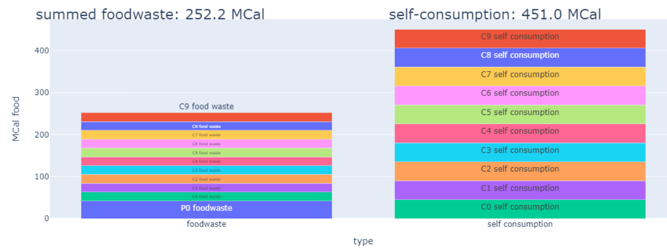

Fig. 3. Food waste and self consumption for base case simulation

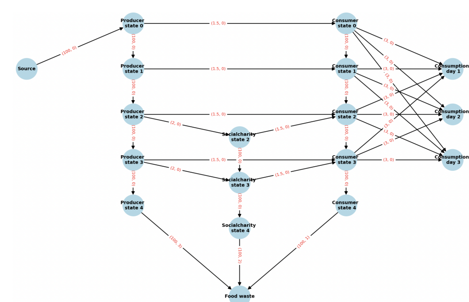

Fig. 4. Weighted graph used to solve minimum-cost flow problem

Here, we can see that the producer can only supply a limited amount of food products to consumers which is ensured by setting the capacity of the corresponding edge to a finite value, e.g., 1.5MCal. Imposing limited edge capacities is also essential for assuring that intermediate agents (i.e., social charity organizations) are still involved in the food distribution process and part of the system. However, here we can soften our constraint of limited flow capacities a little bit because we assume that social charity organizations take whatever they get from the producers. The edge capacity is not arbitrary high, though, since we suppose that producers are not willing to give their entire food stock to these institutions, especially in the case of younger food products.

The resulting food flows computed by the simplex algorithm are depicted in illustration 5. As already expected, the algorithm tries to maximize the food flows along paths containing edges with low weights or cost values. This can be seen for example by that the capacity of the edges starting from producer state 0 to consumer states 0 is fully exploited. Moreover, we can observe that food products are also given to social charity organizations, from where they get redistributed to consumers. Finally, we can see that consumers do not only consume products of a certain age but use a combination of different ages.

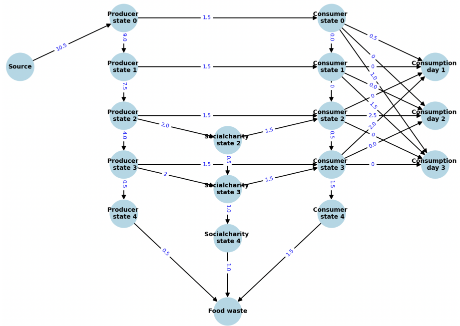

Fig. 5. Resulting network flows computed with Simplex Algorithm

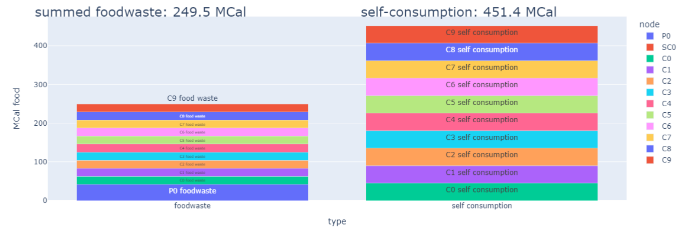

Fig. 8. Summation plot of distributed MPC approach

C. Results of MPC Control Approach

Allowing the consumers and producers not to reduce or increase food intake but smartly choose to produce/consume fresh or old products, the distributed MPC results are visualized below.

In the first plot (Figure 6), the time dependent variables of interest including food flows, food waste and self consumption are depicted. It is visible that these are more or less constant as we are in a steady state and the decentralized MPC has little flexibility to improve the dynamics. In the distribution plot (Figure 7), it can be seen that most of the producer's input is redistributed evenly amongst consumers (middle column) and that the output, representing food waste and self consumption, matches the input, neglecting the initial state, implying that mass-flow balance is fulfilled. Finally, Figure 8 shows the summed food waste and total self consumption of the system, yielding very similar results to the base case scenario.

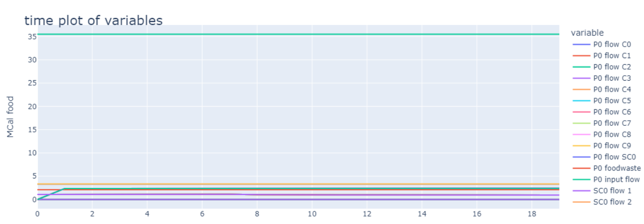

Fig. 6. Time plot of distributed MPC approach

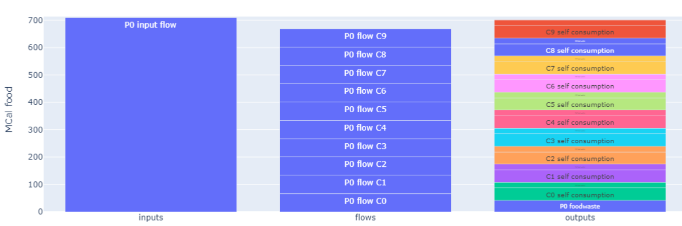

Fig. 7. Distribution plot of distributed MPC approach

Result 1: Flexible food intake with same total production and consumption constraints reduces food waste only minimally by 1%.

Result 1 is the main result of the distributed MPC analysis. This result may sobering at first but does make sense: No matter how much we try to optimize with the current stock of food, there is only little improvement. Considering the constraint that food intake has to fulfilled via self consumption x_{sc}^{Ci}, there is little flexibility in the system to reduce food waste.

D. Results of Greedy Approach

With the greedy approach, we simulate *super sustainable consumers*, as they eat all the old food items first before consuming new ones, until they fulfill a certain food intake demand which is inflexible. As can be seen in the figures below, this is a smart strategy which can reduce food waste but that would require large scale societal changes.

Result 2: Super sustainable consumers alone can reduce total food waste by 38.1% to 156.2 MCal, without changing total food input.

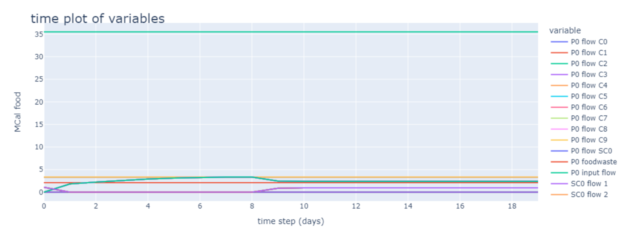

Fig. 9. Time plot of greedy approach

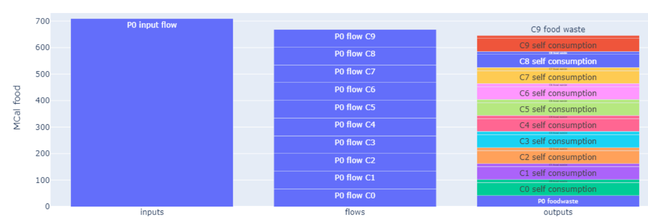

Fig. 10. Distribution plot of greedy approach

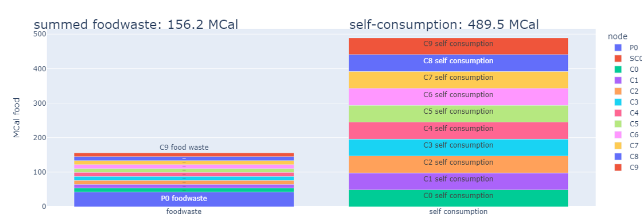

Fig. 11. Summation plot of greedy approach

E. Results of Proportional Feedback Control

Moving on to the proportional feedback control, we have to remember the significant assumptions that we made in the model: the producers have exact information on how much excess food storage the consumers have. Further, with this information the producers are allowed to produce/sell less food products and the consumers can buy less food in total. These are very different assumptions from the ones of the distributed MPC, but this is intended as we want to represent a different scenario. The results of the simulation are depicted in Figure 14.

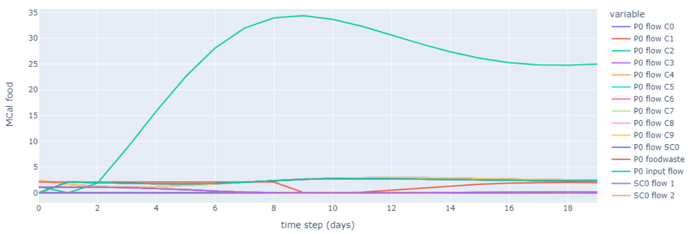

Fig. 12. Time plot of feedback control approach

Fig. 13. Distribution plot of feedback control approach

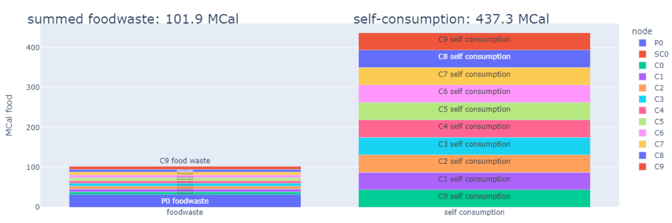

Fig. 14. Summation plot of feedback control approach

As can be seen in Figure 14, the proportional feedback controller works as expected and immediately reduces the food production and therefore flow in the beginning as the consumers have enough stock to feed themselves. When the consumers food stock reduces as they start to consume it, the food flow from producers to consumers starts to increase and eventually converges to 25 MCal/day, significantly less then the 35 MCal/day in the base case. This explains the significant reduction in food waste stated in result 3 (remember, the food flow is mostly consumed, such that the food waste reduction is realistic with such a decrease in input).

Result 3: Allowing adapted production and consumption can reduce total food waste by 59.6% to 101.9 MCal.

F. Heterogeneous network

Similar results can be replicated for a more complex and heterogeneous network that increase the simulations steps and number of producers, consumers and social charities. The results of 3 times as many nodes and 100 simulation steps can be found in the appendix IV.

IV. Conclusions

The results presented in the previous section approved that the food waste reduction problem can be approached by applying different concepts from the field of system theory and control. It is shown that the optimization problem can be modeled as a network flow problem which can be solved using linear programming techniques. The results of the LP approach showcase that the distribution of food flows within the system is of course heavily determined by the network design. Therefore, deriving an appropriate graph representation is very essential for obtaining realistic results and insights into the flow dynamics.

The main findings of the control approaches are pointing to a minimal influence of allowing flexible food intake (see distributed MPC result 1) but to a substantial impact of direct production and consumption adaptation depending on excess food stock (see feedback result 3). Further, sustainable consumers can lead to a dent in food waste in the current system as shown by the greedy approach (result 2). These results point to the relevance of real life human behaviour options: The amount of food in circulation (production and consumption) has a far greater effect then optimising with respect to the food's age, according to our model.

It may be at first surprising that the greedy and feedback method yield better results then the economic MPC. However, these control methods serve different scenarios and it is not the desire of this paper to find the optimal control method but to make use of control to represent different preferences of consumers and producers in real life.

In future work, the role of social-charities may be investigated. As there is limited data on this actor [3], intuitive modelling of this actor could be implemented and different scenarios evaluated. One such scenario could be a high-flow social-charity case in which a producers let social charities pick up significant amount of food items. Another extension of this work would be a large scale model including multiple actors with different behaviors. Further, we suggest game theory would be interesting to employ in this context by modelling the nodes as actors with a set of choices (buying, self-consumption, storing...) and cost function (food waste) that is aimed to be minimized. As a start the paper "Designing Games for Distributed Optimization" [15] may be used.

Acknowledgment

Special thanks to Dr. Claudio Beretta for his willingness to discuss the topic personally, his insights into the food waste issue and his publications on this topic. Also many thanks to our supervisor Dr. Jaap Eising for helping us find possible

control approaches, providing us with valuable feedback and guiding us through this project.

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APPENDIX

Parameter	Value	Description
nv_p_d	3.550	MCal produced per person per day
fw_p_d	1.160	MCal food waste per person per day
horizon	20	simulation horizon
T	10	state / food age size
n_ps	1	Number of producers
n_cs	10	Number of consumers
n_scs	1	Number of social charities

TABLE I

BASE VALUES

Parameter	Value
horizon	20
T	10
n_ps	1
n_cs	10
n_scs	1
fw_model.type	simple
fw_model.store	0.73
T_start	3
T_end	4
alpha_start	0.0
alpha_end	0.0
alpha_first_day	0.2
alpha_last_day	0.3
x0_c	equilibrium value
x0	`np.zeros((10, 1))`
inp_params	`('base case', 100)`
ec_mpc	False
mpc_h	5
ec_mpc_c	False
mpc_h_c	5
food_intake	2.39
fb	{}

TABLE II

BASE CASE VALUES

Parameter	Value	Description
horizon	20	Simulation horizon: has to be sufficiently longer than T for simulation to be correct
T	10	Food waste time horizon
n_ps	1	Number of producers
n_cs	10	Number of consumers
n_scs	1	Number of social charities
fw_model.type	simple	Type of food waste model
fw_model.store	0.73	Relative amount of food stored at every time step
T_start	3	When producers start to give food products to charity
T_end	4	When producers end to give food products to charity
alpha_start	0.0	Amount/percentage of food given to charity at beginning
alpha_end	0.0	Amount/percentage of food given to charity at end
alpha_first_day	0.2	Probability that food gets consumed by consumers on the first day
alpha_last_day	0.3	Probability that food gets consumed by consumers on the last day
x0_c	steady state	Initial consumers' state
x0	`np.zeros((10, 1))`	Nodes initial state
inp_params	`('base case', 100)`	Input parameters (see params.py)
ec_mpc	False	Optimize P input with economic MPC
mpc_h	20	MPC horizon for P
ec_mpc_c	True	Optimize C input with economic MPC
mpc_h_c	20	MPC horizon for C
food_intake	2.39	Daily food intake required by consumers
fb	{}	Feedback parameters

TABLE III

EC_MPC VALUES

Parameter	Value	Description
horizon	20	Simulation horizon: has to be sufficiently longer than T for simulation to be correct
T	10	Food waste time horizon
n_ps	1	Number of producers
n_cs	10	Number of consumers
n_scs	1	Number of social charities
fw_model.type	simple	Type of food waste model
fw_model.store	0.73	Relative amount of food stored at every time step
T_start	3	When producers start to give food products to charity
T_end	4	When producers end to give food products to charity
alpha_start	0.0	Amount/percentage of food given to charity at beginning
alpha_end	0.0	Amount/percentage of food given to charity at end
alpha_first_day	0.2	Probability that food gets consumed from consumer on first day
alpha_last_day	0.3	Probability that food gets consumed from consumer on last day
x0_c	steady state	Initial consumers' state
x0	`np.zeros((10, 1))`	Nodes initial state
inp_params	`('base case', 100)`	Input parameters (see params.py)
ec_mpc	False	Optimize P input with economic MPC
mpc_h	5	MPC horizon for P
ec_mpc_c	False	Optimize C input with economic MPC
mpc_h_c	5	MPC horizon for C
food_intake	2.39	Daily food intake required by consumers
fb.K	0.3	Feedback gain
fb.T	1	Time constant
fb.x0	0	Initial state

TABLE IV

FB1 VALUES

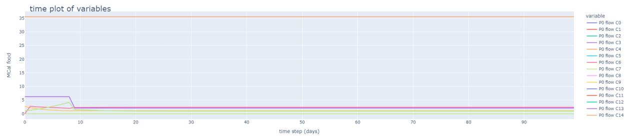

Fig. 15. Time plot of base case simulation with extended network

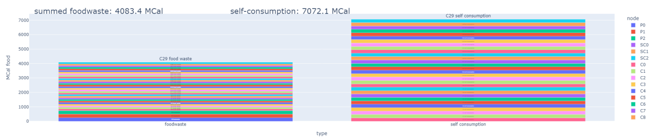

Fig. 16. Distribution plot of base case simulation with extended network

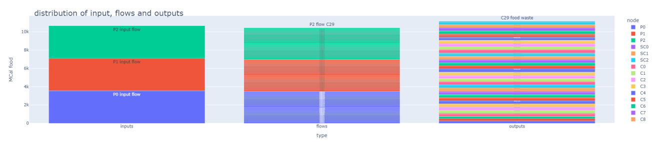

Fig. 17. Summation plot of base case simulation with extended network

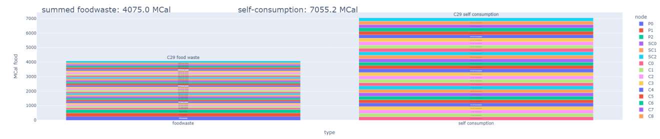

Fig. 18. Distribution plot of distributed MPC approach with extended network

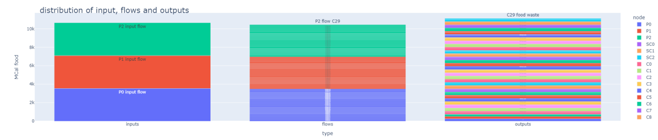

Fig. 19. Summation plot of MPC approach with extended network

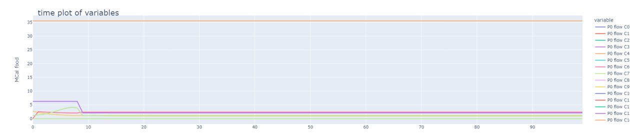

Fig. 20. Time plot of MPC approach with extended network

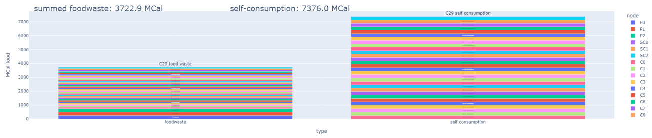

Fig. 21. Distribution plot of greedy approach with extended network

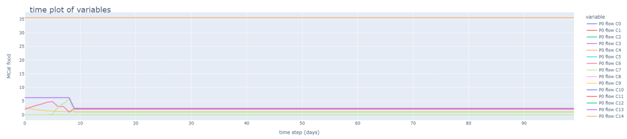

Fig. 22. Time plot of greedy approach with extended network

Fig. 23. Summation plot of greedy approach with extended network

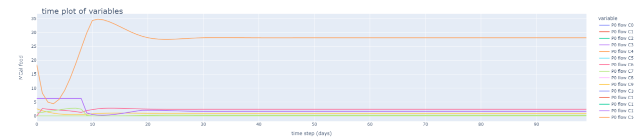

Fig. 24. Time plot of feedback control approach with extended network

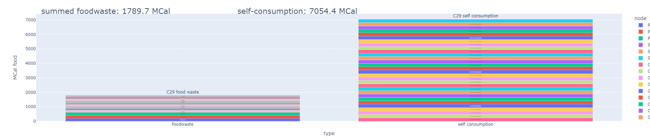

Fig. 25. Distribution plot of feedback control approach with extended network

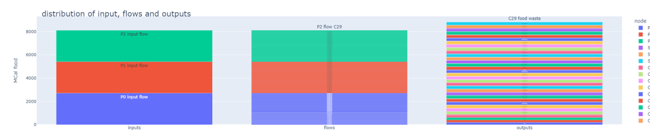

Fig. 26. Summation plot of feedback control approach with extended network