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Published in:
2022 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM 2022

DOI:
10.1109/AIM52237.2022.9863398

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Document Version
Publisher's PDF, also known as Version of record

Publication date:
2022

Link to publication in University of Groningen/UMCG research database

Citation for published version (APA):

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Dynamic Modeling of P(VDF-TrFE-CTFE)-based Soft Actuators via Echo State Networks

Riccardo D’Anniballe1*, Niklas Erdmann1*, Giacomo Selleri2, and Raffaella Carloni1

Abstract—This paper proposes to use a reservoir computation approach to model the non-linear dynamic behaviour of a novel electroactive soft actuator. The soft actuator is fabricated as a unimorph cantilever beam, in which the active layer is a mat of electrospun aligned nanofibers of the P(VDF-TrFE-CTFE) electrostrictive polymer integrated into a PDMS silicone matrix. The passive layer consists of kapton, while the soft electrodes are made of conductive carbon powder. The non-linear dynamic response of three specimens of the soft actuator, when stimulated by both DC and complex electric fields of varying frequency, is modeled by means of an echo state network. The proposed architecture is able to achieve a normalized root mean square error of 0.429 for the tip deflections and of 0.265 for the blocking forces, when compared to experimental data.

I. INTRODUCTION

Electrostrictive soft actuators exhibit mechanical strain when stimulated by an external electric field. In the literature, their non-linear dynamic behavior has been mainly modeled either analytically [1], [2], [3] or with finite element methods [4], [5], [6], which, however, require extensive parameter sweep analysis and can only partially capture the complexity related to the visco-elastic properties of the used materials [7].

Data driven black-box models may be a more flexible tool compared to analytical models, as they can more easily account for the variations of the material properties and for the uncertainties due to the fabrication process. While analytical models require insight into the underlying multi-domain effects, data driven methods simply rely on experimental data collection. Additionally, data driven methods can be more efficiently used after the initial training, as executing the model does not involve a complete simulation but only an approximation of previously observed behaviour [8], [9], [10].

In this paper, we propose to use a reservoir computation approach and, specifically, Echo State Networks (ESNs) [11], to model the dynamical non-linear behaviour of a novel electroactive soft actuator. As an alternative to regular recurrent neural networks, ESNs feature a single, recurrent, untrained layer of neurons (i.e., the reservoir), which is interpreted by a subsequent layer of trained output weights (or neurons), as sketched in Figure 1. This leads to a low amount of neurons being trained overall and facilitates rapid training, while keeping the advantages of recurrent neural networks, such as, capability of maintaining a memory of effects over time [12], of approximating dynamical systems for modeling and control such as, e.g., pneumatic based soft actuators [13], [14], [15], [16]. According to the authors’ investigation, even though ESNs seem excellently suited to model electrostrictive soft actuators, they have not been yet utilized in that capacity.

This paper focuses on electroactive soft actuators, whose active layer is realized with nanofibers of P(VDF-TrFE-CTFE), i.e., poly(vinylidenefluoride-trifluoroethylene-chlorotrifluoroethylene) immersed in a silicone matrix. The actuators are electromechanically characterized to evaluate the tip deflection and blocking force when stimulated by different electric fields with varying frequency. The measurements are used to train the ESN, hence to build the non-linear data driven dynamic model of the actuators. To evaluate the model performances, the normalized root mean square error between the model result and experimental data is calculated.

The remainder of the paper is organized as follows. Section II presents the materials used in this study, the fabrication process and the experimental set-ups used for the electromechanical characterization. Section III describes the training data-set and the ESN model. The results are reported and discussed in Section IV. Finally, concluding remarks are drawn in Section V.

II. THE P(VDF-TrFE-CTFE)-BASED SOFT ACTUATORS

This Section describes the experimental process for the fabrication of the P(VDF-TrFE-CTFE)-based soft actuators and the experimental set-ups used for the electromechanical characterization.
The P(VDF-TrFE-CTFE) has been chosen as it is a relaxor ferroelectric polymer that shows a high electrostrictive strain when exposed to an external electric field [17]. The P(VDF-TrFE-CTFE)-based soft actuators are designed as asymmetric unimorph cantilever beams. The active layer consists of a mat of electrospun aligned nanofiber of P(VDF-TrFE-CTFE), integrated into a polydimethylsiloxane (PDMS) matrix. This active layer is interleaved between two flexible electrodes of PDMS and carbon powder and placed on a Kapton® tape.

A. P(VDF-TrFE-CTFE) Electrospun Aligned Nanofibers

The aligned nanofibers of P(VDF-TrFE-CTFE) have been realized by electrospinning technique [18]. For the fabrication, a solution of P(VDF-TrFE-CTFE) powder (30 wt %), provided by Solvay Specialty Polymers (Bollate, Italy) and Acetone:DMF 55:45 (w/w) was processed by an electrospinning machine (Spinbow™, Bologna, Italy, www.spinbow.it/en), equipped with four needles (length of 55 mm and internal diameter of 0.84 mm) connected to 5 mL syringes via PTFE tubings. The nanofibers have been collected on a rotating drum, covered with poly(ethylene)-coated paper.

A P(VDF-TrFE-CTFE) electrospun nanofiber mat is fabricated, with an average thickness of ~50 μm. From the mat, three specimens are obtained with dimensions of 70 mm length, 20 mm width, ~50 μm thickness, and ~25 mg weight.

Figure 2a displays an image of a portion of the mat, obtained with a Phenom ProX Desktop scanning electron microscope (SEM) (Thermo Fisher Scientific, Waltham (MA), USA, www.thermofisher.com), which shows the aligned nanofibers.

B. Nanofibers Integration in the PDMS Silicone Matrix

The specimens are integrated into a matrix of PDMS silicone elastomer (Sylgard™ 184, Silicone elastomer kit), with a ratio 10:1 of silicone and curing agent. After mixing, the solution is placed into a vacuum to remove air bubbles. The integration of the specimens is realized by depositing the PDMS on the nanofibers, which are placed on a teflon substrate. The excess of material on the nanofiber layer is removed by means of a blade. The overall composite material is then cured at 90°C for 1 h. Figure 2b shows a SEM cross section of the P(VDF-TrFE-CTFE) aligned nanofibers integrated in the PDMS matrix.

C. Soft Electrodes

To preserve the actuator flexibility, soft electrodes are realized by dispersing conductive carbon black nanoparticles with PDMS [19]. In particular, 17.5% wt of carbon nanoparticles (Super P, BET surface area of 62±5.0 m²/g, average particles size of 40 nm) are added to the PDMS. Then, the solution is prepared by adding 300% wt of isopropanol and by magnetically stirring for 1 h at room temperature. Next, the curing agent is added and, after mixing, the solution is placed into an oven at 40°C for 12 min to allow the isopropanol to evaporate. By using a blade, a homogeneous layer of 80 μm thickness is placed on the specimens and cured for 1 h at 90 °C. The same process is repeated for the opposite electrode.

D. Soft Actuator

The complete soft actuator is obtained by placing the fabricated structure, as explained above, on a layer of Kapton® tape that acts as a passive layer. Figure 3 shows the soft actuator, in both rest state (no electric field is applied) and bent state (an electric field is applied). Specifically, when an external electric field is applied across the P(VDF-TrFE-CTFE), a strain is produced in its longitudinal axis due to the synergistic effect of the Maxwell stress (i.e., the electrodes are attracted to each other and, as a consequence, the P(VDF-TrFE-CTFE) is mechanically compressed in the thickness direction and expands in the longitudinal directions) and of the electrostriction (i.e., the applied electric field induces a conformation change of the polymeric chains that may produce a large strain in thickness). The passive layer resists the deformation, resulting in the bending of the actuator.

Let $E$ be the electric field applied to the P(VDF-TrFE-CTFE), the total strain $S$ induced in the material is:

$$S = S_{\text{Maxwell}} + S_{\text{electrostriction}} = -\frac{1}{2} \epsilon_0 \epsilon_r \frac{E^2}{Y} + Q P^2 \quad (1)$$

where $Y$ is the P(VDF-TrFE-CTFE) Young's modulus, $\epsilon_r$ is the polymer dielectric constant, $\epsilon_0$ is the vacuum permittivity, $Q$ is the electrostrictive coefficient, and $P$ is the phase transformation-induced polarization.

Fig. 2: SEM images of the active layer of the soft actuators. (a) P(VDF-TrFE-CTFE) aligned nanofibers. (b) P(VDF-TrFE-CTFE) aligned nanofibers integrated in the PDMS matrix.

Fig. 3: (a) Top view of the soft actuator. (b) The soft actuator is at rest (no electric field). (c) The soft actuator bends when an electric field is applied.
E. Electromechanical characterization

Experimental data have been collected on three different specimens of the soft actuator.

1) Tip Deflection: A digital AM7915MZT(L) 5 MPx microscope (Dino-Lite, AnMo Electronics Corp, Taipei, Taiwan, www.dino-lite.com) is used to record, with a sample rate of 20 Hz, the deflection of the tip of the actuators when stimulated by DC and complex electric fields of varying frequency and magnitude. One extremity of the actuators is kept fixed by a support, designed and 3D printed in ABS material, while the other extremity is free to move. The deflection is recorded in a video with the DinoCapture software (version 2.0) which is, then, analyzed in Matlab (Mathworks, USA). To analyze the deflection of the actuators, a tracking algorithm, based on a previous one featuring a scale invariant feature transform (SIFT) [17] has been designed. SIFT identifies points of high gradient in an image and is able to accurately detect them across subsequent images. The retention of these key-points from one frame to the next is vulnerable to smears in the image caused by the exposure time of the microscope and fast dynamics of the actuators when stimulated by electric fields. Thus, the modified algorithm only considers the relative differences in grey values across two frames, approximating the position of the actuator by keeping track of relatively darker values in the image. Tracking of grey values is achieved via the following equations:

\[ Y = X_1 \cdot \text{greyDiff}(X_1, t) + X_2 \cdot \text{greyDiff}(X_2, t) \]

\[ \text{greyDiff}(X, t) = 1/(\text{abs}(X - t)^2) \]  

(2)

where \( X \) is a frame in the video input and \( Y \) is the combined output. If the threshold \( t \) is chosen based on the general average of grey values on the surface of the actuator, \( \text{greyDiff}() \) returns a weight computed from the absolute difference in pixel value between \( t \) and every pixel in a frame \( X \). This difference is then used to compute a weighted sum of the last and the current frame \((X_1 \text{ and } X_2)\), highlighting all points above a certain grey value in a point cloud. Subsequently, the actuator position is approximated by fitting a linear regression to the index values of the point cloud. Subsequently, the regression line is utilized as an approximation of the current actuator movement, in which a change of position is inferred by knowing the actuator’s length in the image and by tracking the angular rotation of the regression line from one frame to the next. This process, of tracking the change in angle between different regression lines, is illustrated in Figure 4.

2) Blocking Force: The test set-up consists of the test instrument ElectroPuls E1000 (Instron™, Norwood (MA), USA, www.instron.us), equipped with the 5 N Instron™ static load cell 2530-5N and an optical encoder. A 10/10B-HS high-voltage amplifier (Trek Inc., Lockport, New York, USA, www.trekinc.com) is connected through crocodile plugs to the electrodes of the soft actuator and is operated through the DG1022 waveform generator (RIGOL Technologies, Beaverton, Oregon, USA, www.rigolna.com). The Instron™ Wave matrix software records both the forces measured by the load cell and the applied electric fields with a sample rate of 50 Hz. In the test instrument, the soft actuators are held at one extremity by a support, designed and 3D printed in ABS material, while the other extremity is in contact with the load cell that can register the exerted force.

III. DATA-DRIVEN MODEL

This Section presents the ESN model, describing the behaviour of the P(VDF-TrFE-CTFE)-based soft actuator.

A. Echo State Network

ESNs are designed to match their output \( y(n) \) to a target output \( y_{\text{target}}(n) \), where \( n = 1, \ldots, N \) represents discrete time-steps, with \( N \) being the total number of data-points. The model is trained on a set \( D = [u(n), y(n)] \) that consists of pairs of inputs \( u(n) \) and outputs \( y(n) \). The training is achieved by minimizing the error between \( y(n) \) and \( y_{\text{target}}(n) \).

Structure-wise, an ESN features an input layer, an output layer, and the reservoir in between, as shown in Figure 1. There, \( W \) represent the weights respective to each layer and \( x(n) \) is the activation of the reservoir at the current time step. Only the output weights are optimized during training, the weights of the other two layers are randomly drawn from a Gaussian distribution.

The output \( y(n) \) of the network is determined via the internal network activation \( x(n) \), the original input \( u(n) \) and a bias value multiplied with the output weights \( W_{\text{out}} \), i.e.:

\[ y(n) = W_{\text{out}}(t)[1; u(n); x(n)] \]  

(3)

The internal activation of the network is computed as a combination of the current input \( u(n) \) and the previous activation of the reservoir and their respective weights \( W_{\text{in}} \) and \( W \), i.e.: \( x(n) = (1 - \alpha) x(n - 1) + \alpha \cdot \tanh(W_{\text{in}}(u(n)) + W x(n - 1)) \)  

(4)

in which the \( \tanh \) function is the commonly used sigmoid activation function for ESNs [20]. Hereby, \( \alpha \) determines the leakiness of the reservoir neurons, which is an extension to the original ESNs [21].

In order to optimize \( W_{\text{out}} \) as output weights, usually a ridge regression is utilized, as it features a build-in regularization parameter \( \beta \), controlling for overfitting. The regression is
applied utilizing a list of all current activations in response to the input $X$ and their respective target values $Y$, i.e.:

$$W_{out} = Y^{target}X^T(XX^T + \beta I)^{-1}$$

(5)

where $I$ is the identity matrix.

As the goal of the ESN is to model the actuator’s behaviour based on the measured electric field applied to it, $u(n)$ is the applied electric field, while $y(n)$ represents either the tip deflection or the blocking force data. The current time step in the input was used to model the same step in the output, as there was no practical need to predict future behaviour.

As with other machine learning approaches, ESN features a number of hyper-parameters to be optimized. In this case, reservoir size, spectral radius, input scale, leakiness $\alpha$, and regularization $\beta$ are manually optimized. Each hyper-parameter has a different effect on overall model properties, thus have to be adjusted according to the given data-set. Hereby, reservoir size is a driving force for model complexity; more neurons in the reservoir are able to extrapolate more of the information underlying the observed data. Higher reservoir sizes may result in overfitting, but may be mitigated by various regularization methods. The spectral radius is utilized to scale the highest eigenvalue of the reservoir which in turn affects the amount chaos displayed by the system. Higher chaos can result in the loss of the ability to approximate dynamical systems, i.e., the Echo State property, due to stronger internal reservoir activation overshadowing the input. There is some controversy in the literature whether a spectral radius of above one will always result in the loss of the Echo State property, however this is reportedly not the case if the input remains unequal to zero [20]. Next, Input Scale concerns the scaling of each column of the input weights, which can either be optimized separately, or holistically, to minimize on parameters. Generally, Input scaling will influence the linearity of the network, as with lower values in the input, the $tanh$ activation function behaves more linearly, while in turn higher values will result in binary switching of values. The leakiness parameter $\alpha$ impacts the length of each time-step. The setting of this parameter is highly dependent on how fast effects develop in time, which can be subjectively different for different problems. Lastly, the training via ridge regression requires setting of the regularization term $\beta$, which penalizes large output weights and should make the network more able to generalize to new data. Noteworthy, testing for the optimal regularization parameter can be done with the test set only and does not require a repeat of the training as it does not influence the impact of other parameters. In addition to the usage of the electric field as input towards predicting the behaviour of the network, a second variable is used to differentiate between actuator samples. Thereby, actuators are characterized as a constant value by means of their average behaviour (maximal average tip deflection / blocking force) at a defined electric field value. In supplying these bonus information, the network receives a coding variable based on further information about the system, in which values of the variable convey the behaviour of each actuator sample relative to the others.

### B. Data-set

To facilitate later training of the ESN model, several different functions were used as input for the voltage amplifier. The more complex and non-cyclic the function, the more information can be drawn from it by a model approximating the underlying reactive behaviour of the actuators. Internal functions of the waveform generator are used for this purpose, i.e., square functions of different magnitudes, a voice function emulating a human voice pattern, and a quake function. Voice and quake are selected for their widely distributed frequency range which could provide many information on the actuators behaviour to the network. As the measurement equipment features defined sample rates, the frequency ranges need adjustment such that accurate sampling of the actuator behaviour is guaranteed based on the Nyquist rate [22]. Electrowstrictive actuators work typically as high pass filters [17]. Therefore, to control the frequency distribution into a defined range, a band pass filter is implemented between waveform generator and voltage amplifier. Furthermore, the waveform generator allows manipulation of amplitude and period of the given signals which is utilized to further manipulate the input frequency spectrum and the strength of the signal.

In terms of signal length, as a result of this frequency manipulation, voice signals are set to 800 s, quake to 400 s and the square functions to 60 s. The square functions are repeated for 16 different electric field magnitudes, while quake and voice functions are repeated both 3 times. This sample rate resulted in 256000 (3.55 h) and 763900 (4.24 h) raw data points for deflection and blocking force respectively. Before the data is utilized to train and test the ESN model, it is preprocessed in order to contain noise and/or measurement inaccuracies introduced by the methods of observing actuator behaviour. Specifically, all variables are normalized as this makes value distributions more comparable between independent settings. Further, the variables in the blocking force observations are first centered, then detrended, utilizing a linear regression. Noteworthy here is that only samples including voice and quake input functions are detrended, as the linear regression detrend does not translate towards the square functions and is strictly not necessary either. This extra centering and detrending is needed to account for natural shifts in calibration of the load cell. After actual normalization, both force and tip deflection data are subsequently smoothed with a sliding window average filter of size 3 which is utilized to combat noise.

### C. Model Performance

The performance of the network is assessed with the difference between predicted values $Y_i$ and the target values $Y^{target}_i$ which were observed experimentally (training error). In addition to these, network weights are then applied on observations not included in training, yielding a set of differences which is used to assess validity based on unseen data (testing error).
The two sets of differences are summarized in the normalized root mean squared error (NRMSE), i.e.:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( Y_i - Y_i^{target} \right)^2}, \quad NRMSE = \frac{RMSE}{\sigma^{Y_{target}}}$$  \hspace{1cm} (6)

To calculate the NRMSE score, the root of the squared average of the differences between each prediction $Y_i$ and respective target $Y_i^{target}$ are divided by the average standard deviation of the target variable $\sigma^{Y_{target}}$.

This permits understanding of the accuracy of the algorithm without being forced to take the underlying properties of the data into account. An acceptable model should show a NRMSE score between 0 and 1, meaning that the RMSE is smaller than the average standard deviation of the target.

**IV. RESULTS**

This Section reports the results of the electromechanical characterization, used for the training of the network, and the performance of the final model.

**A. Electromechanical Characterization**

Figures 5 and 6 show a representative examples of the data collected during the electromechanical characterization and, specifically, the tip deflection and the blocking force of the actuators when stimulated by electric fields of varying frequencies. It can be noted that the actuators tip deflection and blocking force are not influenced by the polarity of the applied field, respecting the quadratic relationship in Equation 1. The force and the tip deflection follows the electric field inputs, but the response of the actuator is significant only when the electric field reaches at least a magnitude of $\sim 10$ MV/m.

The Fast Fourier Transform (FFT) amplitude in the frequency domain, in the case of the blocking force, is analyzed and plotted in Figure 7. The plot shows amplitude peaks widely distributed between 0 and 10 Hz for voice and quake inputs, as expected from the manipulation of the frequency distribution of the input electric fields.

The training of the neural network is done on the experimental data collected during the electromechanical characterization from all the realized actuators.

**B. ESN Model**

To optimize the ESN, the data-set is first split up with a balanced amount of the three different input functions into a training and testing set. A $k$-fold cross-validation, with $k = 5$, is then applied on the training set to manually adjust hyper-parameters. Thereby, the data is split into four random disjoint sets corresponding to the same amount of input functions. Three of these sets are used to train a model and the fourth one is used to validate its performance. This is repeated four times with all different configurations of training and validation sets. The average validation error is then examined to determine the best hyper-parameter configuration for the model. To reach the most optimal configuration, the model is tested with a range of different hyper-parameters. These are repeatedly and individually optimized, as hyper-parameters could mediate the effectiveness of other hyper-parameters. Further, reservoir activation patterns and the mean absolute output weights are monitored, as weak or inconsistent activation and extreme output weights may indicate problems in the optimization of the network (pointing out a need to further modify hyper-parameters). After the optimization of the model via cross-validation, the optimized model is trained on the whole training set and tested on the testing set, acting as last test towards good generalizability of the model configuration. Finally, plots featuring target and predicted values of the test set are examined for good fit in terms of overall model performance.

The training and testing error of the finalized and optimized models are reported in Table I, while the optimized hyper-parameters in Table II. Some examples of the test plots for the three different soft actuators are shown in Figure 8.

Notably, the network can easily follow the dynamic behaviour of even the more complex input functions voice and quake. The model displays barely any noise compared to the target because these predicted values are generated based on...
electric field measurements, containing less noise. On the other side, voice and quake predictions in the deflection model seem to exhibit overall lower displacement than the target. This may be related to the video tracking script overestimating real movement when they are fast and with a sudden onset. Alternatively, the lower sample rate of the microscope might result in aliasing effects, which may result in less consistent measurements in high frequency settings.

TABLE I: Final NRMSE (RMSE) for each experimental setting.

<table>
<thead>
<tr>
<th>Error type</th>
<th>Tip Deflection</th>
<th>Blocking Force</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training error</td>
<td>0.244 (0.059 mm)</td>
<td>0.256 (0.018 mN)</td>
</tr>
<tr>
<td>Testing error</td>
<td>0.429 (0.104 mm)</td>
<td>0.265 (0.019 mN)</td>
</tr>
</tbody>
</table>

TABLE II: Optimized hyper-parameter settings per each experimental setting.

<table>
<thead>
<tr>
<th>Hyper-Parameter</th>
<th>Tip Deflection</th>
<th>Blocking Force</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reservoir size</td>
<td>100</td>
<td>500</td>
</tr>
<tr>
<td>Input scaling</td>
<td>0.5</td>
<td>1.0</td>
</tr>
<tr>
<td>Spectral radius</td>
<td>0.9</td>
<td>0.6</td>
</tr>
<tr>
<td>Leakiness</td>
<td>0.1</td>
<td>0.3</td>
</tr>
<tr>
<td>Regularization</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

V. CONCLUSION

The paper proposes to use an echo state network to model the behaviour of an electrostrictive soft actuator made of electrospun nanofibers of P(VDF-TrFE-CTFE) integrated into a PDMS silicone matrix. The soft electrodes are realized with a mixture of PDMS and conductive carbon powder, to preserve the actuator flexibility. A cantilever beam actuator is realized placing the composite material on a Kapton tape. Following the same fabrication steps, three soft actuators are realized and electromechanically characterized to evaluate the tip deflection and the blocking force, when stimulated by electric fields of varying frequency and magnitude. The inputs are characterized by a widely distributed frequency range, translating to more abrupt changes in distribution, providing a maximum amount of information on the actuators’ behaviour. The experimental data are used to train the echo state network, modeling the dynamic non-linear behaviour of the actuators. To assess the results, the model is applied on the random half of the data, not used for the training of the network (test data). The resulting performances are evaluated with the normalized root mean square error. The test normalized root mean square error is 0.429 and 0.265 for tip deflection and blocking force, respectively. The obtained results demonstrate the effectiveness of applying a reservoir computation approach for the modeling of the non-linear dynamics of a novel soft actuator when stimulated by electric fields of varying frequency.

ACKNOWLEDGMENTS

The authors would like to thank Prof. Dr. Herbert Jaeger (Dept. of Artificial Intelligence, University of Groningen, The Netherlands) for the valuable advice in the optimization and training of the ESN model.

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Fig. 8: Tip deflection (top) and blocking force (bottom) model output (red) compared with the experimental results (blue) with different electric field inputs.

(a) Tip deflection with 17.50 MV/m square electric field input.
(b) Tip deflection with voice electric field input.
(c) Tip deflection with quake electric field input.
(d) Blocking force with 23.75 MV/m square electric field input.
(e) Blocking force with voice electric field input.
(f) Blocking force with quake electric field input.


