Chapter 1

# Introduction

The use of feedback control in mechanisms developed by humans is marked by the 1769 James Watt's invention, known as the Watt regulator and developed to regulate steam machines spin velocities. From this time until the beginning of the 20th century, control designs were based on trial and error methods. With the emergence of theoretical publications on the subject, such as that of (Tolle, 1921), mathematical models were increasingly used in the design of controllers, mainly in the form of differential equations (Takahashi et al., 1972).

In the 30s and 50s the so-called Classical Control Theory originates, expressing itself basically in the frequency domain and in the $s$-plane, with models given by transfer functions, based on methods developed mainly by Nyquist, Bode, Nichols and Evans.

In the 1960s, a new control theory approach arises, using parametric models and state space representation. this approaches gives rise to the so-called Modern Control Theory and its main branches, such as systems identification, adaptive control, robust control, optimal control and stochastic control, which have been widely studied and developed until today, but still with many challenging topics, both in theoretical and practical aspects (Hou and Wang, 2013).

In both approaches, the classical control theory, mainly based on the use of transfer functions and linear systems, as in the modern control theory, mainly based on state space representations of linear and non-linear systems, a mathematical model of the process to be controlled is required [*]. Such model can be obtained via phenomenological modeling, or via systems identification methods. In the former case, the model is obtained using known laws from specific fields of science resulting in equations that represent it. In the latter case, using input-output data collected from the process and using systems identification techniques, models that represent the process are obtained, with a certain degree of reliability.

colocar referencia para trabalhos relevantes do tipo, para a footnote.

Several methodologies for identifying linear and non-linear models are available in the literature (Aguirre, 2015; Ljung, 1999).

Models obtained using first principles or even by systems identification can result in high order models, with a high degree of non-linearity, which makes difficult or even impractical their use for control purposes.

Furthermore, modeling processes can be an arduous task and sometimes even

[*] with some exceptions like the cases where the controller is designed directly from the frequency response obtained experimentally.

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impracticable, requiring steps to validate and determine the structure of the model.

For this reason, traditional model-based control methods (MBC) are unpractical in some cases. In addition, several processes generate and store large amounts of data and the use of this data for controller design would be very convenient (Hou and Wang, 2013).

Since the input and output data of a plant contains information about its dynamics, as long as it is properly excited, it may seem unnecessary to apply the identification theory to obtain a mathematical model of the plant for controller design (Ikeda et al., 2001). In addition, having obtained a model faithful to the plant, it may be necessary to reduce its order in the design of the controller. In this sense, in several practical control cases in which a mathematical model describing the plant is not available, or is too complex or the uncertainty in the model is too great for the use of MBC strategies, it is very convenient to obtain the controller from measurements obtained directly from the plant.

According to Campi and Weyer (2002), this problem has attracted the attention of control engineers since the work published by Ziegler and Nichols (1942) and several extensions have been proposed since then. However, around the 1990s, new approaches to controller design without the use of models for plants began to appear in the literature, which later came to be called control based on data *(DDC - from English, data-driven control)*. Hou and Wang (2013) claim that the term *data-driven* was first proposed in computer science and only recently entered the vocabulary of the control community and, to date, there are some DDC methods, however they are characterized by different names, such as " *data-driven control* ", " *data-based control* ", " *modeless control* ", among others. Hou and Wang (2013) propose the following definition for DDC, based on 3 other definitions found on the Internet:

**Definition 1.1** (Data-Driven Control)**.** (Hou and Wang, 2013) Data-driven control includes all control theories and methods in which the controller is designed by directly using on-line or off-line I/O data of the controlled system or knowledge from the data processing but not any explicit information from mathematical model of the controlled process, and whose stability, convergence, and robustness can be guaranteed by rigorous mathematical analysis under certain reasonable assumptions.

Therefore, the DDC is different from the MBC in essence, since the controller design does not make direct or indirect use of the process model. Although, at first, they look like adaptive control methods, DDC methods differ from these in that, at first, they do not need any model information, and parameter settings depend on large batches of data, instead of a only a few samples of the input-output signals.

Uma perspectiva do desenvolvimento do assunto na comunidade acadêmica pode ser obtida por uma busca pelo número de publicações na base de dados do **?**, utilizando o termo "*data-driven control*" e pela combinação de termos "*data-driven* or *data-based control* or *mod-*

Some conceptually distinct approaches using DDC appear in the literature in the last years, among them[†]: *Virtual Reference Feedback Tuning* (VRFT), Iterative Feedback

[†]it was chosen here to mention some techniques that the author found most relevant to this proposal, however others can be found in the literature (**?**Safonov and Tsao, 1995; Karimi et al., 2007; Huang and Kadali, 2008; Schaal and Atkeson, 1994; Shi and Skelton, 2000)

Tuning (IFT), *Frequency Domain Tuning* (FDT), *Correlation Based Tuning* (CbT), originally presented by Campi and Weyer (2002), Hjalmarsson et al. (1994), Kammer et al. (2000) and Karimi et al. (2002), respectively. Since the input and output data of a plant contains information about its dynamics, as long as it is properly excited, it may seem unnecessary to apply the identification theory to obtain a mathematical model of the plant for controller design (Ikeda et al., 2001). In addition, having obtained a model faithful to the plant, it may be necessary to reduce its order in the design of the controller. In this sense, in several practical control cases in which a mathematical model describing the plant is not available, or is too complex or the uncertainty in the model is too great for the use of MBC strategies, it is very convenient to obtain the controller from measurements obtained directly from the plant.

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and Karimi et al. (2002), respectively. Most of these methodologies use the concept of optimization from the minimization of a cost function, in general, measured in terms of the $H_2$ norm of a signal. Several DDC methods available in the literature do this optimization in an iterative way, among them, the IFT, CbT, ILC, ADP. Others do so in batches, such as the VRFT and *Noniterative data-driven model reference control* methods.

In iterative cases, the minimization of the cost function is done, typically, by gradient descent methodologies, from input-output data collected in a batch way (**?**). One drawback of these methodologies is the lack of conditions that guarantee convergence to a global minimum for the cost function in many cases. In order to solve the problem of convergence to a global minimum of a $H_2$ performance criterion, the VRFT focus on making the cost function to be optimized sufficiently "well behaved" making optimization to converge properly. In this sense, Huusom et al. (2009) present a study which extends the IFT method in order to improve the convergence properties and reduce the number of process experiments required by IFT.

At first, given ideal conditions, convergence to the global minimum is not a problem when using the VRFT method, as it is a batch method. In addition, VRFT has no initialization problems and does not access the plant several times for experimentation, in contrast to iterative methods, allowing to maintaining the process normal operation.

The VRTF method in its first versions presented by **?**Campi and Weyer (2002), deals with the design of SISO systems and results in a linear controller. Extensions for non-linear controllers designs have been proposed since then (**???**).

Devido a suas características atrativas pretende-se, neste trabalho, pelo menos a princípio, utilizar a abordagem VRFT. Esta abordagem formula o problema de sintonia do controlador como um problema de identificação via a introdução de um sinal virtual de referência (Hou and Wang, 2013). O objetivo de controle é minimizar um funcional de custo dado pela norma $H_2$ da diferença entre função de transferência em malha fechada e um modelo de referência, ambos multiplicados pelo sinal de referência $r$. O problema em achar o mínimo é que não há modelo disponível, impedindo o cálculo do modelo em malha fechada. Visando contornar este problema, o conceito de sinais virtuais é usado. Estes sinais, dados por $e^{vir}$ (erro virtual) e $u^{vir}$ (sinal de controle virtual), são criados a partir do sinal de saída da planta e do modelo de referência inverso, possibilitando o uso de um novo funcional de custo dado por $J_{vir} = ||C(\theta, z^{-1})e^{vir} - u^{vir}||$, em que $C(\theta, z^{-1})$ representa o modelo do controlador cujos parâmetros $\theta$ devem ser identificados por otimização. Campi and Weyer (2002) mostram que ao minimizar $J_{vir}$, minimiza-se o primeiro critério sob certas condições. A minimização do novo funcional pode ser feita por técnicas de estimadores de mínimos quadrados (MQ), variáveis instrumentais (VI), dentre outras (Aguirre, 2015). Bazanella et al. (2012) mostram exemplos do uso de variáveis instrumentais para resolver o problema de polarização dos parâmetros identificados para casos de sinais ruidosos.

Até o momento, com base na literatura, encontrou-se técnicas que estendem a abordagem VRFT para casos não lineares (**??????**). Mas de acordo com **?**, diferentemente do VRFT linear, estas versões estendidas para sistemas não lineares ou não são em batelada, ou suas soluções não podem ser determinadas por métodos MQ, perdendo uma vantagem considerável do VRFT. Porém **?** mostram que o VRFT pode ser estendido para o controle de sistemas não lineares do tipo Hammerstein e Wiener de forma que é mantido a característica não iterativa do VRFT. Três anos depois, **?** apresentam um método onde somente a não linearidade estática (ou sua inversa), representada por séries *B-spline*, é estimada simultaneamente com o controlador sem a necessidade de otimização não linear ou procedimentos iterativos.

Uma pergunta que surge é: seria possível o uso de técnicas de estimação do tipo MQ com restrições para modelos não lineares NARX (do inglês *Nonlinear model with eXogenous inputs*) ou MQ estendido para modelos NARMAX (do inglês *Nonlinear AutoRegressive Moving Average model with eXogenous inputs*) neste tipo de abordagem? Apesar de já terem sido desenvolvidas técnicas para incorporar informação auxiliar no processo de identificação, por exemplo via restrições e otimização multiobjetivo (Barroso, 2006), todas estas restrições dizem respeito à planta. Neste sentido surgem questões como: de que forma estas técnicas podem ser usadas na abordagem DDC? Seria possível encontrar um análogo da informação auxiliar, usada em métodos tradicionais, para estratégias DDC, em que não há informação da planta? Poderia esta ser definida, por exemplo, a partir restrições que garantam aspectos relevantes ao controle, como limitações de ganho devido a saturação de atuadores, ou até mesmo relativos a robustez? Since the input and output data of a plant contains information about its dynamics, as long as it is properly excited, it may seem unnecessary to apply the identification theory to obtain a mathematical model of the plant for controller design (Ikeda et al., 2001). In addition, having obtained a model faithful to the plant, it may be necessary to reduce its order in the design of the controller. In this sense, in several practical control cases in which a mathematical model describing the plant is not available, or is too complex or the uncertainty in the model is too great for the use of MBC strategies, it is very convenient to obtain the controller from measurements obtained directly from the plant.

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**Definition 1.3** (Data-Driven Control)**.** (Hou and Wang, 2013) Data-driven control includes all control theories and methods in which the controller is designed by directly using on-line or off-line I/O data of the controlled system or knowledge from the data processing but not any explicit information from mathematical model of the controlled process, and whose stability, convergence, and robustness can be guaranteed by rigorous mathematical analysis under certain reasonable assumptions.

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Chapter 2

# Virtual Reference Feedback Tuning

O método *Virtual Reference Feedback Tunning*, ou simplesmente VRFT, é um procedimento que visa o projeto de controladores realimentados a partir somente de dados amostrados do processo, sem a necessidade de um modelo que descreva este último. Com isso, se classifica como um método de controle baseado em dados, ou DDC.

O principal objetivo deste método é ajustar os parâmetros de um controlador, definido por uma função paramétrica, a partir de dados amostrados do processo, a fim de que o sinal de saída do processo controlado tenha um comportamento o mais próximo possível do sinal de saída de um modelo de referência previamente definido. Para alcançar este objetivo o VRFT visa otimizar o erro de rastreamento a partir da minimização de um índice de desempenho $J_y(\theta)$, definido por

$$J_y(\boldsymbol{\theta}) \triangleq \lim_{N\to\infty} \frac{1}{N} \sum_{k=1}^{N} \left[y_r(k,\boldsymbol{\theta}) - y_{MR}(k)\right]^2, \tag{2.1}$$

sendo $N$ o número de dados amostrados, $\boldsymbol{\theta} = \begin{bmatrix}\theta_1 & \theta_2 & \cdots & \theta_N\end{bmatrix}^T \in \mathbb{R}^n$ um vetor de parâmetros, $k$ um índice temporal com $y_r(k,\boldsymbol{\theta})$ e $y_{MR}(k)$, definidos como se segue:

- $y_r(k,\boldsymbol{\theta})$ representa a resposta obtida em malha fechada quando sobre o efeito de um sinal de referência $r(k)$, ou seja

  $$y_r(k,\boldsymbol{\theta}) \triangleq T(q,\boldsymbol{\theta})r(k), \tag{2.2}$$

  onde $T(q,\boldsymbol{\theta})$ representa o modelo em malha fechada, função do vetor de parâmetros $\boldsymbol{\theta}$ e $q$ um operador de deslocamento temporal.

- $y_{MR}(k)$ representa a resposta temporal obtida ao se aplicar o sinal de referência $r(k)$ como sinal de entrada de um modelo $T_{MR}(q)$, conhecido como *modelo de referência* e que representa o comportamento desejado em malha fechada, ou seja

  $$y_{MR}(k) \triangleq T_{MR}(q)r(k), \tag{2.3}$$

Para alcançar o objetivo de minimizar (2.1), Campi et al. (2002), para o caso linear, e Campi and Savaresi (2006), para o caso não linear, mostram que, sob certas condições, apresentadas na sequência, ao se minimizar um índice de custo definido como

$$J_{VR}(\boldsymbol{\theta}) \triangleq \lim_{N\to\infty} \frac{1}{N} \sum_{k=1}^{N} \left[u(k) - C(q,\boldsymbol{\theta})e(k)\right]^2, \tag{2.4}$$

minimiza-se também o índice $J_y(\theta)$ definido em (2.1). Em (2.4), $u(k)$ representa o sinal de entrada aplicado ao processo durante a coleta de dados, $C(q,\boldsymbol{\theta})$ o modelo do controlador a ser ajustado e $e(k)$ é o chamado *erro virtual*, definido como

$$\bar{e}(k) = \bar{r}(k) - y(k), \tag{2.5}$$

onde $\bar{r}$ é o sinal de *referência virtual*, obtido ao se filtrar a saída $y(k)$ pelo modelo de referência inverso, na forma

$$\bar{r}(k) = T_{MR}^{-1}(q)y(k). \tag{2.6}$$

O termo "virtual" é adotado em referência (ou erro) virtual para enfatizar que nenhum destes sinais são fisicamente disponíveis, mas apenas calculados para fins de projeto do controlador.

melhorar isso aqui.

Como mencionado anteriormente, para que $J_y(\boldsymbol{\theta})$ e $J_{VR}(\boldsymbol{\theta})$ apresentem seus valores mínimos para a mesma solução de parâmetros $\boldsymbol{\theta}$, certas condições devem ser satisfeitas. Estas condições são apresentadas na sequência, logo após algumas definições que se mostram importantes para o restante do capítulo.

**Definition 2.1** (Ideal Controller)**.** asdf

**Assumption 2.1** (Noise free)**.** The system is not affected by noise.

**Assumption 2.2** (Matched control)**.** The ideal controller belongs to control model class considered, i.e. $C_d(q) \in \mathscr{C}$, or, equivalently

$$\exists \boldsymbol{\theta}_d : C(q,\boldsymbol{\theta}_d) = C_d(q). \tag{2.7}$$

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