



DEVELOPMENT OF AN ANFIS–SQP-BASED ALGORITHM FOR OPTIMAL PARAMETER SELECTION AND CONTROL DECISIONS IN PULSED ELECTRIC TREATMENT OF PLANTS

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ABSTRACT

This study presents an integrated neuro-fuzzy modelling and constrained optimization approach for selecting technological parameters and forming control decisions in pulsed electric treatment of plants. The proposed procedure links an adaptive neuro-fuzzy inference system (ANFIS), used to approximate a nonlinear treatment-response relationship, with sequential quadratic programming (SQP), used to search for an admissible operating point. The source study considers 105 combinations of voltage, capacitor capacitance and treatment duration. A first-order Takagi–Sugeno ANFIS structure with three Gaussian membership functions per input and 27 fuzzy rules is described. The reported model-based optimization result is a voltage of 2528.7 V, capacitance of 517.54 pF and treatment duration of 0.1999 s, with a predicted treatment-response index of 71.3%. The corresponding ideal capacitor energy is approximately 1.655 mJ per pulse. The paper distinguishes calculated predictions from experimentally verified outcomes and identifies the need for independent model validation, a complete equipment-level power model and confirmation of the selected operating point. The contribution is an explicit decision-forming workflow integrating prediction, constrained search and validation rather than an experimentally confirmed optimum.

Keywords: Pulsed Electric Treatment; Plant Tissue; ANFIS; Sequential Quadratic Programming; Parameter Optimization; Decision-Support Algorithm

1 INTRODUCTION

Pulsed electric field treatment modifies electrical conditions in biological tissues and has been investigated in relation to membrane permeabilization and various processing objectives [1–4]. The response of a plant-treatment system depends on the combined action of electrical and temporal variables; increasing voltage alone does not establish a

generally optimal operating condition. When treatment efficacy and operating limits must be considered together, parameter selection is naturally framed as a constrained optimization problem.

Previous work addressed electroimpulse processing for plant health applications [5], simulation and parameter optimization [6], and data-driven neuro-fuzzy decision support [7,8]. Numerical optimization algorithms provide a framework for updating candidate solutions while respecting defined constraints [9]. Related investigations by the present author considered treatment-response modelling [10], plant protection methods [11,13], a pulse-field processing block scheme [12], pulse propagation in affected plant tissue [14], treatment effects [15], and fuzzy modelling [16]. These studies establish the basis for linking a predictive model with a formal decision-making procedure.

The objective of this study is to formulate and analyze an ANFIS–SQP algorithm that (i) estimates a treatment-response index from three controlled variables, (ii) searches for a candidate operating point within the investigated domain, (iii) checks energy feasibility at the single-pulse level, and (iv) specifies validation steps before the predicted point is accepted as a control decision. The central contribution is the integrated sequence of these operations.

2 MATERIALS AND METHODS

2.1 Experimental design and model variables

The source study reports 105 experimental parameter combinations, constituting a $7 \times 5 \times 3$ design [10]. The input vector contains applied voltage U , capacitor capacitance C and treatment duration τ . The reported response K_z is expressed as a percentage and is interpreted here as the treatment decontamination index. The experimental response-measurement protocol and independent repetitions are not documented in sufficient detail in the supplied paper to reproduce the dataset; consequently, no new measurement-level conclusions are inferred.

Table 1: Experimental factors and ranges reported in the source study

Variable	Symbol	Levels / investigated values
Voltage	U (V)	1000, 1500, 2000, 2500, 3000, 3500, 4000
Capacitance	C (pF)	200, 300, 470, 1000, 1470
Treatment duration	τ (s)	0.1, 0.2, 0.3

$$\mathbf{x} = [U, C, \tau]^T, \quad \hat{K}_z = \text{fANFIS}(U, C, \tau). \quad (1)$$

2.2 ANFIS approximation of treatment response

The model in the supplied article is specified as a Takagi–Sugeno ANFIS with three Gaussian membership functions for each of the three inputs, giving $3^3 = 27$ rules, and a reported 50 training epochs. For a first-order consequent, a generic rule r has a linear output in U , C and τ , whereas its firing strength is determined by the product of premise membership grades. The normalized weighted sum of these rule outputs defines the estimated response [7].

$$\hat{K}_z(\mathbf{x}) = \sum_r \bar{w}_r(\mathbf{x}) (a_r U + b_r C + c_r \tau + d_r), \quad r = 1, \dots, 27. \quad (2)$$

The initial paper states that fit quality was assessed using R^2 , root-mean-square error (RMSE), mean absolute error (MAE) and Pearson correlation. However, it does not supply a reproducible training/validation/test partition or separate held-out performance estimates. Accordingly, any exceptionally low reported errors are treated as source-reported fit statistics, not proof of generalization. With 105 design points and a comparatively flexible rule base, independent assessment is especially important.

2.3 Constrained parameter selection by SQP

The optimizer operates on the trained ANFIS response surface. The objective is to maximize the predicted decontamination index while maintaining the candidate within the admissible domain. SQP approximates the constrained nonlinear problem by a sequence of quadratic subproblems [9]. The reported study uses observed factor limits for screening candidate solutions.

$$\mathbf{x}^* = \arg \max_{\mathbf{x}} \hat{K}_z(\mathbf{x}), \quad \mathbf{x} \in \Omega. \quad (3)$$

$$\Omega = \{\mathbf{x} : 1000 \leq U \leq 4000 \text{ V}; 200 \leq C \leq 1470 \text{ pF}; 0.1 \leq \tau \leq 0.3 \text{ s}\}. \quad (4)$$

If a physical energy limit $E_{\max}$ is imposed, the additional admissibility condition is $E_{\text{imp}}(U,C) \leq E_{\max}$, where the ideal energy stored in a capacitor is

$$E_{\text{imp}} = \frac{1}{2} C U^2, \quad \text{with } C \text{ expressed in farads.} \quad (5)$$

Equation (5) characterizes theoretical energy per pulse only. It does not determine device input power or establish compliance with a rated power limit without pulse repetition information, conversion losses and auxiliary consumption. The present reconstruction therefore does not claim power feasibility from capacitor energy alone.

2.4 Decision-making algorithm

The algorithm proceeds through experimental data screening and normalization, ANFIS training, separate validation, definition of the objective and technical constraints, SQP search, admissibility testing and experimental confirmation. A decision is issued only after the proposed setting is verified against both modelling and physical requirements. Figure 1 depicts the logic of the proposed workflow in English.

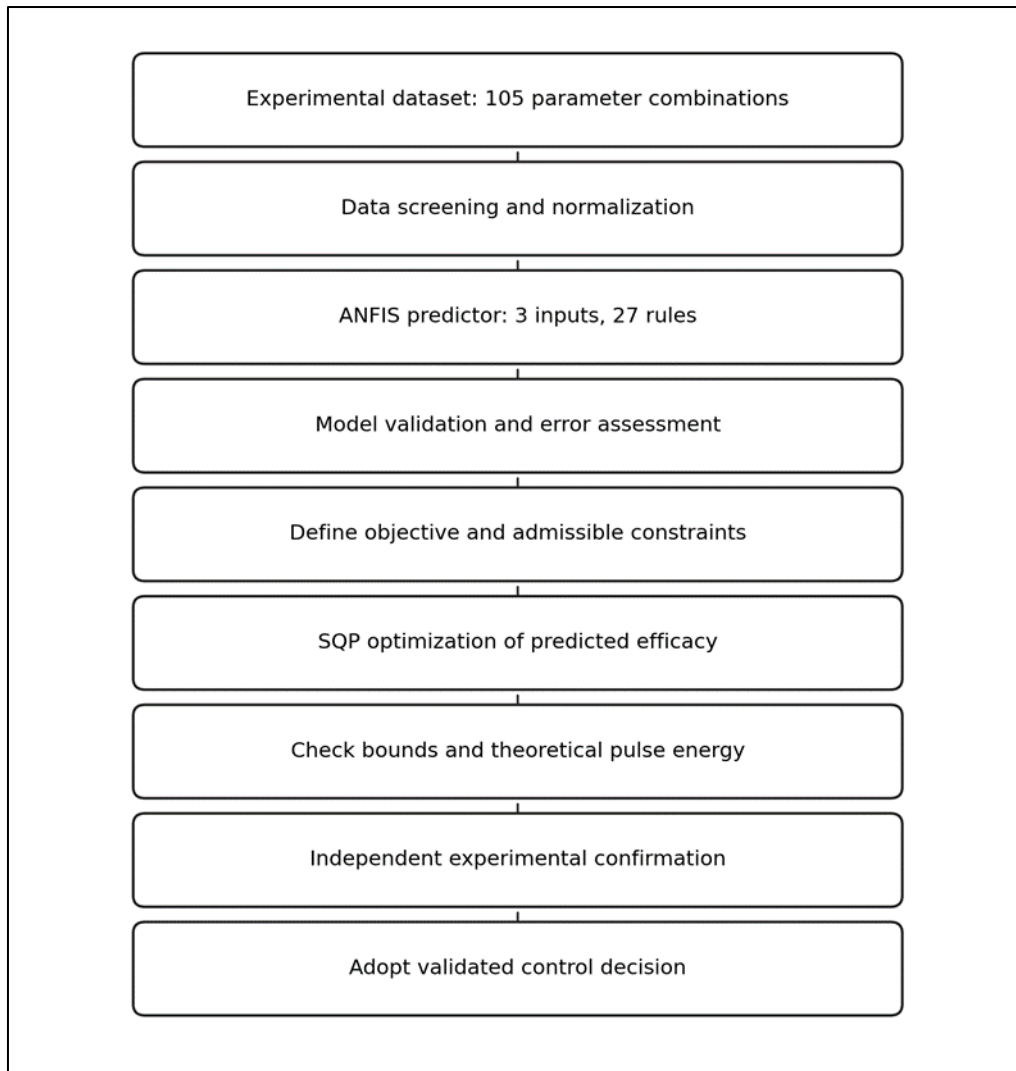


Figure 1: Proposed ANFIS–SQP algorithm for parameter selection and control decision-making.

3 RESULTS

The source article reports an initial predicted K_z of 35.2% and an SQP final predicted K_z of 71.3%, an improvement of 36.1 percentage points in the source calculation. Its selected candidate is $U = 2528.7$ V, $C = 517.54$ pF and $\tau = 0.1999$ s. These values are transferred from the supplied study and have not been recalculated here from raw measurements or trained ANFIS coefficients.

Table 2: Values reported by the source ANFIS–SQP calculation

Indicator	Initial/source baseline	Final predicted candidate
Treatment-response index Kz	35.2%	71.3%
Voltage U	Not specified	2528.7 V
Capacitance C	Not specified	517.54 pF
Duration τ	Not specified	0.1999 s
Ideal energy per pulse Eimp	Not specified	≈ 1.655 mJ

At the reported candidate point, Eq. (5) gives $0.5 \times 517.54 \times 10^{-12} \times (2528.7)^2 \text{ J} \approx 0.001655 \text{ J}$, or 1.655 mJ per pulse. The arithmetic confirms the cited ideal capacitor-energy value; it does not constitute evidence of experimentally achieved treatment efficacy. The original document also reports RMSE = 0.24873% and MAE = 0.1332%, but its incomplete partition reporting prevents attribution of these figures to held-out tests.

4 DISCUSSION

The proposed algorithm offers a structured alternative to choosing the pulse voltage, capacitance and treatment duration independently. ANFIS captures a data-dependent nonlinear mapping, whereas SQP searches the corresponding response surface for a constrained candidate. A significant methodological benefit is the explicit separation of three operations: prediction of expected treatment response, numerical selection of candidate variables and acceptance of a decision after verification.

Several qualification points are necessary. First, the 71.3% figure is a model-predicted optimization result, not an independently observed field outcome. Second, the 27-rule first-order ANFIS may have many adjustable coefficients relative to 105 combinations, so evaluation on an independent test set is required to assess possible overfitting. Third, a numerical optimizer can exploit local inaccuracies in a fitted response surface; consequently, the selected point requires a confirmatory experiment rather than being assumed optimal in physical operation.

Fourth, the duration τ is an experimental factor rather than a directly established pulse width or pulse repetition period. The energy of a single ideal capacitor discharge must not be conflated with average process power. Device-level assessment would require a justified model of pulse count or frequency, charge/discharge efficiency, auxiliary loads and duty cycle. Finally, the source does not specify the full biological protocol or measurement uncertainty needed for an independent efficacy comparison. These gaps define necessary validation work rather than additional results obtained in this paper.

5 CONCLUSION

An integrated ANFIS–SQP decision-making framework has been formulated for selecting three control variables in pulsed electric treatment of plants. Based on values reported in the underlying study, the proposed computational candidate is 2528.7 V, 517.54 pF and 0.1999 s, giving a predicted decontamination index of 71.3% and an ideal single-pulse capacitor energy of approximately 1.655 mJ. The contribution lies in linking a nonlinear predictor, constrained optimization, admissibility checks and experimental decision validation within a single reproducible conceptual workflow. Before practical deployment, the reported prediction and model errors must be tested independently, physical power constraints must be specified and the candidate operating point must be experimentally confirmed.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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