IDENTIFICATION AND CONTROL METHODS FOR HIGH POWER ELECTRON BEAM-DRIVEN MICROWAVE TUBES

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ABSTRACT

The goal of this paper is to introduce some identification and control systems concepts to the field of high power microwave (HPM) tubes. These concepts are well known to the control systems community, but have not yet been fully exploited within the HPM community. The simpler mathematical approach used is contrasted with the more physical modeling, using first principles and advocated by experimental results. The paper also reports on a preliminary application of these ideas to the Sinus-6 electron beam accelerator. We present simulation results which show that a simple nonlinear model using static neural networks is sufficient to accurately model the input/output behavior of the Sinus-6 driven Backward wave oscillator (BWO).

INTRODUCTION

The University of New Mexico pulsed power and plasma science laboratory and systems group are currently engaged in a experimental/theoretical study of ways to identify and control the high-power, repetitively-pulsed electron beam accelerator known as the Sinus-6. Initial experimentation with the Sinus-6-driven BWO has been reported elsewhere [1], and has yielded input/output data which will be used in the proposed research.

The initial stage of our research consists of obtaining a model that describes the input/output data collected for the Sinus-6. For the purposes of modeling, a square pulse is presented at the input of the system. The three output signals are the the total peak power, frequency, and RF efficiency. The model is then used in conjunction with standard classical control designs in order to improve the shape and characteristics of the output waveforms. Another control objective will be to improve the RF conversion efficiency.

On a parallel track, a more sophisticated nonlinear identification scheme is being attempted. The Sinus-6, as are most physical systems, is linear only to a first approximation. We therefore use this nonlinear approach to fit the input-output behavior of the Sinus-6. The obvious advantage of such an approach is that a smaller nonlinear model may be called for, at the expense of a more difficult control design.

Finally, it turns out that the Sinus-6 is extremely fast to warrant the inclusion of dynamical effects, and that a static, neural network model appropriately fits the experimental data [2].

IDENTIFICATION

The task of identifying a system is one of the most important in trying to understand its behavior. In general, identifying is a prelude to prediction or to control. In our particular case, we are interested in controlling the operation of the Sinus-6.

Identification Objectives

As stated above, there are usually two objectives to identification: 1) prediction and 2) control. The prediction objective arises in applications such as forecasting, and time series prediction where a record of the input/output behavior is available up to a certain point in time, but the user is interested in predicting the behavior at future times. If one believes that the behavior of the data can be explained using a deterministic model, then it may be feasible to determine the differential or difference equations relating the input to the output of such a model, consistent with the available data. The future may then be predicted by simply running a simulation of the deterministic model on a digital computer. The model may then be refined as new data becomes available. Our objective in the present paper however is to control the future behavior rather than to just predict it. Therefore, we shall divide our identification step into two parts: In the first part, we try to fit the available data to a deterministic model. In the second part, we use the model to design a controller that will then be implemented on the Sinus-6.

Identification Approaches

There are many identification approaches and methods, depending on the type and format of the available data [3]. We shall concentrate here on deterministic methods. In addition, due to the extremely fast dynamics of our system, it turns out that a static but nonlinear model is sufficient to account for the system's experimental behavior.

Nonlinear, Parametric: In many cases, the behavior of the system can not be satisfactorily explained using a small-order linear model. The basic breakdown of a linear model occurs because of the following reasoning: A linear, time-invariant (LTI) system can not create at its output frequencies that are not present in the input signal. In fact, the steady-state behavior of a stable LTI system subjected to a sum of sinusoidal signals will be a sum of sinusoids at the same frequencies but with different magnitudes and phases. Therefore, in order to explain the rich behavior of a physical system (new frequencies at the output) one must introduce these frequencies as new modes of the linear model, thus increasing the order of the system. Note that a similar dichotomy to the linear case exists between dynamical models (whose outputs are related to their inputs using differential equations) and static ones (whose input/output relationship is algebraic).

It turns out for our particular case, a static, nonlinear model is sufficiently rich to explain the experimental data for the Sinus-6.

CONTROL

Control Objectives

As it relates to the Sinus-6 BWO system the following control objectives are stated:

1. Maximize the output power
2. Maximize the RF conversion efficiency.

Control Approaches

Many control approaches are available to us, once a model of the Sinus-6 is obtained. These approaches are dictated by the model itself and by the performance objectives. In this section, we shall discuss some of the approaches we feel can be successfully used in our problem.

Classical Control: The classical control approach applies to single-input-single-output (SISO), linear-time-invariant (LTI) systems. Strictly speaking, our system is nonlinear and as such, the classical control approach will not apply. We will however consider the control problem as it relates to the basic concepts of the classical approach.

Learning Control: The Sinus-6 is a repetitively-pulsed electron beam accelerator, and as such will lend itself to a control approach known as "learning control". The basic idea of this approach is that since the system will be repeating the same maneuver over and over, it should be learning to improve its behavior when it is subjected to the same input. The Sinus-6 is subjected to a square-pulse input of duration 12 ns, which repeats every 10 s. The time between pulses is then available to the computer in order to improve on the performance of the system by adjusting the controller's parameters when necessary. In fact, learning control is effectively an external loop which adds to the control input designed using any of the previous 3 methods as shown in Figure 1.

IDENTIFICATION RESULTS

A neural network approach has been used in order to fit the experimental input/output data. See Figure 2 for a block-diagram description of the experimental set-up, and [1] for a more detailed description. The data was collected in four separate experiments, where the A-K spark gap was adjusted to four different values. We shall denote these four experimental phases as E_1, E_2, E_3, and E_4. The experimental data consists of the Cathode Voltage input and the 3 outputs: total peak power, frequency, and RF efficiency. A 1-hidden

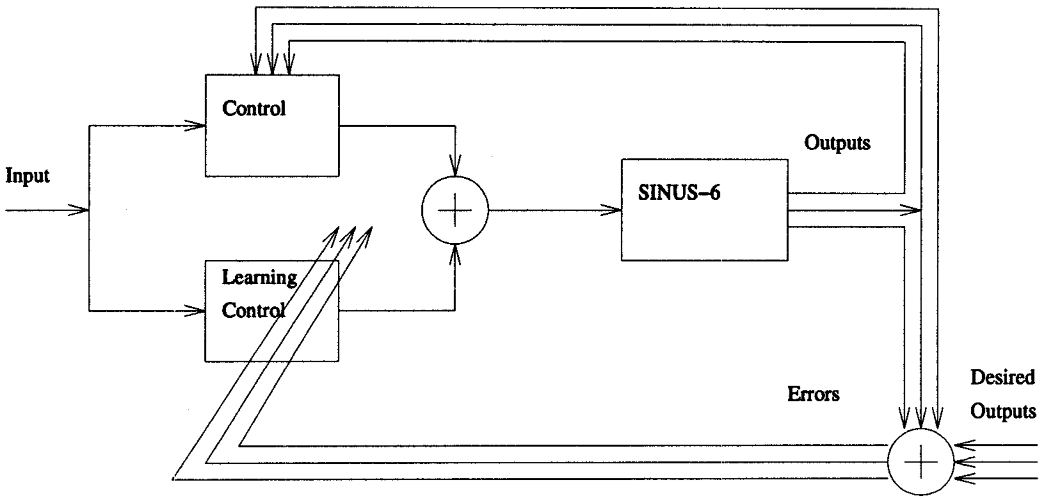

Figure 1: Block-diagram of learning control system.

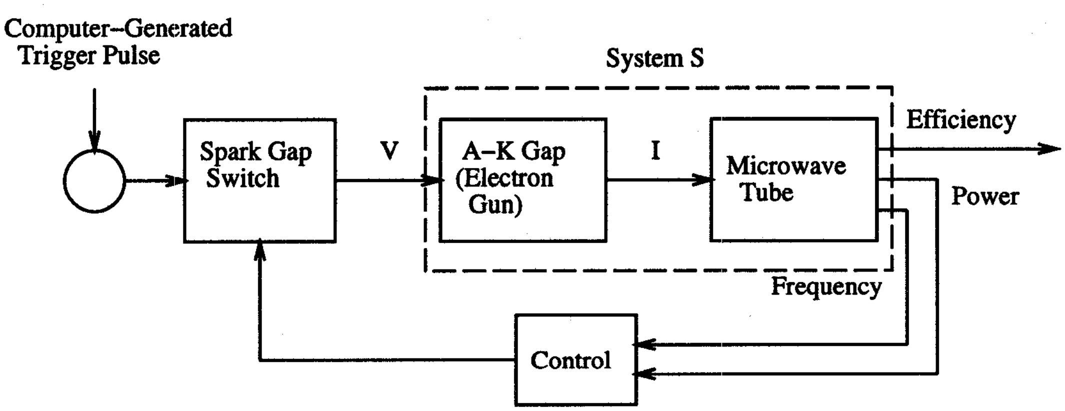

Figure 2: Block-diagram of system.

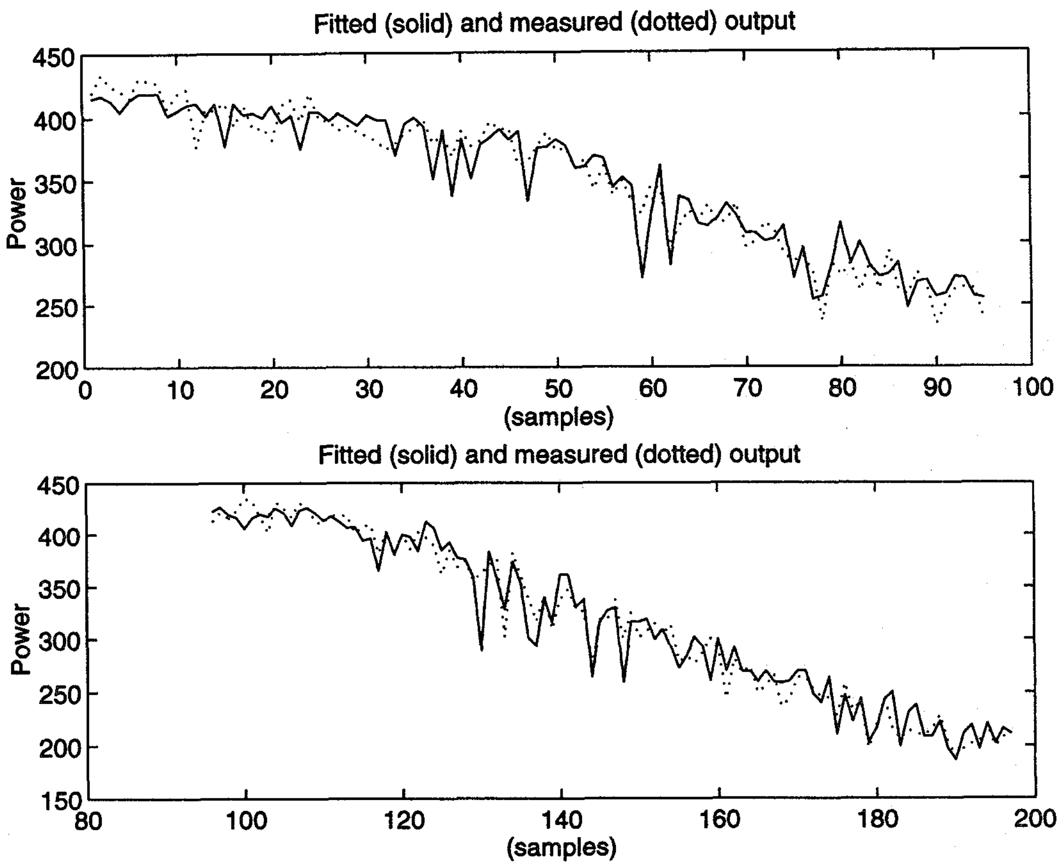

Figure 3: Experimental total power output (dotted) and learned by the neural network (solid).

layer, contains 5 weights in the hidden layer, Multi-Layer-Perceptron (MLP) [2] was used to fit the data. The results of fitting the first 95 points of the total peak power are shown in Figure 3 (top part), and the next 100 points (with a different network) are shown in Figure 3 (bottom part). In Figure 4, we show the performance of the neural network under the following scenarios: In the top part of Figure 4, four separate neural networks were trained on the four experimental phases as E_1, E_2, E_3, and E_4. The bottom part of Figure 4, shows the performance of a single neural network trained on the total data. Finally, Figure 5 represents the relative errors under the same scenario described for Figure 4. As can be seen from the simulation results, a simple neural network was able to efficiently model the experimental input/output relations.

FUTURE RESEARCH

Although the static neural network mode was successful in modeling the data, much remains to be done both in terms of modeling and control:

1. **Filter the data:** As can be seen, the output waveforms are noisy. In fact, the neural network in attempting to fit the data, is also trying to fit some noise. Since data is not uniformly spaced in time, a classical filtering technique could not be used. However, one can attempt to fit the output data with a polynomial (in the least-square sense) and then attempt to use a neural network model.

2. **Validate the Model:** Although the neural network model seems to be an effective model of the experimental data, it is merely interpolating between the data already collected. A more robust measure of the "goodness" of the model is its extrapolating capabilities. In other words, new experiments will be designed to show that the model accurately describes the expected behavior of the Sinus-6 BWO, when subjected to a known input.

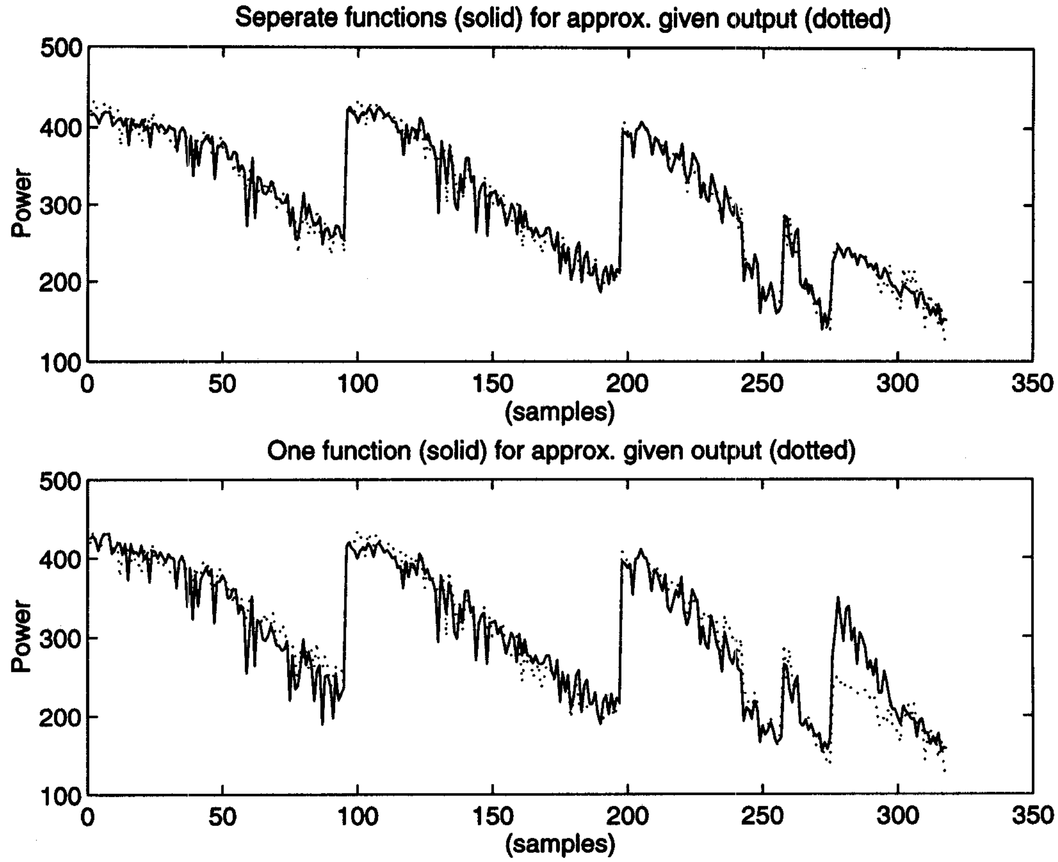

Figure 4: Total output power using one neural network (dotted) and four separate neural networks (solid).

3. **Control:** Since the model is static, dynamics need to be introduced in the controller in order to avoid an "ill-posed" problem, whereby the relationship between inputs and outputs is non-causal. In order to design a controller, the control objectives need to be translated into mathematical requirements on the output power, and RF efficiency.

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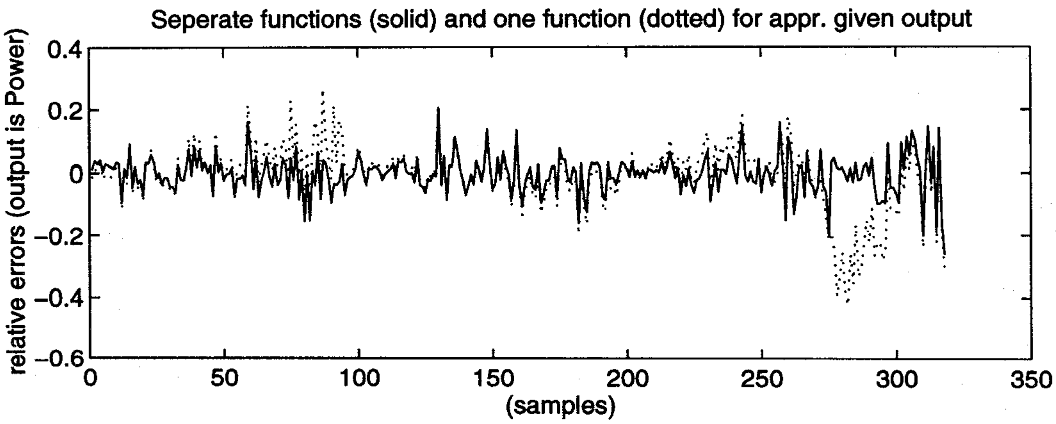

Figure 5: Errors using one neural network (dotted) and four separate neural networks (solid).

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