Modeling thermal behavior on the FTU liquid lithium limiter

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***Abstract*—Preventing disruptions and instabilities occurrences during nuclear fusion experiments represents one of the main goal for the nuclear fusion community. The first plasma-wall material may play a crucial role in this sense since it deals with plasma impurities leading to plasma break-down conditions. In particular, the performance of the limiter recently adopted in the Frascati Tokamak Upgrade (FTU), Cooled Lithium Limiter (CLL), strictly depends on its temperature. In other words, more the temperature is uniformly distributed over the limiter surface and less impurities are present in the plasma. Thus, being the thermal limiter behavior strictly related to plasma performances, monitoring the CLL thermal evolution may help to diagnose unwanted plasma behaviors. In this paper, a data-driven model identification of the CLL temperature is presented. In particular, different linear autoregressive models have been identified and a final comparison will be provided showing the best models in terms of performance during the training and testing phase.**

I. Introduction

Nuclear fusion technology has been widely investigated in the last centuries. From one hand , it would face the heavy energy demand guaranteeing inexhaustible, safe and environmentally-friendly energy production , from the other hand a lot of works have to be done in order to make nuclear fusion a real source able to satisfy the world-wide growing energy consumption demand. Although many efforts have been made in order to face its practical limitations, several issues are still open. The hard conditions required to allow nuclear fusion to take place make this technology one of the main challenge the scientific community is dealing with.

Generally speaking , nuclear fusion technology needs high temperature and pressure conditions in order to generate particles nuclear fusion since colliding particles have to overcome the repulsive force acting among them. As a consequence, these hard conditions strongly decreases the probability to obtain stable plasma confinement and to observe self-sustained reactions leading to energy production.

Nowadays, the main adopted device used to reach self-sustained nuclear fusion reactions thus obtaining a stable plasma is Tokamak. It is a toroidal chamber magnetically confining high temperature plasma in a torus shape by means of strong toroidal and poloidal magnetic fields. The main issue is that plasma confinement is not maintained for enough time making fusion plant energetically not efficient. This scenario is mainly due to the occurrences of instabilities phenomena of different natures that should be identified and avoided in order to improve plasma performance. For instance , often impurities in plasma appears because of the interaction of the last closed magnetic surface (LCMS) and the first material facing plasma inside the reactor chamber. These impurities affects plasma performances thus leading to plasma disruption.

In this perspective , it seems evident that the nuclear fusion field involves several disciplines ranging from math to chemistry to physics to engineering. Thus, many researcher from different fields get involved in nuclear fusion experimentation all over the world. In particular, the main Italian research center for nuclear fusion is located at the ENEA institution in Rome. Here, a medium-size Tokamak called Frascati Tokamak Upgrade (FTU) operates since 1990. FTU creates high density plasma by mean of 8T magnetic fields and plasma currents of MA orders. It adopts a capillary porous system (CPS) cooled liquid lithium (CLL) as first plasma wall surface [2]. It is an actively cooled system where water circulates at high pressure and at the temperature of about $200°$C heating lithium up to the melting point and removing the heat during plasma discharges [3]. More the temperature is uniformly distributed better the CLL performance is.

As a consequence, monitoring the temperature evolution is very important in order to both analyze and enhance CLL as well as nuclear fusion experiment performances. The diagnostics systems devoted to this purpose are two thermocouples located on the limiter water circulation system and a fast infrared camera (IR) looking at the whole limiter surface. While the thermocouples give information of the temperature at 2 specific point very close but exactly not on the CLL surface, the IR gives an high resolution thermal information. These collected data may be used to drive thermal models able to predict the dynamical behavior of temperatures thus can help in controlling the plasma behavior far from instabilities and disruptions. Besides, these models can help to reconstruct missing data usually lost in real industrial plants.

Several control strategies have been implemented in the last years in order to regulate the temperature of different kind of limiters. They mainly have been implemented exploiting physical models such as in [5] where an ideal approximation of the limiter is taken into account thus loosing information when undesired behaviors emerge. Geometrical and spatial variables are easier to be controlled so that are the ones more often taken into account when designing a control strategy, especially when disruptions are about to occur.

In this paper, it is explored the opportunity to identify a data-driven predictive model that would me more suitable in reproducing thermal behavior in working conditions far from the ideal ones.

In this perspective, different linear autoregressive models (ARX) are identified when using both spatial variables and past temperature data as input and a comparison of them is given.

The paper is organized as follows: in Section II the identification of quantities relevant to the model design is presented, in Section III the linear and nonlinear models adopted are described, while Section IV is devoted to the comparative analysis of models performance. Conclusive remarks on the suitability of the modeling approach are given in Section V.

II. Data selection and pre-processing

A big amount of data is collected in the FTU plant related to both measured and reconstructed variables relevant for nuclear fusion experiments. In order to achieve our purpose , the first step is deciding which experimental campaign is the most suitable . In fact, in order to catch the desired thermal dynamical behavior , variables with a significant transient regime are desirable.

As previously said, the IR camera represents the main source of thermal information due to the fact that it points to the whole limiter surface thus providing punctual information about the temperature that the CLL reaches when plasma irradiates heat to it. In fact, each pixel image value represents the thermal value associated to a specific point of the limiter. The IR camera output is a video stream with frame rate up to 365 fps that is pre-processed in order to correct images from systematics errors, e.g. emissivity error due to the fact that the limiter is not a perfect black body. The detailed description of the pre-processing stage is given in [4].

One of the most important phase in model identification is the choice of the input variables to be used. In particular, firstly they have to be highly related to the model output and secondly they have to be suitable to be used in a controlling strategy . Thus, after carrying out a correlation analysis in which the most correlated variables are chosen, a selection of the ones that are more suitable for a control system implementation is made. As previously stated, the model output is the thermal information coming from the IR camera. The input variables candidates are the geometrical features of the plasma ring characterizing plasma shape. In fact, four direct measurements plus an indirect ones , fully characterize plasma position : the internal and external plasma radius , the upper and lower plasma radius as direct measurement and elongation as indirect measurement,i.e. the ratio between semi-axes.

Usually cross-correlation is adopted as a measure of variables similarity, thus revealing which candidates are more appropriate as model inputs . As a consequence, a cross-correlation analysis between each candidate and the IR camera measurements is performed for each pixel. In particular, Fig.1 and Fig.2 show the cross-correlation maps when elongation E and upper radius $Z1$ are taken into account, where each pixel represents the correlation coefficient, colorcoded according to the reported colorbar, of the transient regime of the same pixel with respect to related plasma configuration parameter.

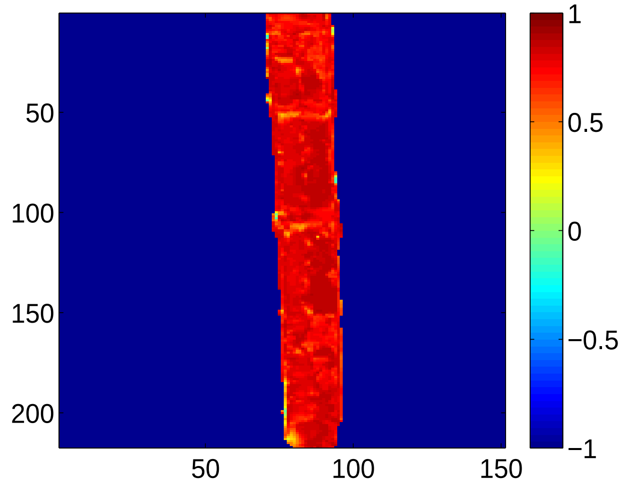

Fig. 1. Correlation analysis between plasma ring elongation and temperatures over the limiter surface. The values of the correlation coefficient are color-coded according to the colorbar: the temperatures measured by the camera are highly correlated with the plasma ring elongation over the entire surface.

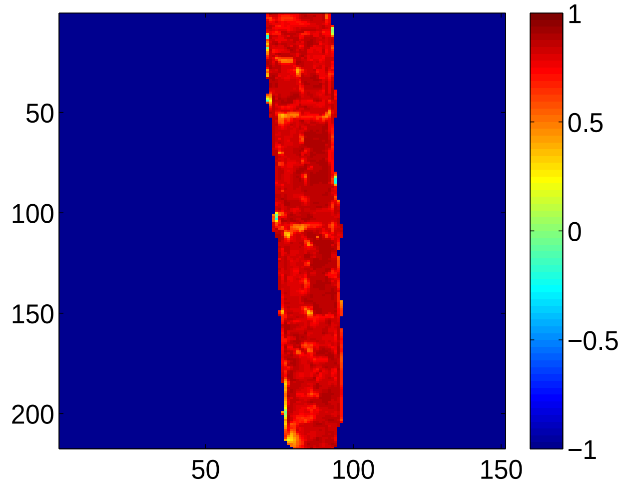

Fig. 2. Correlation analysis between plasma ring elongation and temperatures over the limiter surface. The values of the correlation coefficient are color-coded according to the colorbar: the temperatures measured by the camera are highly correlated with the plasma ring elongation over the entire surface.

Further information is provided by the cross-correlation plot as a function of the lag between each candidate and the thermocamera temperature. In Fig.3 cross-correlation is shown for a specific pixel with respect to each measured plasma configuration parameter. It is noteworthy that both $Z1$ and E have high correlation level over the entire limiter surface thus appearing suitable for model identification.

Being the heat spreading a diffusion process, temperature evolution of a specific pixel will depend also on its neighbors

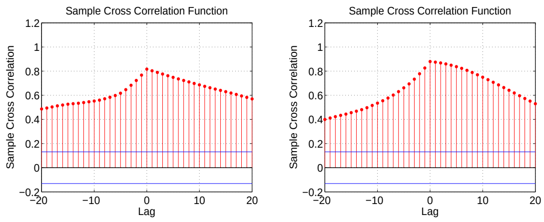

Fig. 3. Plot showing the correlation coefficient as a function of the lag between a specific pixel of the IR camera and each geometrical plasma variables

temperature. As a consequence, in order to catch thermal dynamical behavior for a given pixel , the the contributions of the pixels at a given distance should be considered.

On the basis of the correlation analysis, the following set of input variables has been selected to model the temperature of pixel (i, j):

- $E(k)$: elongation of the plasma ring;
- $Z1(k)$: upper radius of the plasma ring;
- $T_{i+N_i,j}(k), \ldots, T_{i+1,j}(k), T_{i-N_i,j}(k), \ldots, T_{i-1,j}(k)$, $T_{i,j+N_j}(k), \ldots, T_{i,j+1}(k), T_{i,j-N_j}(k), \ldots, T_{i,j-1}(k)$: temperature of the proximal pixels.

where N_i and N_j represent the number of proximal pixels along the vertical and horizontal axes with respect to pixel (i, j).

The consistency of the relevance of the geometrical features of the plasma ring on the thermal behavior is confirmed in the existent literature [5]. The correlation analysis has been performed over all the available transient regimes of each pixel.

A deep inspection of the available data has been carried out and outliers have been neglected from the training dataset.

So a training set of 30 time-series, each related to the trend of the temperature of a specific pixel of the video stream, and a validation set of 20 pixels have been selected. Each time-series consists of 233 samples taken with a sampling time of $0.0085s$, for a grand total of 4860 training patterns and 3645 validation patterns.

III. Model identification

In this paper, we compare the performances of different ARX models identified by using the same dataset. Namely, we focused on a linear autoregressive model with exogenous inputs (ARX) when different number of regressors area taken into account.

A normalization phase is required in order to make comparable measurements magnitudes coming from different processes such as geometrical features and temperatures. Thus, the whole dataset has been normalized in the range $\left[\ -1; \quad 1 \ \right]$.

On the basis of the outcome of the preliminary analysis of available datasets we used the following regressors structure to estimate the output at time k:

$$\begin{aligned}
&(T_{i,j}(k-n), \ldots, T_{i,j}(k-1),\\
&E(k-n_1), \ldots, E(k-1),\\
&Z_1(k-n_2), \ldots, Z_1(k-1),\\
&T_{i+N_i,j}(k-n_3), \ldots, T_{i+N_i,j}(k-1), \ldots,\\
&T_{i+1,j}(k-n_3), \ldots, T_{i+1,j}(k-1),\\
&T_{i-N_i,j}(k-n_3), \ldots, T_{i-N_i,j}(k-1), \ldots,\\
&T_{i-1,j}(k-n_3), \ldots, T_{i-1,j}(k-1),\\
&T_{i,j+N_j}(k-n_3), \ldots, T_{i,j+N_j}(k-1), \ldots,\\
&T_{i,j+1}(k-n_3), \ldots, T_{i,j+1}(k-1),\\
&T_{i,j-N_j}(k-n_3), \ldots, T_{i,j-N_j}(k-1), \ldots,\\
&T_{i,j-1}(k-n_3), \ldots, T_{i,j-1}(k-1))
\end{aligned} \tag{1}$$

where $T_{i,j}(k)$ is the temperature of the $i, j-th$ pixel at time k, $E(k)$ is the elongation of the plasma ring at time k, $Z_1(k)$ is the upper radius of the plasma ring at time k, N_i is the number of proximal pixel along the horizontal axis, N_j is the number of proximal pixel along the vertical axis. The number of regressors is defined by n (regressors of the state), n_1 (regressors of the elongation), n_2 (regressors of the internal radius), and n_3 (regressors of the proximal temperatures).

Nine ARX models with different number of regressors are considered and their performances compared. Starting from the model with $n = 1$ pole, and one zeros, i.e. $n_1 = n_2 = n_3 = 1$ to the model with $n = 3$ poles, and three zeros, i.e. $n_1 = n_2 = n_3 = 3$.

Results after denormalization of the model outputs, are reported in Figure 4 where the trend of the temperature obtained as output of the identified model and the corresponding measured temperature of a pixel belonging to the test set are show. As it can be observed from Figure 4, the ARX models performance are satisfactory.

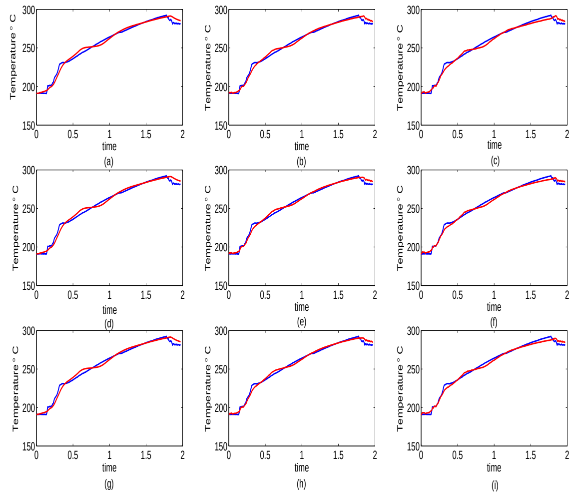

Fig. 4. Plot showing both model output(red signal) and target (blue signal)for each ARX model : (a) $n = 1, n1 = n2 = n3 = 1$, (b) $n = 1, n1 = n2 = n3 = 2$, (c) $n = 1, n1 = n2 = n3 = 3$, (d) $n = 2, n1 = n2 = n3 = 1$, (e) $n = 2, n1 = n2 = n3 = 2$, (f) $n = 2, n1 = n2 = n3 = 3$, (g) $n = 3, n1 = n2 = n3 = 1$, (h) $n = 3, n1 = n2 = n3 = 2$, (i) $n = 3, n1 = n2 = n3 = 3$

IV. Comparative analysis

In this section the models identified have been evaluated and compared by means of a number of performance indices. In Table I the values of the correlation coefficient (CC) between estimated and measured output, the root mean square error (RMS), the maximum of the absolute value of the error (MAE) are reported for the training phase for the two models identified. The same quantities for the test phase are reported in Table II.

TABLE I
Performance indices for the training phase.

	CC	RMS	MAE
$n=1, n1=n2=n3=1$	0.9830	5.3092	20.7847
$n=1, n1=n2=n3=2$	0.9853	4.9741	19.4387
$n=1, n1=n2=n3=3$	0.9840	4.9626	17.7008
$n=2, n1=n2=n3=1$	0.9830	5.3061	20.7738
$n=2, n1=n2=n3=2$	0.9854	5.0628	18.0593
$n=2, n1=n2=n3=3$	0.9840	5.1009	16.1029
$n=3, n1=n2=n3=1$	0.9830	5.3006	20.7837
$n=3, n1=n2=n3=2$	0.9854	5.0612	18.0376
$n=3, n1=n2=n3=3$	0.9836	5.1246	16.3162

TABLE II
Performance indices for the test phase.

	CC	RMS	MAE
$n=1, n1=n2=n3=1$	0.9707	8.8565	24.0167
$n=1, n1=n2=n3=2$	0.9731	8.3111	22.7386
$n=1, n1=n2=n3=3$	0.9647	8.6587	24.3664
$n=2, n1=n2=n3=1$	0.9708	8.8683	23.9787
$n=2, n1=n2=n3=2$	0.9728	8.6802	20.9390
$n=2, n1=n2=n3=3$	0.9648	9.1732	21.4273
$n=3, n1=n2=n3=1$	0.9708	8.8606	23.9470
$n=3, n1=n2=n3=2$	0.9727	8.6661	20.8996
$n=3, n1=n2=n3=3$	0.9637	9.1695	21.6343

The models provides comparable performance as it can be noticed in Fig. 4 and from the index in the tables, however it appears that models with $n = 3, n1 = n2 = n3 = 3$ and $n = 2, n1 = n2 = n3 = 2$ appear to be the best ones as it can be seen from the performance index in the testing phase.

V. Conclusion

A fundamental step toward the control of plasma experiments far from disruption is represented by the identification of a real model of the temperature distribution over the limiter surface, thus adopting data-driven models rather than a physical ones.

In this work a comparison of different linear autoregressive models estimating the temporal evolution of the limiter surface operating at the FTU is proposed . The effects of a set of the geometrical features of the plasma ring and the effects of the temperatures of neighboring regions are taken into account.

Nine different ARX models have been identified exploiting data collected during FTU experimental campaign. Models produce comparable results although the performance of the ones with $n = 3, n1 = n2 = n3 = 3$ and $n = 2, n1 = n2 = n3 = 2$ appear to be slightly higher than the others. Thus, in the future perspective, a deepen investigation of other models may be conducted and a further comparison with the analyzed ARX models performed.

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