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Data-Driven Aggregation Control for Thermoelectric Loads in Demand Response

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Abstract: Within the concept of a smart grid, aggregators have the task of coordinating the behavior of large sets of Distributed Energy Resources, each of them offering small power/energy capacities, which help to balance the power grid and can serve as providers of services. Adequate coordination strategies are required to optimally exploit these resources in the ancillary services market. However, deriving model-based control policies for them is complex due to the heterogeneity and uncertainty related to the large set of associated agents. Then, a data-driven model is an adequate solution for this sort of situation. This paper presents the application of the Youla–Kucera Data-Driven Control strategy for the development of an aggregator to regulate the power consumption of a set of thermoelectric refrigerators, avoiding the modeling process and directly designing a controller from data. A detailed simulation framework was executed to verify the validity of the proposed methodology. It is shown that the derived aggregator is able to offer frequency containment reserves service, achieving the required settling time of 30 seconds and with a tracking error below 4.7%.

Keywords: Data-driven control, Learning based control, Youla Kucera parametrization, Aggregator, Thermometric refrigeration, Flexible loads

1. INTRODUCTION

Nowadays modern grids are composed of a large set of Distributed Energy Resources (DERs) such as photovoltaic systems, electric vehicles, power plants, energy storage systems, etc. Some of these resources consume and produce energy in an uncontrollable way producing congestion and imbalances, and increasing the uncertainty in the grid. In order to maintain a dynamic power balance, some control strategies have been proposed with the aim of reducing variability on the demand side. For example, Gao et al. (2019), tries to manage the flexibility of batteries, electro-thermal heating units equipped with thermal storage, electric vehicles, and deferrable loads.Wang et al. (2020) has used an Alternating Direction Method of Multipliers (ADMM) in order to manage the uncertainty in the grid. Also, Model Predictive Control (MPC) methods have been applied by Ojand and Dagdougui (2022), and Diekerhof et al. (2018) to solve the load management problem.

Flexible Loads (FL) are resources that help to balance the power grid and can serve as service providers. FL benefit the power systems by increasing or regulating the energy consumption. Although, the reduced capacity of every single load and the distributed location of the resources pose limitations in this approach. A large set of FL are employed to offer services to the grid effectively.To do this an agent called aggregator is required to coordinate the set. However, it generates a complex system behavior challenging their control and operation.

A challenge to achieve efficient management of these resources is to develop adequate aggregation strategies, able to coordinate and dispatch large sets of flexible loads. The aggregated behavior of homogeneous loads, such as, Thermostatically Controlled Loads (TCLs), Heating, ventilation, and air conditioning (HVAC), electric vehicles and smart water heating, and ice-based thermal storage has been deeply studied in the literature, see e.g., Abbas and Chowdhury (2021),Cui et al. (2020). Once the load characterization is made, it is possible to get a controller which allows to achieve the balance in the grid mitigating supply-demand mismatch (Coffman et al., 2021), (Ju et al., 2019).

In general a dynamic model which represents the behavior of the FL is required for designing aggregation strategies, see Diaz-Londono et al. (2019). Nevertheless, due to the complex behavior of the flexible loads is not possible to build analytic models which represent the system's dynamics.Therefore, a data-driven model is an adequate solution for these applications.

When a set of input-output samples are available, there are two main methods in the literature for designing a controller, *i*) derive a model from the available information and then design a controller for the found model; *ii*) a controller can be obtained directly from the data (Formentin et al., 2014). The direct methods are useful to avoid the system identification step. Sakaki et al. (2018) shows a method which uses a set of experimental data for designing a Two Degrees Of Freedom (2DOF) controller based on Virtual reference feedback tuning (VRFT) and fictitious reference iterative tuning (FRIT) methods. The controller is found through the desired reference model conditioned with the stability margin quantified by the

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sensitivity function. Also, some methods such as VRFT are modified in order to afford better approaches in a continuous time and deterministic set-up(Formentin et al., 2019). Also, Valderrama and Ruiz (2022) proposed a direct design methodology of controllers, assuming that the data sets are generated by a stable, linear, time-invariant, SISO system. The Youla–Kucera Data-Driven Control (YK-DDC) strategy relies on errors in variable identification for estimating a Finite Impulse Response filter through Youla Kucera parametrization that avoids the selection of a fixed controller structure.The YK-DDC strategy is an adequate solution tool for designing data-driven aggregation controllers for FL, because the method is able to avoid the modeling process of the aggregate behavior of the FL and directly design a controller to regulate the power consumption of the set, also it offers a large number of degrees of freedom during the tunning process.

This paper proposed a simplified controller design methodology in energy services with the goal of obtaining a dynamic power balance and reduce grid congestion. The method is an innovative application work that involves the Data-Driven technique presented by Valderrama and Ruiz (2022) and the aggregation problem of Thermoelectric Refrigerators studied in Diaz-Londono et al. (2020). It is shown that the YK-DDC method is able to tune controllers for different performance requirements.

The framework of the paper is as follows. In Section 2, the description of the Thermoelectric Refrigerator (TER) as a flexible load is presented. In Section 3, the Youla–Kucera parametrization for controller tunning is briefly described. Section 4 describes the data-driven aggregator strategy for TERs followed by section 5 where is presented the analysis of results and the conclusions end the paper in Section 6.

2. TERS AS FLEXIBLE LOADS

Thermoelectric Refrigerators are solid-state devices that convert electrical energy into thermal energy. TERs can operate in temperatures between 2°C and 8°C and they are becoming popular due to their high reliability, temperature stability, operation in severe environment and good controllability within ±0,1°C (Zhao and Tan, 2014).

Diaz-Londono et al. (2020) proposed an aggregation strategy for TERs as Flexible loads. When a temperature set-point of a TER is modified, it changes its power consumption and this demand variation is exploited to offer balancing services.To do this, three states are established for each TER where the temperature set-point (T_{sp}) is defined as:

- 0: Nominal operating set-point, which is defined from the set {3, 4, 5, 6, 7}°C;
- 1: High set-point = 8°C;
- 1: Low set-point = 2°C;

When the system operator (SO) requests a power deviation, an aggregator decides how many and which TERs should activate their flexibility to achieve the requested service within the established times, see Fig. 1. First, the controller specifies the number of TERs to be activated through the signal $u(k)$. Then, the selector decides which TERs must change the temperature set point through the vector β, both of them operate with a sampling time (Ts) of 1s.A PI controller was tuned based on a linear model of the aggregated loads estimated from a step response.

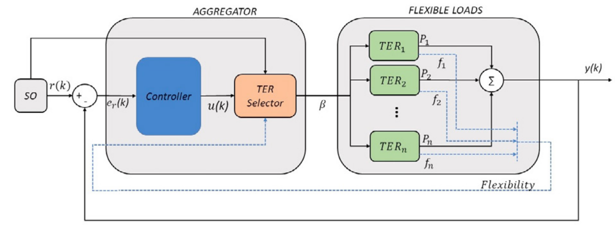


Fig. 1. TER aggregator scheme.

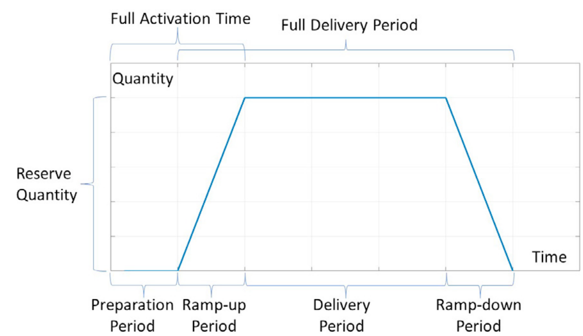


Fig. 2. Standard structure of balancing services provision.

In this work, it is considered a set of $n = 100$ TERs that offer flexibility to the power grid. It is assumed that an aggregation framework as the one shown in Fig. 1 already exists and a controller is required to coordinate the FL in order to provide balancing services to the electrical grid.

An energy balance service is divided into four stages, preparation period, ramp-up period, delivery period and ramp-down period as shown in Fig. 2. One of the most critical parameters in this application is the settling time of the ramp-up period. The European Commission (European-Commission, 2017) defines three services, *Frequency Containment Reserves* (FCR) with a maximum settling time $S_T = 30\ s$ and the delivery of 50% of the reserve fulfilled within 15s, *Frequency Restoration Reserves* (FRR) with a settling time up to 12 min and finally *Replacement Reserves* (RR) with a settling time up to 30 min. This work is focused on FCR services which is more challenging than the others.

3. YOULA-KUCERA PARAMETRIZATION FOR CONTROLLER TUNING DESCRIPTION

The Youla-Kucera framework allows parametrizing controllers for a given linear time-invariant plant. However, it has been extended to solve the controller design from data problems when the plant is unknown, avoiding the plant identification step and directly designing controllers in Valderrama and Ruiz (2022).

In order to define the framework of the tuning problem, the control system is shown in Fig. 3, where $P(z)$ is a stable single-input single-output (SISO) plant, $C(z,\theta)$ is the controller, parameterized by the vector θ, $r(k)$ is the reference, $u(k)$ the manipulated variable, $y(k)$ the controlled variable, $v(k)$ is output noise/disturbances and

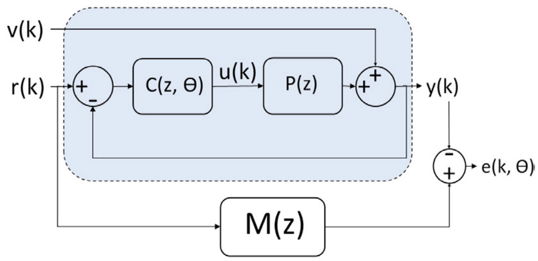


Fig. 3. Assumed feedback control structure.

$M(z)$ is the reference model that represents the desired behavior of the closed-loop.

Given a reference model $M(z)$, the aim of the controller tuning procedure is to find a set of parameters θ, usually solving an optimization problem and guaranteeing the internal stability of the loop by minimizing the cost function

$$J_{RM}(\theta) = \left\| M(z) - \frac{P(z)C(z,\theta)}{1 + P(z)C(z,\theta)} \right\|_2^2. \tag{1}$$

When $P(z)$ is unknown but there is a data set of input/output samples, which contains information about the behavior of the plant, it is possible to tune a data-driven controller taking into account that all the information is produced in open-loop, i.e, $u(k)$ is applied directly to $P(z)$ and $y(k)$ is the output information composed by the response of the plant to the input $u(k)$ plus an additive noise $v(k)$.

From Youla-Kucera parametrization if a plant is stable any $C(z,\theta)$ that achieves internal stability can be parametrized as,

$$\begin{gathered} C(z,\theta) = Q(z,\theta) * (1 - P(z) * Q(z,\theta))^{-1} \\ Q(z,\theta) \in H_\infty, \end{gathered} \tag{2}$$

$Q(z,\theta)$ is chosen as a Finite Impulse Response (FIR) filter with impulse response length m_q as

$$Q(z,\theta) = \sum_{i=1}^{m_q} \theta_i z^{-(i-1)}. \tag{3}$$

Consequently, the model matching error for a given parameter θ can be defined as

$$\Delta_M(z,\theta) = M(z) - Q(z,\theta)P(z) \tag{4}$$

From Valderrama and Ruiz (2022), it can be inferred that the cost function (1) is equal to the norm of the correlation between the model matching error and $x(k)$ a set of instrumental variables which satisfy

$$J_{RM}(\theta) = ||R_{ex}(\tau,\theta)||_2^2 = \sum_{\tau=-\infty}^{\infty} R_{ex}^2(\tau,\theta) \tag{5}$$

where

$$\begin{aligned} R_{ex}(z,\theta) &= \mathbb{E}[e(k,\theta)x(k-\tau)], \\ e(k,\theta) &= M(z)u(k) - Q(z,\theta)y(k), \\ x(k) &= W(z)u(k) \end{aligned}$$

and

$$|W(e^{jw})| = |\Phi_u(jw)|^{-1}$$

being $W(z)$ a Bounded-Input Bounded-Output (BIBO) stable system.

Given a set of input-output samples of the plant, the optimal impulse response coefficients of the filter $Q(z,\theta)$ are obtained by least-squares estimation as

$$\hat{\theta} = (X^T X)^{-1} X^T Z \tag{6}$$

where the correlation matrices are

$$X = \frac{1}{N} \sum_{t=1}^{N} \zeta(k)\phi^T(k) \tag{7}$$

$$Z = \frac{1}{N} \sum_{t=1}^{N} \zeta(k) M(z) u(k) \tag{8}$$

for the regressors

$$\begin{aligned} \phi(k) &= [y(k),\ y(k-1),\ \ldots,\ y(k-m_q+1)] \\ \zeta(k) &= [x(k+l),\ \cdots x(k),\ \cdots,\ x(k-l)]^T \end{aligned}$$

and l is the length of the correlation which is an tuning parameter, sufficiently long to get a good approximation.

Then, the controller is derived as

$$C_{DD}(z,\hat{\theta}) = Q(z,\hat{\theta})(1 - M(z))^{-1}. \tag{9}$$

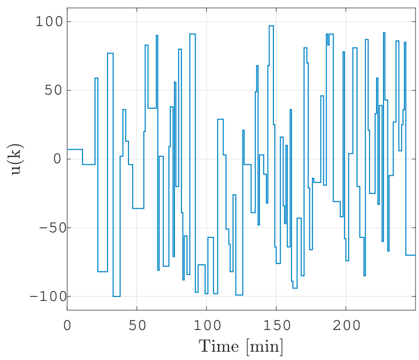
Finally, to assess the stability of the loop, based on the Small Gain theorem, the sufficient but not necessary condition $||\Delta M(e^{j\omega})||_\infty \leq 1$ can be verified employing only the data-set.

4. DATA-DRIVEN AGGREGATOR DESIGN FOR TER

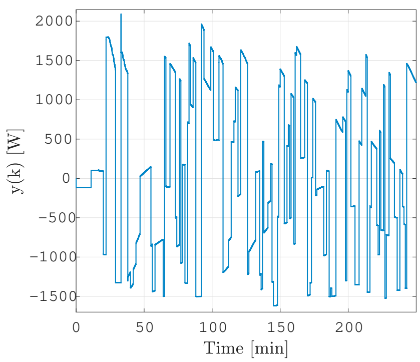
This section shows the methodology employed for obtaining the desired Controller for the TER aggregation strategy formulated in Section 2 through the data-driven procedure presented in the previous section.

Using MATLAB/Simulink with the Simscape toolbox a simulation environment with a pool of $n = 100$ TERs was developed taking into account that every TER has its own dynamics, thermal capacity, and it is subject to different perturbations.

To apply the methodology of YK-DDC, a set of input/output data was generated. A Pseudorandom Multilevel Sequence (PRMS) is assembled as input $u(k)$, using a clock period of 30 seconds. $u(k)$ belong to the interval [-100,100], so $u(k)$ is equal to the number of TERs with activated flexibility at time k, that is, with a modified setpoint. When $u(k)$ is positive the set point is reduced to $2°C$ and vice versa, as described in Section 2. The amplitude



(a)



(b)

Fig. 4. Data set for controller design. (a) Input u(k): number of TERS with activated flexibility. (b) Output y(k): Aggregated power deviation of the TERs.

of the signal is produced as samples of a discrete uniform distribution function. Fig. 4 shows a segment of the signal's behavior where the aggregated i the reduced power. From the system simulation a data set $\mathcal{D} = \{u(k), y(k), k = 1, 2, ..., N\}$ is built with $Ts = 1s$, $N = 30000$ samples which are used for tunning the controller.

One of the main characteristics of providing flexibility by shifting the power consumption is to avoid overshoots and rebounds in the power demand, which not only reduces the waste of energy but also prevents fatigue and damage to the grid. Therefore,based on the characteristics mentioned, the following first-order system

$$M(z) = \frac{1 - e^{(\frac{-Ts}{\tau})}}{z - e^{(\frac{-Ts}{\tau})}} \qquad (10)$$

is chosen as reference model $M(z)$ to parametrize the desired performance of the control loop to fulfill the requirements of an energy balance services provider. Based on the service requirements presented in Section 2, reference model time constant τ with the values $\{0.4, 2, 3, 4, 6, 8, 10, 12\}s$ are considered to design the controllers.

The FIR filter length m_q is selected following the guidelines given by Valderrama and Ruiz (2022). It is found that m_q needs to be adapted to the time constant τ. The filter parameters are found by solving equation (6) and the derived controller with the equation (9). The filter $W(z)$ was estimated through the available data set using the MATLAB system Identification Toolbox.

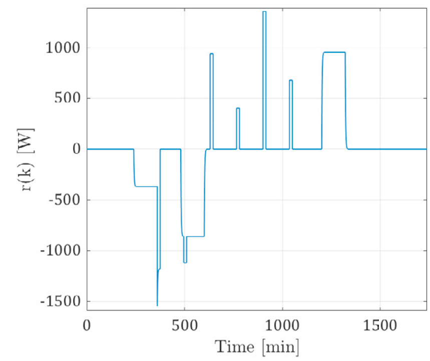


Fig. 5. Reference signal r(k) for controllers validation.

τ [s]	m_q	$\|\|\Delta\hat{M}(j\omega)\|\|_\infty$	E_{rms} [W]	E_{rms} %
0.4	10	0.718	17.88	4.36
2	15	0.717	15.69	3.83
3	20	0.717	16.56	4.04
4	30	0.715	17.50	4.27
6	35	0.715	19.24	4.70
8	50	0.713	20.95	5.11
10	60	0.712	22.46	5.48
12	65	0.713	24.05	5.87

Table 1. Filter length, stability margin and tracking error of controllers designed for different time constants.

5. RESULTS

This section shows the outcome of the methodology applied to the set of TERs. Table 1 shows the results obtained for controllers with diverse values of τ evaluated in closed-loop for the reference signal shown in Fig. 5. It is reported the FIR filter length m_q, the model matching error norm $||\Delta\hat{M}(j\omega)||_\infty$, the root mean squared error E_{rms}, as well as the percentage root mean squared error $E_{rms}\%$ between the power reference and the total power reduced by the TERs aggregation.

From the simulated results, it can be concluded that when τ decreases, the system is faster, the tracking error is lower but it losses stability margin, reflected in the increment of $||\Delta\hat{M}(j\omega)||_\infty$. Also, the controllers with $\tau < 8$ have an E_{rms} lower than 5% which fulfils with the requirements of the balancing services. Controllers with higher τ present a higher error due to the bandwidth limitation. Consequently, the method is suitable for designing controllers with different time constants.

Fig. 6 shows the step response of the closed-loop system and Fig. 7 the manipulated variable, for controllers greater than $\tau = 0.4$ s. It is appreciated that $u(k)$ does not oscillate and the system is stable. Fig. 8 shows the controlled variable (Fig. 8a) and manipulated variable (Fig. 8b), for a step response with the controller designed for $\tau = 0.4$ s. The overshoot is around 91%, which implies power losses and risks for the grid operation. Also, analyzing the manipulated variable, the amount of TERs whose flexibility is activated, exceeds by 113% the actual requirement of flexible loads, affecting directly the performance of the system and reducing the capacity for future services. Accordingly, all the values of the requested time constant can be achieved,

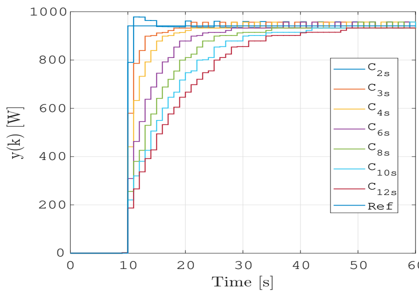


Fig. 6. Closed-loop step responses of controllers designed for different time constants.

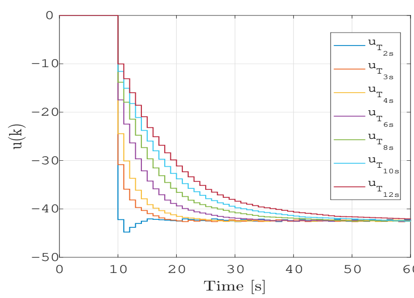
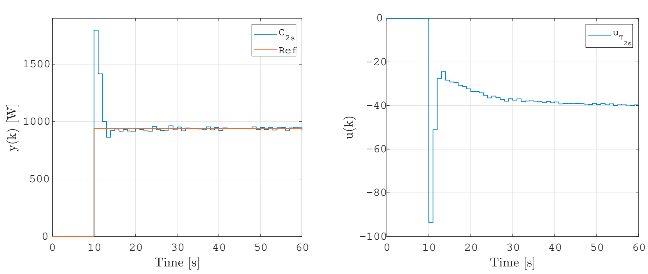


Fig. 7. Manipulated variable of the closed-loop step responses shown in Fig. 6



(a) (b)

Fig. 8. (a) Closed-loop step response, and (b) manipulated variable, of the controller designed for a time constant of 0.4 s.

except by $\tau = 2$ s and $\tau = 0.4$ s which present overshoot on both controlled and manipulated variable.

In view of the guidelines on electricity balancing, a controller with $\tau = 6s$ is defined in Diaz-Londono et al. (2020) for providing all the services requirements. Fig. 9 and Fig. 10 show the responses of the YK-DDC controller with $\tau = 6$ s for the reference in Fig. 5.

The aggregator designed with the YK-DDC methodology follows the power requests without overshooting or rebounds at the end of the service. It also fulfills the critical settling time of 30 seconds as required by the service. The flexibility of the set of FL that is called to modify the temperature set-point responds properly to the SO request without exceeding the number of available TERs, for both power increments and reductions.

Diaz-Londono et al. (2020) show that the aggregated TERs system can be represented approximately as a linear transfer function (TF). Considering the TF proposed there and using a loop shaping method, two model based controllers

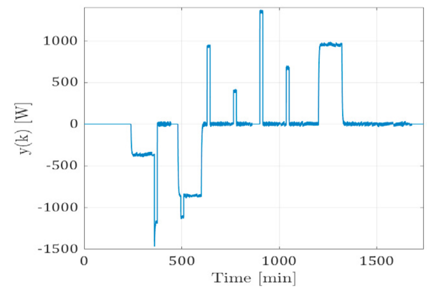


Fig. 9. Closed-loop response for the input shown in Fig. 5 of the controller designed for a time constant of 6 s.

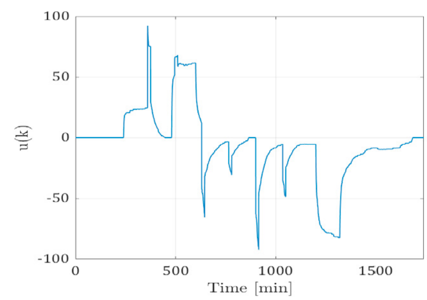
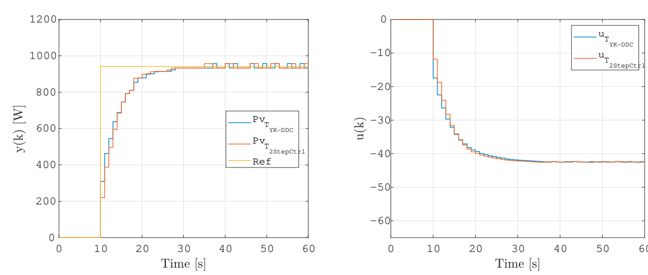


Fig. 10. Manipulated variable of the closed-loop response shown in Fig. 9



(a) (b)

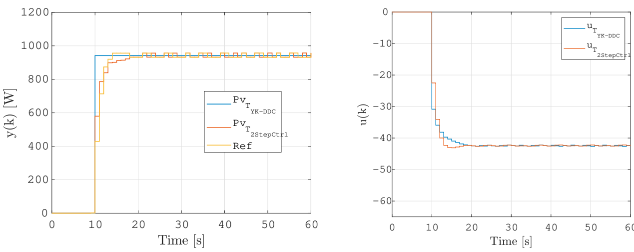
Fig. 11. (a) Closed-loop step response, and (b) manipulated variable, of the controller designed for a time constant of 6 s.

Controller	E_{rms} [W]	E_{rms} %
$2SMBC$ - $\tau = 6$	20.45	4.99
$YK-DDC$ - $\tau = 6$	19.24	4.7
$2SMBC$ - $\tau = 3$	17.66	4.31
$YK-DDC$ - $\tau = 3$	16.56	4.04

Table 2. Tracking error comparison between YK-DDC and 2SMBC

(2SMBC) have been designed to achieve first-order closed-loop responses with $\tau = \{3, 6\}s$, following the approach presented in section 2. Then, they are evaluated in closed-loop on the detail simulation framework for the reference signal shown in Fig. 5. Table 2 shows a comparison between the 2SMBC and the YK-DDC. Fig. 11 and Fig. 12 show the step responses for the two controllers.

Considering the results presented in Table 2, the performance is similar in terms of E_{rms}, however, the YK-DDC method achieves slightly lower tracking errors. From Fig. 12 the $2SMBC$ with $\tau = 3$s presents an overshoot in both the controlled and manipulated variables. While,



(a) (b)

Fig. 12. (a) Closed-loop step response, and (b) manipulated variable, of the controller designed for a time constant of 3 s.

Fig. 11 shows a comparable response between both methods for $\tau = 6$s. Therefore, if a slow system response is requested the behavior is similar for both methods, while, if a higher bandwidth is required the YK-DDC method is more efficient in using the experimental data.

6. CONCLUSIONS

In this work, it has been presented the development of a data-driven controller for an aggregation problem of flexible loads in modern grids. The capacity of thermoelectric refrigerators to behave as flexible loads is exploited to offer frequency containment reserve services to the grid by properly manipulating the temperature set-point. However, the dynamics of the aggregated system have complex behavior that increases with the number of elements. Therefore, it is not possible to build analytical models which represent the system's dynamics. Then, the Youla–Kucera Data-Driven Control strategy is proposed as a solution tool for aggregation issues, avoiding the modeling process and directly designing a controller to regulate the power consumption.

A simulation environment with a pool of $n = 100$ TERs, developed using MATLAB/Simulink and the Simscape toolbox, is employed to approximate the behavior of the aggregated set of flexible loads, taking into account that each TER has different dynamics, thermal capacities, and internal control with random perturbations.

It was illustrated that the method is suitable for designing controllers to achieve a first-order behaviour, with different time constants, from .4 s until 12 s with the same data sets. The aggregator complies with the requirements imposed by the European Commission, with a settling time of 30 seconds, a percentage tracking error of 4.7%, no overshoots or rebounds and verified stability margins.

In future works, it is expected to expand the method to larger systems, with multiple-variables and stronger nonlinearities, as well as different kinds of flexible loads.

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