

# Toward “Smart Tubes” Using Iterative Learning Control

Chaouki T. Abdallah, *Senior Member, IEEE*, Vatche S. Soualian, and Edl Schamiloglu, *Senior Member, IEEE*

**Abstract**— In this paper, we present our progress toward designing a “smart” high-peak power microwave (HPM) tube. We use iterative learning-control (ILC) methodologies in order to control a repetitively pulsed high-power backward-wave oscillator (BWO). The learning-control algorithm is used to drive the error between the actual output and its desired value to zero. The desired output may be a given power level, a given frequency, or a combination of both. The learning-control methodology is then verified in simulation. This methodology is applicable to a wide variety of HPM sources.

**Index Terms**— Backward-wave oscillator, frequency agility, high-peak power microwave, iterative learning control.

## I. INTRODUCTION

PRESENT-DAY high-peak power microwave (HPM) sources typically operate in the single-shot regime because of practical limitations imposed by the pulsed power systems used to drive them [1], [2]. There are commercial HPM systems that operate at modest repetition rates, two examples of which include a system based on the Reltron source [3] operating at 1 Hz, and a system based on a magnetron source [4] operating at a 10-pulse/second burst mode. It is clear that a modest pulse repetition rate is attractive for a practical implementation of an HPM system.

The physics of the interaction between a relativistic electron beam and various slow-wave structure (SWS) configurations in a short-pulse backward-wave oscillator (BWO) has been studied experimentally and computationally in a collaborative effort between the University of New Mexico, Albuquerque, and the Institute of High Current Electronics, Tomsk, Russia [5], [6]. The electron-beam accelerator used in those studies is a Sinus-6 device that produces a 10-ns full width at half maximum (FWHM) beam current pulsewidth, and can operate at a pulse repetition rate as large as 200 Hz. In practice, the accelerator operates at a pulse repetition rate no greater than 0.1 Hz, limited by the capacitor bank used to energize the magnetic field-producing solenoidal coil. A novel result of this effort was a demonstration of enhanced frequency agility of a high-power BWO for constant electron-beam and applied magnetic-field parameters [6]. This agility was

obtained through an axial displacement of the SWS with respect to the “cutoff neck” inlet to the electrodynamic system. Furthermore, a companion study to this paper provided a static affine model of the input/output characteristics of the Sinus-6-driven BWO, and described how this information can be used as part of an algorithm to meet specific control objectives, such as maximizing the radiated frequency bandwidth for a fixed-peak radiated-microwave-power level [7]. The next step in the research is then to automate the control algorithms in order to build a “smart-tube” HPM source. By *smart tube*, we mean an HPM source capable of adjusting its output characteristics to achieve certain preset criteria without operator intervention. Furthermore, a *smart-tube* HPM source will *learn* from its earlier operation to affect its future performance. We believe that a *smart-tube* HPM source represents an important development and will further the embodiment of these research devices into practical systems.

From a controls perspective, it turns out that the fast dynamics and changes in the operating characteristics of the BWO render traditional automatic-control methods ineffective. In fact, our results in [7] for the Sinus-6-driven BWO have shown that a static affine model is an accurate representation of its input/output characteristics. A static model is too fast to be controlled in real time while maintaining the same-order dynamics (and thus, the same bandwidth and speed of response) of the open-loop system. However, and since the BWO is repetitively pulsed, one can attempt to achieve the control objectives between pulses. More specifically, for control design purpose, an engineer is usually provided with a mathematical model of a *dynamical* system, which can be described by differential/difference equations. The design problem is then reduced to finding a suitable control law to achieve some desired response. Research in controls has focused on the control of dynamical systems since most physical systems exhibit some kind of dynamic behavior. Although a quantitative model may be difficult to obtain, once such a model is made available, the design part is relatively well developed. On the other hand, the control problem for static systems is relatively undeveloped. Control issues for static systems have recently arisen in many areas such as rapid thermal processing [8] or in pulsed power systems [7]. Static systems may, in fact, have dynamics, but their input–output response is so fast that they defy the usual description with differential/difference equations. One then has no hope of controlling such systems using standard control methodologies unless their maneuvers are repeated over and over. Moreover, standard control issues such as stability may not arise when

Manuscript received November 4, 1997; revised January 23, 1998. This paper was presented in part at the International Workshop on High Power Microwave Generation and Pulse Shortening, Edinburgh, U.K., June 1997. This work was supported by a High Energy Microwave Devices Consortium under an AFOSR/DOD MURI Grant, administered through Texas Tech University.

The authors are with the Department of Electrical and Computer Engineering, University of New Mexico, Albuquerque, NM 87131 USA.

Publisher Item Identifier S 0093-3813(98)04391-4.

dealing with static systems, but others such as improving performance, optimality, and disturbance rejection will.

In this paper, we use an *iterative learning-control* (ILC) methodology on the static model of the repetitively pulsed Sinus-6 BWO. Given a mathematical model of the Sinus-6-driven BWO, one can solve for the desired input, given a desired output, by finding the inverse system. This open-loop control strategy works well if the system model is exact, is invertible when no disturbances are present, and no issues of stability are involved. In practice, however, the model is obtained from a set of noisy input–output data points, and an open-loop control strategy is not sufficient. In addition, the BWO characteristics may be slowly varying due to changes in its operating conditions (jitter). In such a case, one has to account for any perturbations in the model and design a controller that takes them into account in generating the control law. Since, as discussed above, the BWO system is extremely fast, we are not able to generate a control signal in real time while maintaining the speed of the response, and it is, therefore, logical to apply any control effort adjustments off-line or in between successive shots [9]. One way to design such an off-line controller is to use ILC algorithms, which have been widely applied in the robotics industry and elsewhere [9], [10]–[15]. The learning controller accounts for the unmodeled effects, and is thus suitable in applications where the same maneuver is repeated over and over. This paper presents the results of an ILC simulation to achieve specified control objectives based on actual input/output data from the experiments. The experimental implementation of an ILC is presently underway. In fact, a computer-controlled motor-driven vacuum SWS axial displacement mechanism has been constructed and installed on the experiment.

This paper is organized as follows. In Section II, a brief description of learning control is given. Section III discusses the experimental setup and the model of the Sinus-6. In Section IV, we discuss the design of ILC's and the two control objectives, and present our simulation results. Our conclusions and directions for future research are given in Section V.

## II. PROBLEM DESCRIPTION AND ILC APPROACH

The problem studied in this paper is the design of a feedback system which can automatically adjust the inputs to the Sinus-6-driven BWO in order to achieve frequency agility or to regulate the power and frequency of the radiated energy at desired set points.

### A. Learning Control

Modern control theory has been successfully employed in controlling many industrial processes. Currently, there are many analytical methods to choose a controller that achieves asymptotic stability and an acceptable steady-state error, but few for specifying the transient response of systems [16]. These limitations motivated researchers to develop new control concepts for systems which repeat the same maneuvers, known as ILC. ILC deals with processes where the same task, which lasts a finite time interval  $[0, T]$ , is repeated over and over. The objective of the controller is thus to improve the performance

with each trial. The concept of iterative learning control was first introduced by Arimoto [10], who proposed a new control concept called betterment process. In [10], Arimoto suggested a new controller which adds a correcting term to the existing control input after each trial. Since then, similar algorithms for different classes of nonlinear systems have been developed [11], [17]–[19]. A survey of recent developments in the subject can be found in [9] and [14].

The basic idea behind designing an iterative learning controller is generically described in [14] as follows. Consider a nonlinear system described by an operator  $f: \mathcal{U} \rightarrow \mathcal{Y}$  where both  $\mathcal{U}$  and  $\mathcal{Y}$  are normed vector spaces [20]. The control objective is to drive the output  $y(t) = f(u(t), t)$  to a desired function  $y_d(t)$ . This should be achieved by choosing the appropriate input  $u^*(t)$  such that a norm  $\|y_d(t) - f(u^*(t), t)\|$  is minimized. If the system  $f(\cdot)$  is left-invertible, one may choose  $u^*(t) = f^{-1}(y_d(t), t)$ . In the following, we use  $f(\cdot)$  to denote a system which when evaluated at a particular  $u$  gives  $f(u)$ .

In most cases,  $f(\cdot)$  may not be exactly known, and calculating the inverse system may be difficult, if not impossible. In such cases, we would like to find a sequence of inputs

$$u_{k+1}(t) = g(u_k(t), y_k(t), y_d(t), t) \quad (1)$$

such that  $u_k(t)$  converges to  $u^*(t)$  as the iteration number  $k$  goes to infinity. Moreover, we would like to do so without the explicit knowledge of  $f(\cdot)$  if possible. This is then the essence of iterative learning control. It turns out that in our particular problem, the BWO model is static and time-invariant so that  $y = f(u)$ . A contraction mapping theorem, which is the basis of the ILC's described in this paper, may be found in [9] and [14].

A block diagram of a learning-control scheme is described in Fig. 1. The signal  $y_d$  is the desired output, which we try to make the actual output  $y$  track. The error is defined as the difference  $y_d - y$ . Note that in the figure, the controller actually contains two parts, one which is based on the known model and is thus fixed and produces  $u_m$ , and another denoted by  $u_k$  and obtained as the output of the learning controller. In our simulations, the known model is obtained from the identification we performed in [7], which is the neural network fitted to the actual experimental data.

In the following section, we review our experimental setup and present the static model of the BWO to which we apply the learning-control ideas described above.

## III. EXPERIMENTAL SETUP

Initial experimentation with the Sinus-6-driven BWO has been reported elsewhere [5], [6], and has yielded input/output data which was used to obtain the model used in this research. Next, we refer to the block diagram in Fig. 2. The block labeled *System S* is identified as the mathematical model in our experiment. The model of the high-power BWO consists of an  $A$ - $K$  gap (electron gun) delivering an intense electron-beam current  $I$  that is guided through a SWS by a strong axial magnetic field. There are actually two inputs into this system: the cathode potential  $u_1 = V$  and the current  $u_2 = I$ , while the

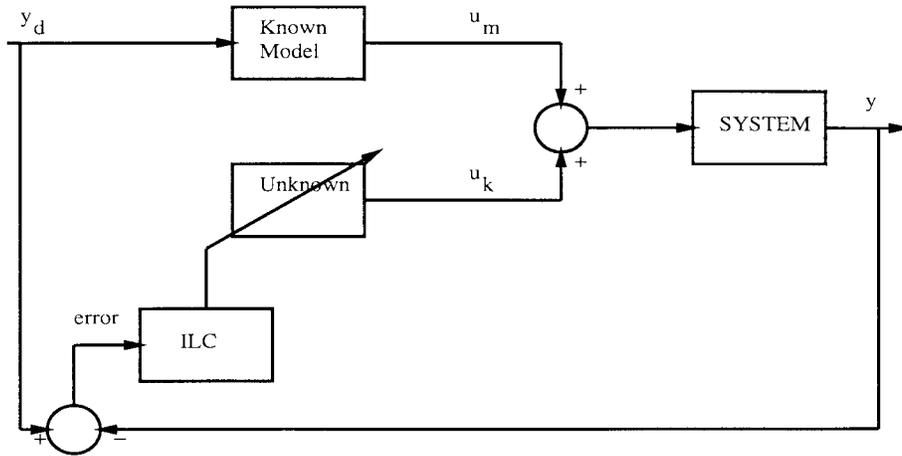


Fig. 1. Learning-control scheme.

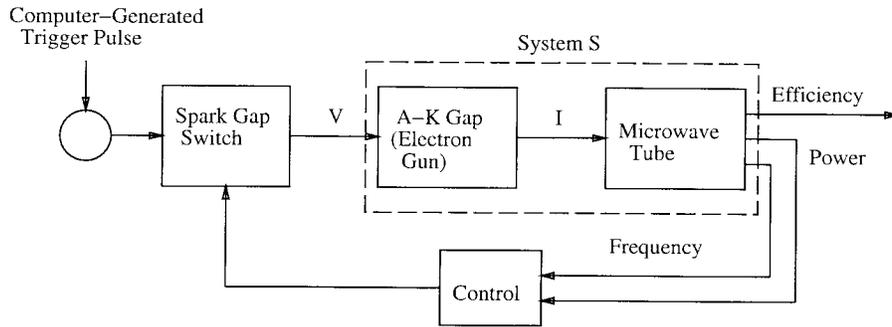


Fig. 2. Block diagram of system.

two measured outputs are the microwave power  $y_1 = P$  and the microwave frequency  $y_2 = F$ . The microwave conversion efficiency  $z_1 = E$  is obtained by dividing the peak output microwave power by the input beam power  $V \times I$ . The voltage  $V$  may be manipulated by changing the spark gap pressure, while the current  $I$  may be changed by adjusting the  $A-K$  gap. In this research, the  $A-K$  gap remains constant, thus fixing the input impedance  $Z$ . This translates into a control algorithm whose only output is the voltage  $V$  since  $I$  is dependent on  $V$  through  $I = V/Z$ . Another control parameter which allows one to achieve frequency agility is the axial displacement of the SWS with respect to the “cutoff neck” inlet to the electromagnetic system [6]. This is what we term “shifting” in this paper.

In this paper, we propose and simulate two control algorithms: the first regulates the output power and frequency to desired set values, and the other achieves frequency agility by allowing the frequency to change around a center value while maintaining a constant output power. In order to achieve these objectives, the ILC takes the outputs from the BWO and calculates the desired voltage applied to the system to regulate the power and frequency, adjust the output frequency, or to maximize the efficiency.

As discussed above, and from the research described in [5], we have access to a set of input cathode voltage  $V$ , current  $I$ , output microwave efficiency  $E$ , power  $P$ , and frequency  $F$ . Due to the complexity of obtaining a physics-based model of high-power BWO’s, researchers utilize fully electromagnetic

particle-in-cell (PIC) codes like MAGIC [21] in order to simulate certain aspects of the operation of these devices. In order to obtain a model suitable for applying our control algorithms, we choose instead to build a model based on the input/output data with the physics providing guidance. We have thus obtained the following static nonlinear, but affine, model for the Sinus-6-driven BWO:

$$y = Au + B, \quad u_{\min} \leq u \leq u_{\max} \quad (2)$$

where  $A \in \mathbb{R}^{2 \times 2}$  and  $B \in \mathbb{R}^{2 \times 1}$ . More specifically, we consider

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \quad (3)$$

$$z_1 = g(u_1, u_2, y_1, y_2).$$

This model was motivated by the fact that the affine model can simplify the control system design.

The experimental data was collected in four separate experiments, where the  $A-K$  gap was adjusted to four different values (the  $A-K$  gap determines the electron-beam diode impedance). We shall denote these four experimental phase as  $E_1, E_2, E_3$ , and  $E_4$ . The four intervals were divided into 95 sampling points for the first experiment, 102 sampling point for the second experiment, 78 sampling points for the third experiment, and 43 sampling points for the fourth experiment. The experimental data consists of the cathode voltage input  $u_1 = V$ , the current  $u_2 = I$ , and the two outputs: total peak

power  $y_1$  and frequency  $y_2$ . The RF generation efficiency  $z_1$  was calculated from the formula

$$z_1 = \frac{P}{V \times I} = \frac{y_1}{u_1 \times u_2}. \quad (4)$$

It turns out that, for the case that output is frequency and total power, four affine neural networks can be used to approximate four experiment phases  $E_1$ ,  $E_2$ ,  $E_3$ , and  $E_4$ . But for the case that output is the efficiency, it cannot. This is obvious, because from (4) we see that RF efficiency is not a linear function of the voltage. Instead, we obtain a bilinear fit of the efficiency by taking the ratio of  $P$  by the product  $V \times I$ , where  $I$  itself is fitted linearly as a function of  $V$ . The affine neural-network model was used to fit the experimental input/output data. The objective of the fit is to minimize the following performance objective:

$$J = \frac{1}{N} \sum_{i=1}^N [F(W) - y]^2$$

where

$$W = [a_{11} \ a_{12} \ a_{21} \ a_{22} \ b_1 \ b_2]^T \quad (5)$$

by a choice of the weights  $W$ . In general, this is accomplished by a gradient descent procedure of updating the weights as described, for example, in [22]. In this research, we have used the *back-propagation* training algorithm implemented in the neural-network toolbox of MATLAB [23]. The learned parameters are given in [7] and will be used in Section IV to simulate the controllers.

#### IV. DESIGN OF ITERATIVE LEARNING CONTROLLERS

The design of ILC's consists of choosing the mapping  $g(\cdot)$  in (1) so that it is a contraction mapping, as described in [9]. The idea of using a contraction mapping is useful in trying to show the convergence in many algorithms since once a mapping is shown to contract distances, and using the fact that vectors getting close to each other must be getting close to a unique vector, convergence of the iteration algorithm is guaranteed. For our case, the system to be controlled is given as in (2) by  $y = Au + B$ . Note again, that because our system is static, no time dependence appears. The ILC structure used is of the form

$$\begin{aligned} u_{k+1} &= u_k + p(e_k) \\ e_k &= y_d - y_k \end{aligned} \quad (6)$$

where  $y_k = Au_k + B$ ,  $k$  is the iteration number, and  $p$  is an operator (static or dynamic) to be designed such that the conditions of the contraction mapping are satisfied [9], [14]. In the following, we show how to choose  $p$  for two different control objectives.

##### A. Controlling Radiated Power and Frequency

Next, we discuss an approach of obtaining voltage and current set points which will maximize the output power along with the RF conversion efficiency. In order to solve the set-point design problem, we resort to the use of quantifier elimination (QE) methods. We used a software package called QEPCAD [24] in order to implement such algorithms.

TABLE I  
RESULTS OF QEPCAD FOR EXPERIMENT  $E_1$

$v's$	$I^*$	$V^*$	$F^*$	$P^*$	$E^*$
$0 \leq v_2 \leq 310^{-8}$	6	700	9.936	540.398	0.129
$v_2 = 410^{-8}$	6	532	9.883	495.112	0.155
$v_2 = 510^{-8}$	6	426	9.85	466.539	0.182
$610^{-8} \leq v_2 \leq 10^{-6}$	6	375	9.834	452.791	0.201
$v_2 = 210^{-6}$	3.50	375	9.688	291.373	0.222
$310^{-6} \leq v_2 \leq 1$	2.75	375	9.645	242.948	0.236

QEPCAD software produced the results in Table I for experiment  $E_1$ , and for different  $v_1$ ,  $v_2$  combinations. A more detailed description of this approach may be found in [25]. We can see that with  $I$  decreasing and  $V$  decreasing, the power  $P$  is decreased, but the efficiency  $E$  is increased. Now that we have the desired set points, we present to implement the ILC to regulate  $V$  and  $I$ . In what follows, we use the following ILC:

$$u_{k+1} = u_k + p(t) * e_k$$

where the symbol  $*$  denotes convolution and the filter whose impulse response is  $p(t)$  is chosen to satisfy the norm inequality

$$\|I - P(jw)A\|_\infty = \sup_w \bar{\sigma}(I - P(jw)A) < 1, \forall w \in \mathcal{R} \quad (7)$$

where  $\bar{\sigma}$  denotes the largest singular value and  $\sup$  denotes the supremum. This then insures that the conditions of the contraction mapping theorem holds. We choose  $I - P(jw)A = H(jw)$ , where  $H(jw) \in \mathcal{R}^{2 \times 2}$  satisfies inequality (7), and  $\mathcal{R}$  is the set of rational transfer functions. For our purpose, we have chosen  $H(jw)$  diagonal with entries having norm less than one. Then,  $P(jw)$  can be computed as follows:

$$\begin{aligned} P(jw)A &= H(jw) + I \\ P(jw)A &= \begin{bmatrix} H_{11}(jw) + 1 & 0 \\ 0 & H_{22}(jw) + 1 \end{bmatrix} \end{aligned} \quad (8)$$

where  $\|H_{11}(jw)\|_\infty$  and  $\|H_{22}(jw)\|_\infty$  are less than 1. For simulation purposes, we choose

$$H_{11}(jw) = H_{22}(jw) = \frac{K}{s + \alpha}, \quad \alpha > 0, \quad |K/\alpha| < 1.$$

In order to illustrate our ILC performance, we choose a nominal model in our simulation, as obtained from [7]

$$A_m = \begin{bmatrix} 0.0016 & -0.0533 \\ 1.1428 & -13.533 \end{bmatrix} \quad B_m = \begin{bmatrix} 9.0741 \\ -237.37 \end{bmatrix} \quad (9)$$

and assume that the actual plant is given by

$$A = \begin{bmatrix} 0.0004 & 0.0627 \\ 0.5331 & 72.379 \end{bmatrix} \quad B = \begin{bmatrix} 9.2798 \\ -246.25 \end{bmatrix}. \quad (10)$$

The desired output response were  $F_d = 9.834$  GHz and  $P_d = 452.791$  MW. We thus use the structure in Fig. 1 to design an ILC controller with a nominal component obtained from the nominal model, and a learning controller designed based on the ILC concepts. The simulation results are shown in Fig. 3. Note that both frequency and peak power are regulated

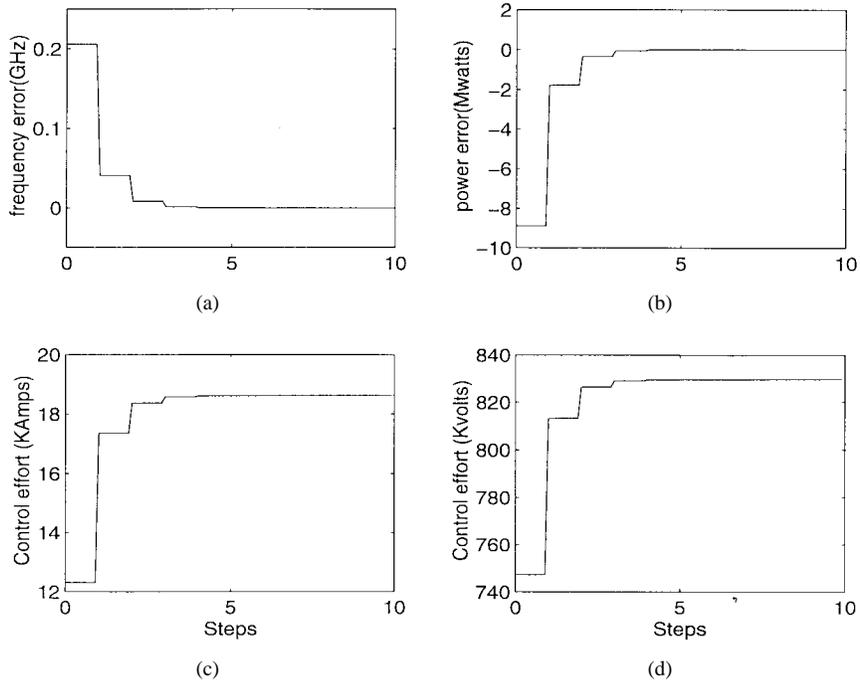


Fig. 3. Plot of the output error and control effort response for  $\alpha = 5, K = 1$ .

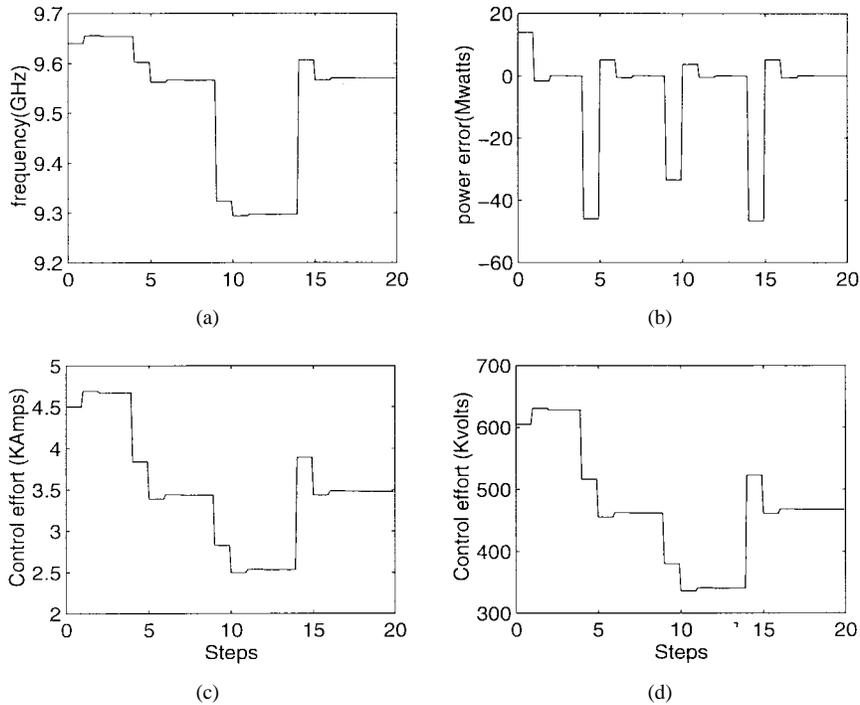


Fig. 4. The frequency agile ILC performance.

to their desired values after a couple of iterations, and that the current and voltage inputs stabilize to their desired values. Note that in practice this takes a very short time, allowing time for the mechanical adjustment between successive firings of the accelerator.

**B. Frequency Agility**

In this case, our control objective is to keep a constant output power when we axially displace the SWS, and thus change

the output frequency [6]. Note that in the previous section, the main concern was to control both output variables, namely the frequency and power, by adjusting the input current and voltage with no constraints on the inputs. In practice, this is possible if the control variables are independent. However, as mentioned earlier, our only accessible variable is the pressure (or voltage), and the input current is a linear function of this voltage:

$$V = I \times Z. \tag{11}$$

The frequency–agility control problem can thus be reformulated as follows: given a desired output power, find the control signal to drive the error between the measured output power and the desired one to zero, with the constraint  $(V_k/I_k) = Z = \text{const.}$ , where  $k$  denotes the iteration number. Now that the only output variable to be controlled is the power, we have

$$P_k = a_{11}V_k + a_{12}I_k + b_1 = \left(a_{11} + \frac{a_{12}}{Z}\right) V_k + b_1 \quad (12)$$

where the pair  $(a_{11}, a_{12})$  is the first row of the matrix  $A$ ,  $V_k$  and  $I_k$  are the control efforts at the  $k$ th trial, and  $P_k$  the corresponding output measured power. Now define  $\alpha = (a_{11} + (a_{12}/Z))$  and  $u_k = V_k$ . The control effort is of the form

$$u_k = u_{k-1} + \Gamma e(k-1) \quad (13)$$

where  $\Gamma \in \mathbb{R}$  is the vector gain to be calculated and  $e(k) = P_d - P_k$ , where  $P_d$  is the desired output power. The actual output power can then be written in the form

$$\begin{aligned} P_k &= \alpha u_k + b_1 \\ &= \alpha(u_{k-1} + \Gamma e_{k-1}) + b_1 \\ P_k &= P_{k-1} + \alpha\Gamma e_{k-1} \end{aligned}$$

or, finally,

$$\begin{aligned} P_d - P_k &= P_d - P_{k-1} - \alpha\Gamma e_{k-1} \\ e_k &= [1 - (\alpha\Gamma)]e_{k-1}. \end{aligned} \quad (14)$$

From (14), it is easy to see that in order to satisfy the conditions of contraction mappings [9], we need to choose  $\Gamma$  such that  $0 < \alpha\Gamma < 1$ . We have chosen in our simulations the value  $\alpha\Gamma = 0.8$ , and  $(V_k/I_k) = 135 \Omega$ . Note that in reality, and since  $\Gamma$  is not exactly known, we may need to design an adaptive gain  $\alpha$  in order to guarantee that  $\alpha\Gamma < 1$ . This will be a topic of future research. The simulation was performed for four different shifts of the SWS, and the plots in Fig. 4 show that for every shift in the SWS, the control efforts are automatically adjusted, keeping the impedance value constant. In fact, notice that the difference between the desired peak-power output and the actual output goes to zero after each shift and after one shot. The frequency of the output is allowed to vary between 9.3–9.65 GHz, while the voltage input (and thus, the current) is adjusted to counteract the effect of shifting on radiated power [6].

## V. CONCLUSIONS AND FUTURE WORK

In this paper, we have presented an iterative learning-controller approach in trying to design smart microwave tubes. This control structure was chosen because of its ability to improve its performance in systems such as the repetitively pulsed Sinus-6 BWO. Our control design was built around our previous experience in modeling the Sinus-6 BWO, our earlier research on frequency agility, and on our control-system experience. The controller we designed and simulated was shown effective in regulating the output frequency and peak power output, and in achieving frequency agility. The frequency and power set points were chosen using QE methods. The

frequency agility was simulated by modeling the displacement of the SWS while adjusting the voltage input.

We are currently in the process of implementing these controllers on the Sinus-6 BWO. We have constructed a computer-controlled motor-driven vacuum SWS axial-displacement mechanism and have installed it on the experiment. While displacing the SWS, we will be automatically adjusting the spark gap pressure according to the control algorithm in order to affect the input voltage. This represents only one of the parameters which can be eventually adjusted to implement the final controller. Eventually, we will also adjust the  $A$ – $K$  gap, thus changing the input impedance and achieving an independent change in the input current in order to achieve our control objectives. The final controller will be implemented in software and will be tunable to different operating conditions and to different microwave tubes.

## REFERENCES

- [1] J. Benford and J. Swegle, *High Power Microwaves*. Norwood, MA: Artech House, 1992.
- [2] C. Taylor and D. Giri, *High-Power Microwave Systems and Effects*. Washington, DC: Taylor & Francis, 1994.
- [3] R. B. Miller, "Pulse shortening in high-peak-power Reltron tubes," this issue, pp. 340–347.
- [4] D. Price, J. S. Levine, and J. Benford, "Diode plasma effects on the microwave pulse length from relativistic magnetrons," this issue, pp. 348–353.
- [5] L. Moreland, E. Schamiloglu, R. Lemke, S. Korovin, V. Rostov, A. Roitman, K. Hendricks, and T. Spencer, "Efficiency enhancement of high power vacuum BWO using nonuniform slow wave structures," *IEEE Trans. Plasma Sci.*, vol. 22, pp. 554–565, Apr. 1994.
- [6] L. Moreland, E. Schamiloglu, R. Lemke, A. Roitman, S. Korovin, and V. Rostov, "Enhanced frequency agility of high power relativistic backward wave oscillators," *IEEE Trans. Plasma Sci.*, vol. 24, pp. 852–858, Apr. 1996.
- [7] C. Abdallah, W. Yang, E. Schamiloglu, and L. Moreland, "A neural network model of the input/output characteristics of a high power backward-wave oscillator," *IEEE Trans. Plasma Sci.*, vol. 24, pp. 879–883, Mar. 1996.
- [8] R. Smith and A. Packard, "Optimal control of perturbed linear static systems," *IEEE Trans. Automat. Contr.*, vol. 41, pp. 579–584, Sept. 1996.
- [9] K. L. Moore, *Iterative Learning Control For Deterministic Systems*, 1st ed. Berlin, Germany: Springer-Verlag, 1992.
- [10] S. Arimoto, S. Kawamura, and F. Miyazaki, "Bettering operation of dynamic systems by learning: A new control theory for servomechanism or mechatronic systems," in *Proc. 23rd Conf. Decision Control*, vol. 2, Las Vegas, NV, Dec. 1984, pp. 1064–1069.
- [11] T. Sugie and T. Ono, "An iterative learning control law for dynamical systems," *Automatika*, vol. 27, no. 4, pp. 729–732, 1991.
- [12] S. Hara, Y. Yamamoto, T. Omata, and M. Nakano, "Repetitive control system: A new type servo system for periodic exogenous signals," *IEEE Trans. Automat. Contr.*, vol. 33, pp. 659–667, July 1988.
- [13] J. J. Craig, *Adaptive Control of Mechanical Manipulators*, 1st ed. Reading, MA: Addison-Wesley, 1988.
- [14] K. L. Moore, "Iterative learning control—an expository overview," *Appl. Computational Controls, Signal Processing, Circuits*, to be published.
- [15] E. Rogers and D. H. Owens, *Stability Analysis for Linear Repetitive Processes*, 1st ed. Berlin, Germany: Springer-Verlag, 1992.
- [16] T. Kailath, *Linear Systems*, 1st ed. Englewood Cliffs, NJ: Prentice-Hall, 1980.
- [17] T.-Y. Kuc, J. S. Lee, and K. Nam, "An iterative learning control theory for a class of nonlinear dynamical systems," *Automatika*, vol. 28, no. 6, pp. 1215–1221, 1992.
- [18] P. Bondi, G. Casalino, and L. Gambardella, "On the iterative learning control theory for robotic manipulators," *IEEE J. Robot. Automat.*, vol. 4, pp. 14–22, Feb. 1988.
- [19] T.-Y. Kuc, K. Nam, and J. S. Lee, "An iterative learning control of robot manipulators," *IEEE Trans. Robot. Automat.*, vol. 7, pp. 835–842, Dec. 1991.

- [20] M. Vidyasagar, *Nonlinear Systems Analysis*, 2nd ed. Englewood Cliffs, NJ: Prentice-Hall, 1993.
- [21] B. Goplen, L. Ludeking, D. Smithe, and G. Warren, "User-configurable magic for electromagnetic PIC calculations," *Comput. Phys. Commun.*, vol. 87, pp. 54–86, 1995.
- [22] P. Baldi, "Gradient descent learning algorithm overview: A general dynamical systems perspective," *IEEE Trans. Neural Networks*, vol. 6, pp. 182–195, Jan. 1995.
- [23] H. Demuth and M. Beale, *Neural Network Toolbox*. Natick, MA: Math Works, 1993.
- [24] H. Hong, "Parallelization of quantifier elimination on workstation network," Johannes Kepler Univ., RISC-Linz, Tech. Rep. 91-55.0, 1991.
- [25] C. Abdallah, W. Yang, E. Schamiloglu, and V. Souvalian, "On the control of a high power backward-wave oscillator using quantifier elimination methods," in *Proc. Amer. Control Conf.*, Albuquerque, NM, June 1997, pp. 3255–3256.



**Chaouki T. Abdallah** (S'81–M'83–SM'95) received the B.E. degree in electrical engineering from Youngstown State University, Youngstown, OH, in 1981, and the M.S. and the Ph.D. degrees in electrical engineering from the Georgia Institute of Technology, Atlanta, in 1982 and 1988, respectively.

From 1983 to 1985, he was with SAWTEK Inc., Orlando FL. He joined the Department of Electrical and Computer Engineering, University of New Mexico, Albuquerque, in 1988, and was promoted to Associate Professor in 1994. He co-edited *Robot Control: Dynamics, Motion Planning, and Analysis* (New York: IEEE Press, 1992), co-authored *Control of Robot Manipulators* (New York: Macmillan, 1993), and *Linear Quadratic Control: An Introduction* (Englewood Cliffs, NJ: Prentice-Hall, 1994). His research interests are in the areas of robust control, adaptive and nonlinear systems, and robotics.

Dr. Abdallah was exhibit chairman of the 1990 International Conference on Acoustics, Speech, and Signal Processing (ICASSP), and is currently serving as the local arrangements chairman for the 1997 American Control Conference.



**Vatche S. Souvalian** received the B.E. degree in electrical engineering from the American University of Beirut, Beirut, Lebanon, in 1995, and is currently working toward the M.S. degree in electrical engineering at the University of New Mexico, Albuquerque.

During the summer of 1994, he worked in the O.G.D. 545, on a shore gas development project in the United Arab Emirates. In 1996, he joined the Department of Electrical and Computer Engineering, University of New Mexico, Albuquerque. His

research interests are in the areas of iterative learning control and statistical signal processing.

**Edl Schamiloglu** (M'90–SM'95), for a photograph and biography, see this issue, p. 234.