

Deep-learning-assisted design of a gray shark-inspired bionic triboelectric nanogenerator for water-flow energy harvesting

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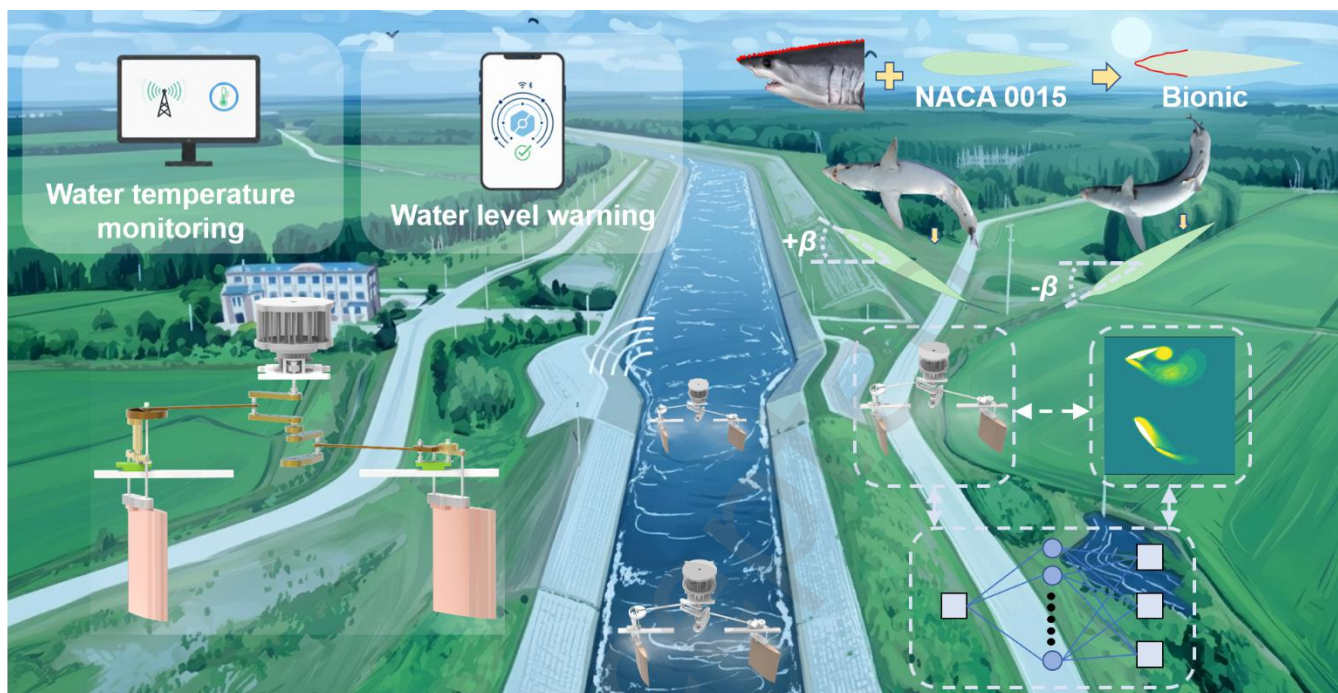
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ABSTRACT: Distributed hydrokinetic energy harvesting is essential for enabling sustainable self-powered sensing in aquatic environments. However, natural water flows are typically low-frequency, weak, and highly stochastic, which limits the efficiency of conventional energy harvesters. Here, a gray shark-inspired parallel flapping triboelectric nanogenerator (GS-TENG) is proposed for efficient hydrokinetic energy harvesting and environmental monitoring. A biomimetic flapping hydrofoil inspired by the streamlined morphology of the shark is developed and coupled with an energy storage–release mechanism to enhance energy capture under low-flow conditions. In addition, a deep-learning-assisted framework is employed to optimize key structural parameters of the flapping foil. The optimized biomimetic hydrofoil improves average power by 92.4% compared with the conventional NACA0015 airfoil. The energy storage–release mechanism converts irregular low-frequency flow excitation into stable rotational motion, resulting in a 71.7% enhancement in electrical output. The GS-TENG achieves a peak power of 46.65 mW and a power density of 29.32 W m⁻³. Laboratory and open-channel experiments demonstrate that the GS-TENG can continuously power water temperature and water level sensors, highlighting its potential for self-powered water-environment monitoring.

KEYWORDS: triboelectric nanogenerator, deep learning, bionic foil, hydrokinetic energy harvesting

1 Introduction

Distributed hydrokinetic energy harvesting plays a crucial role in enabling sustainable and autonomous power supplies for water-environment monitoring and Internet of Things (IoT) systems [1–3]. However, natural water flows are typically characterized by low frequency, weak driving forces, and strong stochasticity, which severely constrain efficient energy harvesting and stable electrical output [4–7]. First reported in 2012, the triboelectric nanogenerator (TENG) converts low-frequency and irregular mechanical energy into electricity via coupled triboelectrification and electrostatic induction [8–11]. Owing to its high energy conversion efficiency [12,13], lightweight structural design [14,15], and broad material versatility [16,17], TENG has attracted considerable attention in areas such as wave energy harvesting, hydrokinetic energy collection, and self-powered sensing. It is therefore widely regarded as a promising candidate for overcoming the technological bottlenecks in distributed water-energy harvesting systems [18–22].

Despite these advantages, TENGs still face significant challenges in practical water-environment applications [23,24]. Natural water flows are typically characterized by low velocities, weak excitation, and highly unsteady conditions, which severely limit the electrical output of conventional TENGs [25,26]. Moreover, the direct coupling between water flow and the generator exposes TENGs to environmental fluctuations, making their performance highly dependent on surrounding hydrodynamic conditions [27,28].

In recent years, bio-inspired designs have emerged as an effective strategy for enhancing hydrokinetic energy harvesting performance by mimicking the morphology and locomotion mechanisms of aquatic and flying organisms. Fish-inspired structures have attracted considerable attention due to their capability to efficiently extract kinetic energy from flowing water. For example, Jing et al. developed a three-dimensional enclosed fish-shaped triboelectric nanogenerator for hydrokinetic energy harvesting [29], while Zhang et al. proposed a soft-fin-assisted triboelectric–electromagnetic hybrid generator that

actively induced vortex formation to improve energy capture efficiency [30]. Inspired by the flapping motions of birds and insects, several studies have explored oscillating-wing energy harvesters for low-flow environments. Zhang et al. integrated a Savonius rotor with a flapping-wing mechanism to improve energy extraction performance [31]. Inspired by the phase-coordinated forewing-hindwing motion of dragonflies, Lu et al. developed a TENG/EMG hybrid generator with enhanced aerodynamic performance [32]. Beyond fish and flying organisms, other biological inspirations have also been investigated. Zhang et al. designed a flexible rolling triboelectric nanogenerator based on the rhythmic gill-cover motion of whale sharks [33]. Li et al. reported a shark dorsal-fin-inspired triboelectric-electromagnetic hybrid generator for river energy harvesting [34]. Telescopic bionic blades inspired by vulture wings were further employed to develop a multimode triboelectric-electromagnetic hybrid generator [35]. Wang et al. proposed a NACA0015-based bionic flapping TENG capable of simultaneously monitoring water level and flow velocity while harvesting hydrokinetic energy [36]. In addition, various biomimetic energy harvesting systems inspired by ducks, jellyfish, kelp, pythons, and sunflowers have been reported for wave and water-flow energy harvesting [37–43]. These studies demonstrate the significant potential of biomimetic strategies for improving energy capture efficiency and environmental adaptability. However, most existing bio-inspired TENGs mainly rely on empirical structural designs, and systematic optimization of biomimetic geometries and hydrodynamic performance remains limited. Therefore, developing intelligent design methodologies capable of simultaneously integrating biomimetic concepts and data-driven optimization is still highly desirable.

Based on the above considerations, a gray shark-inspired parallel flapping triboelectric nanogenerator (GS-TENG) is proposed for hydrokinetic energy harvesting and self-powered sensing. The device integrates a biomimetic flapping hydrofoil, derived from the morphology of a gray shark, with an energy storage–release mechanism. In addition, a deep-learning-assisted framework is introduced to optimize the biomimetic hydrofoil and the parallel activation configuration, enabling improved hydrodynamic performance and enhanced vortex regulation under low-flow conditions. Compared with the conventional NACA0015 airfoil, the optimized biomimetic foil achieves a 92.4% enhancement in average power. Meanwhile, the energy storage–release mechanism converts disordered flow excitation into intermittent yet stable rotational motion, resulting in a 71.7% improvement in electrical output. Specifically, the GS-TENG delivers a peak power of 46.65 mW and a peak power density of 29.32 W m⁻³. Laboratory experiments and field tests in a natural water channel demonstrate that the GS-TENG can continuously harvest hydrokinetic energy and power water temperature and water level sensors, highlighting its potential for self-powered water-environment monitoring. Overall, this work provides an effective strategy for harvesting energy from disordered water flows and offers a general framework for optimizing TENG-based hydrokinetic energy harvesters.

2 Results and Discussion

2.1 Design and working principle of the GS-TENG

Figure 1a illustrates the application concept of the GS-TENG in an open-channel water environment for water temperature and water level monitoring. The device is deployed in flowing water to directly harvest electrical energy from hydrokinetic flow. Monitoring water temperature and water level in channel environments is of critical importance for agricultural management, particularly in field or remote areas where conventional monitoring systems are difficult to sustain due to limited power supply and high deployment costs. The GS-TENG adopts a biomimetic structural design to enhance energy-harvesting performance and is further integrated with an energy storage–release mechanism to adapt to varying environmental conditions. As a result, the device is capable of delivering continuous and stable energy output under low-frequency and disordered water-flow conditions.

As shown in Figure 1b(i), the GS-TENG consists of a pair of biomimetic flapping mechanisms and an energy storage–release TENG unit (Figure 1b(ii)), in which the TENG operates in the independent-layer mode. A prototype of the GS-TENG is presented in Figure S1 in the ESM. Inspired by the head morphology of a gray shark and the conventional NACA0015 airfoil, a hybrid biomimetic flapping foil is designed by integrating a shark-inspired leading edge with the trailing-edge profile of the NACA0015 airfoil, forming a novel biomimetic hydrofoil configuration. Specifically, representative contour images of the shark head were collected from published biological studies and image databases, and the leading-edge profile was extracted through digital image processing and curve-fitting techniques. The extracted biological contour was subsequently transformed into an engineering leading-edge geometry through normalized geometric parameterization, allowing its integration into the hydrofoil design framework. Similar biomimetic approaches have been widely adopted in previous studies [25,27,44]. Subsequently, an adaptive pitching-angle mechanism is developed by mimicking the natural oscillatory motion of a shark tail (Figure 1c). Figure 1d illustrates the coupled kinematic behavior of the two flapping foils. A phase difference is introduced between them, allowing the rotational shaft to be alternately driven during operation. More detailed descriptions of the working principle and mechanical analysis of the GS-TENG are provided in Figure S2 in the ESM and the Supporting Notes.

The operation of the prototype can be divided into two operating stages: energy storage and energy release, as illustrated in Figure 1e. During the energy storage stage, the flapping foils undergo periodic reciprocating motion driven by hydrodynamic forces, while the spring is gradually compressed, leading to the accumulation of mechanical energy. In the energy release stage, once the spring deformation reaches a critical threshold, the stored elastic potential energy is rapidly released, driving the TENG rotor to accelerate instantaneously and achieve continuous rotational motion. This energy storage–release mechanism enhances the electrical output of the TENG by converting low-frequency and unstable water-flow excitations into intermittent yet stable rotational motion. As a result,

frequency up-conversion is achieved, significantly improving the overall energy-harvesting efficiency.

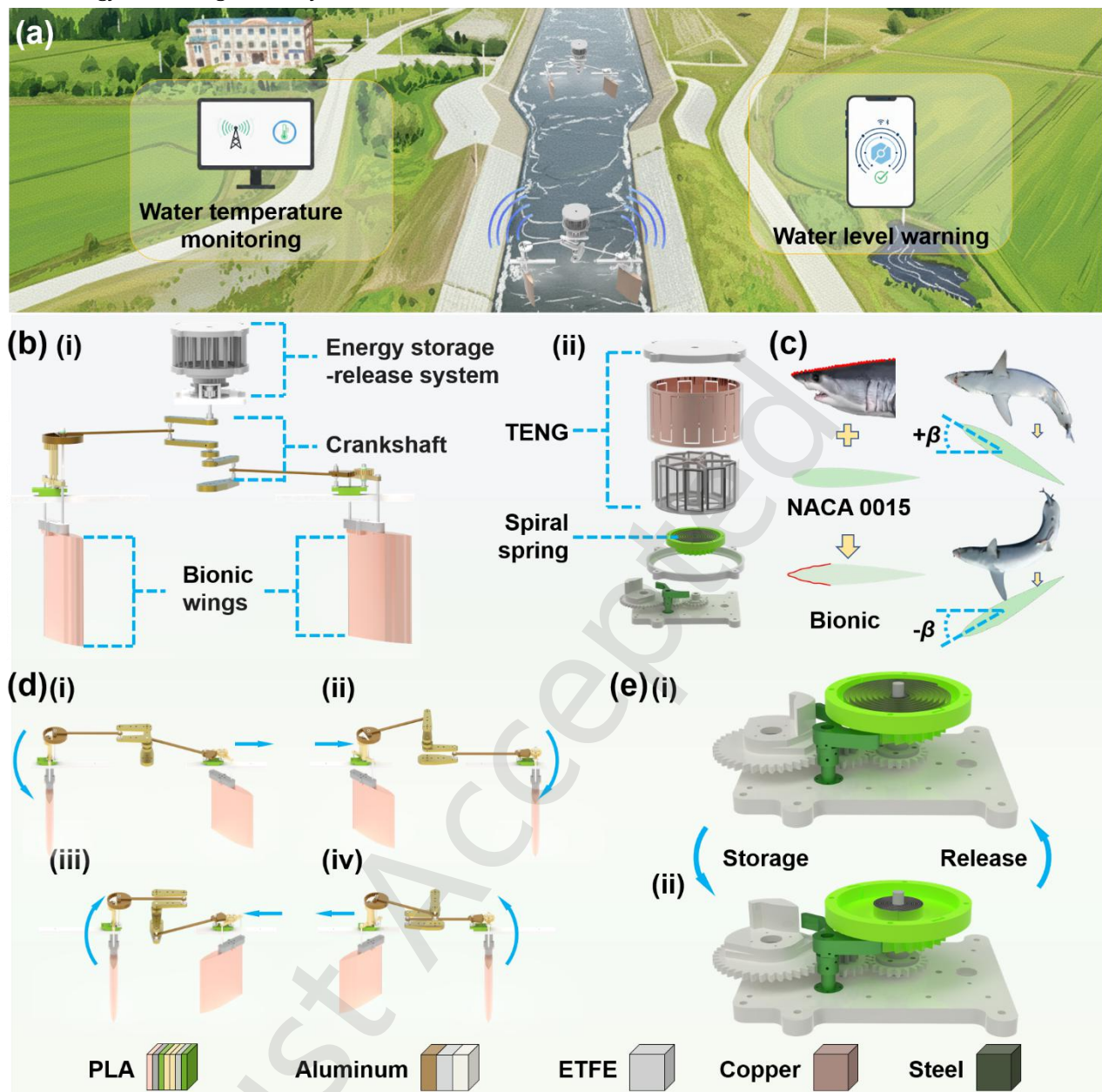


Fig. 1. Self-powered concept and working principle of the GS-TENG. a) Schematic illustration of the GS-TENG in operation. b) Biomimetic flapping foils and the energy storage-release system. c) Biological inspiration of the biomimetic hydrofoil. d) Working mechanism of the biomimetic flapping system.

2.2 Deep-learning-assisted structural optimization

To enhance the hydrodynamic performance of the biomimetic flapping foil, a deep-learning-assisted optimization framework is developed to extract latent features and establish the mapping between key structural parameters and performance metrics. Detailed information regarding the model architecture, parameter scale, training dataset size, and cross-validation performance is provided in the Supplementary Methods.

The overall workflow of the proposed framework is illustrated in Figure 2a, while the interaction between the deep learning model and the computational fluid dynamics (CFD) simulations is further described in Figure S3 in the ESM. First, a parametric model of the flapping foil is constructed, and a dataset of flapping configurations is generated by systematically varying key structural

parameters, including the pitching angle, phase difference, and pitching-axis location. Subsequently, CFD simulations are performed to evaluate the corresponding flow-field characteristics, such as average power, which serve as training data for the deep learning model. This workflow enables efficient exploration of the design space and significantly reduces the computational cost compared with conventional trial-and-error or exhaustive CFD-based optimization approaches.

The resulting data are organized into 100×3 matrices and fed into a deep learning model implemented in TensorFlow for training and prediction. The model learns the underlying input-output relationships and establishes an end-to-end mapping from structural parameters to hydrodynamic performance metrics.

The internal architecture of the Convolutional Neural

Network (CNN) model is illustrated in Figure 2b. The model begins with a one-dimensional convolutional (1D-CNN) layer to extract fundamental features from the input data, followed by a max-pooling layer for dimensionality reduction and feature compression. Subsequently, a second 1D convolutional layer is employed to further integrate and refine the extracted features, thereby enhancing the model's representational capacity. A global max-pooling layer is then introduced to perform structured dimensionality reduction while retaining the most salient features. Finally, a fully connected regression layer maps the learned feature representations to the output space corresponding to the average power metrics.

To evaluate the model performance, five baseline models are selected for comparison, including a multilayer perceptron (MLP), an autoencoder with a regression head (RegAE), a standard Transformer, a residual network (ResNet), and a graph neural network (GNN). The mean

squared error (MSE) is adopted as the loss function for training the CNN model. As shown in Figure 2c(i), all models converge within training epochs. Notably, the CNN achieves rapid convergence within the first 50 epochs and consistently attains the lowest average MSE in predicting hydrodynamic performance metrics, indicating superior learning efficiency and generalization capability. Figure 2d further presents the validation loss curves of the CNN model, which exhibit a high degree of overlap, suggesting minimal overfitting and strong model robustness.

In terms of quantitative prediction accuracy, the CNN model achieves a relative prediction error of 2.4% (Figure 2e), outperforming all five baseline models. Moreover, as illustrated in Figure 2f, the CNN exhibits a remarkably short inference time of only 0.594 s, demonstrating an excellent balance between predictive accuracy and computational efficiency.

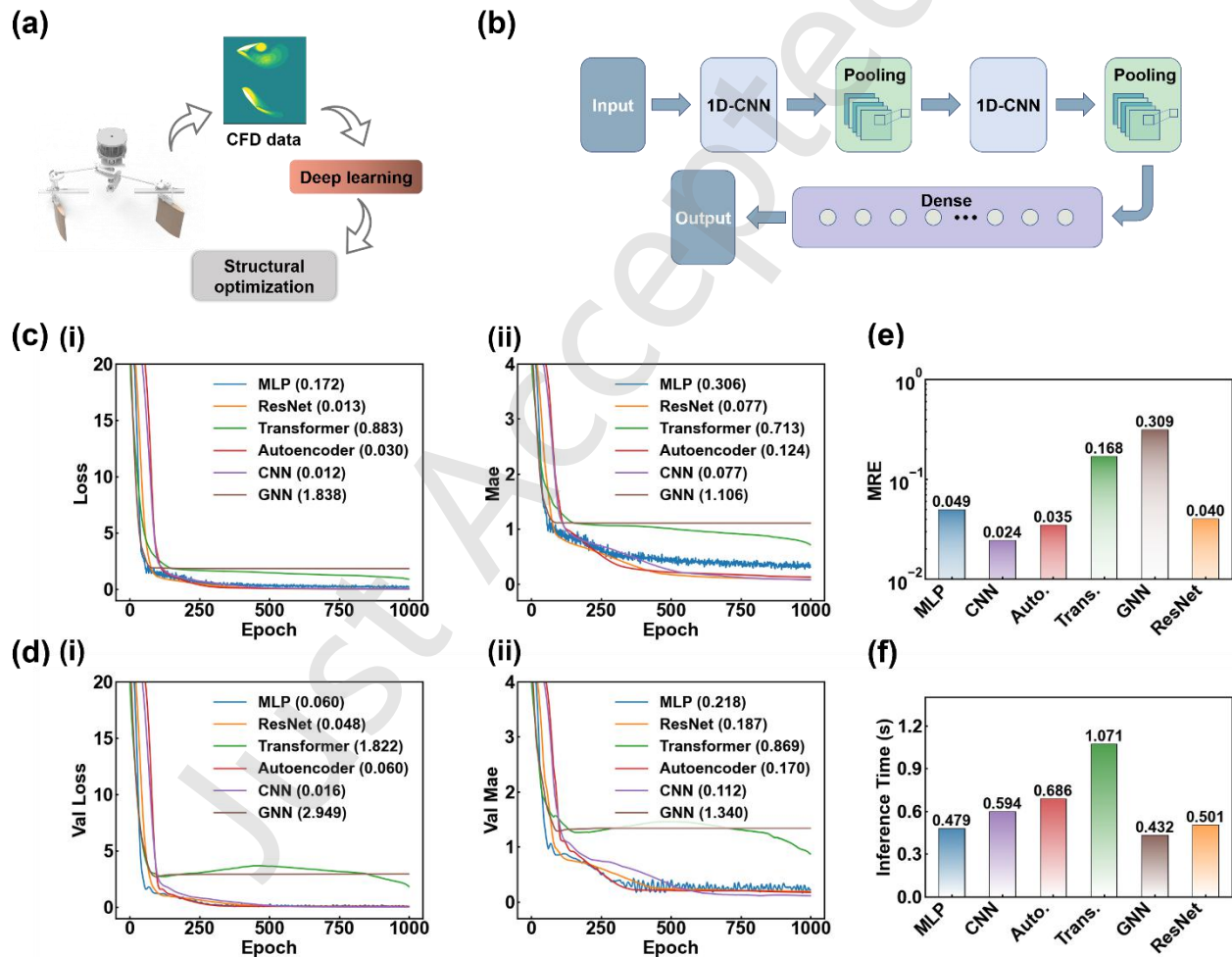


Fig. 2. Deep learning-assisted structural parameter optimization. a) Workflow from structural parameterization to performance optimization. b) Architecture of the CNN model, including 1D convolutional layers, max-pooling layers, global pooling layer, and fully connected layer. c) Loss and MAE curves during training. d) Loss and MAE curves of each model on the validation set. e) Relative prediction error of each model on the test set. f) Comparison of inference time among different models.

To further investigate the interpretability of the proposed CNN model, SHapley Additive exPlanations (SHAP) analysis was performed to quantify the contribution of each input parameter to the predicted average power. Figure S4 in the ESM presents the SHAP feature-importance rankings and dependence plots for the three governing parameters.

The SHAP importance results indicate that the pitching-

axis position is the most influential parameter affecting the system performance, followed by the pitching amplitude and phase difference. This finding highlights the dominant role of pitching-axis location in modulating the fluid-structure interaction and hydrodynamic energy extraction process.

The dependence plots further reveal the nonlinear relationships learned by the CNN model. Specifically, the

predicted performance increases monotonically with increasing pitching amplitude, indicating enhanced energy-harvesting capability under larger oscillation amplitudes. In contrast, the effect of pitching-axis position exhibits an initial enhancement followed by a saturation trend, suggesting that excessive downstream displacement yields diminishing performance improvement. Meanwhile, the phase difference demonstrates a non-monotonic behavior characterized by an increase followed by a decrease, implying the existence of an optimal phase synchronization condition for maximizing hydrodynamic coupling efficiency.

These physically consistent trends demonstrate that the CNN model successfully captures the underlying nonlinear dynamics of the system rather than merely performing numerical fitting.

To further evaluate the effectiveness of the proposed deep-learning-assisted optimization framework, its performance was compared with conventional response surface methodology (RSM). As shown in Tab. S1 in the ESM, the fourth-order response surface model achieved an average power output of 8.9635, whereas the deep learning model yielded a slightly higher value of 8.9751. Although both approaches successfully identified near-optimal solutions, the deep learning model demonstrated superior capability in capturing complex nonlinear interactions among the design variables, resulting in the best overall performance.

Overall, the CNN-based optimization framework effectively overcomes the limitations of empirical parameter tuning and significantly reduces the computational cost compared with conventional large-scale CFD-based exhaustive optimization. This approach provides a general and efficient strategy for the data-driven and intelligent structural design of TENG-based energy-harvesting systems.

2.3 Flow field mechanism analysis of the GS-TENG

CFD simulations are conducted to investigate the hydrodynamic mechanisms of the GS-TENG. The boundary conditions and mesh configurations used in the numerical simulations are provided in Figure S5 in the ESM. To accurately capture the rotational behavior of the GS-TENG, a fluid-structure interaction (FSI) model is implemented and validated, with the corresponding computational workflow illustrated in Figure S6 in the ESM.

Figure 3a compares the flow-field characteristics of three flapping foil configurations, namely the conventional NACA 0015 airfoil, the initial biomimetic flapping foil, and the optimized biomimetic flapping foil. The temporal evolution of the vorticity and pressure fields around the flapping foils is also presented. For the NACA 0015 airfoil, the leading-edge vortex (LEV) exhibits the weakest intensity, accompanied by a relatively small pressure difference between the upper and lower surfaces, resulting in a limited lift amplitude.

For the initial biomimetic flapping foil, the modified

leading-edge geometry promotes the formation of the LEV; however, its distribution remains relatively disordered and unstable. In contrast, the optimized biomimetic flapping foil generates a strong and coherent LEV at the leading edge, accompanied by a pronounced pressure differential across the foil surfaces. Specifically, the low-pressure region on the suction side is further intensified, while a high-pressure region accumulates on the pressure side, leading to a significant enhancement in instantaneous lift.

Figure 3a compares the flow-field characteristics of three flapping foil configurations: the conventional NACA 0015 airfoil, the initial biomimetic flapping foil, and the optimized biomimetic flapping foil. The temporal evolution of the vorticity and pressure fields around the foils is also presented. For the NACA 0015 airfoil, the leading-edge vortex exhibits the weakest intensity, accompanied by a relatively small pressure differential between the upper and lower surfaces, resulting in limited lift generation.

For the initial biomimetic flapping foil, the modified leading-edge geometry facilitates the formation of the LEV; however, its distribution remains relatively disordered and unstable, thereby limiting its contribution to lift enhancement. In contrast, the optimized biomimetic flapping foil generates a strong and coherent LEV at the leading edge, accompanied by a pronounced pressure differential across the foil surfaces. Specifically, the low-pressure region on the suction side is significantly intensified, while a high-pressure region develops on the pressure side, leading to a substantial increase in instantaneous lift. These results indicate that the optimized biomimetic design effectively enhances vortex coherence and strengthens pressure asymmetry, thereby significantly improving lift generation. Detailed flow-field evolution is presented in Video S1.

The temporal variations in lift coefficient and flapping velocity provide a quantitative characterization of the aforementioned flow-field phenomena, as shown in Figure 3b and c. Although a phase difference exists between the upper and lower foils in the parallel flapping configuration, their overall hydrodynamic responses remain similar.

As shown in Figure 3b, the three airfoil configurations exhibit comparable peak lift coefficients, indicating that the differences in instantaneous lift generation are relatively limited. In contrast, Figure 3c reveals a pronounced increase in flapping velocity for the optimized biomimetic foil compared with both the conventional NACA 0015 airfoil and the initial biomimetic design. This improvement can be attributed to the optimized structural parameters, which enhance the efficiency of hydrodynamic force transmission during the flapping motion. Consequently, the optimized flapping foil demonstrates a higher lift amplitude and increased flow-induced velocity. These results indicate that the optimized biomimetic design can extract greater hydrodynamic energy from the incoming flow while providing stronger mechanical excitation for the subsequent energy conversion process of the TENG.

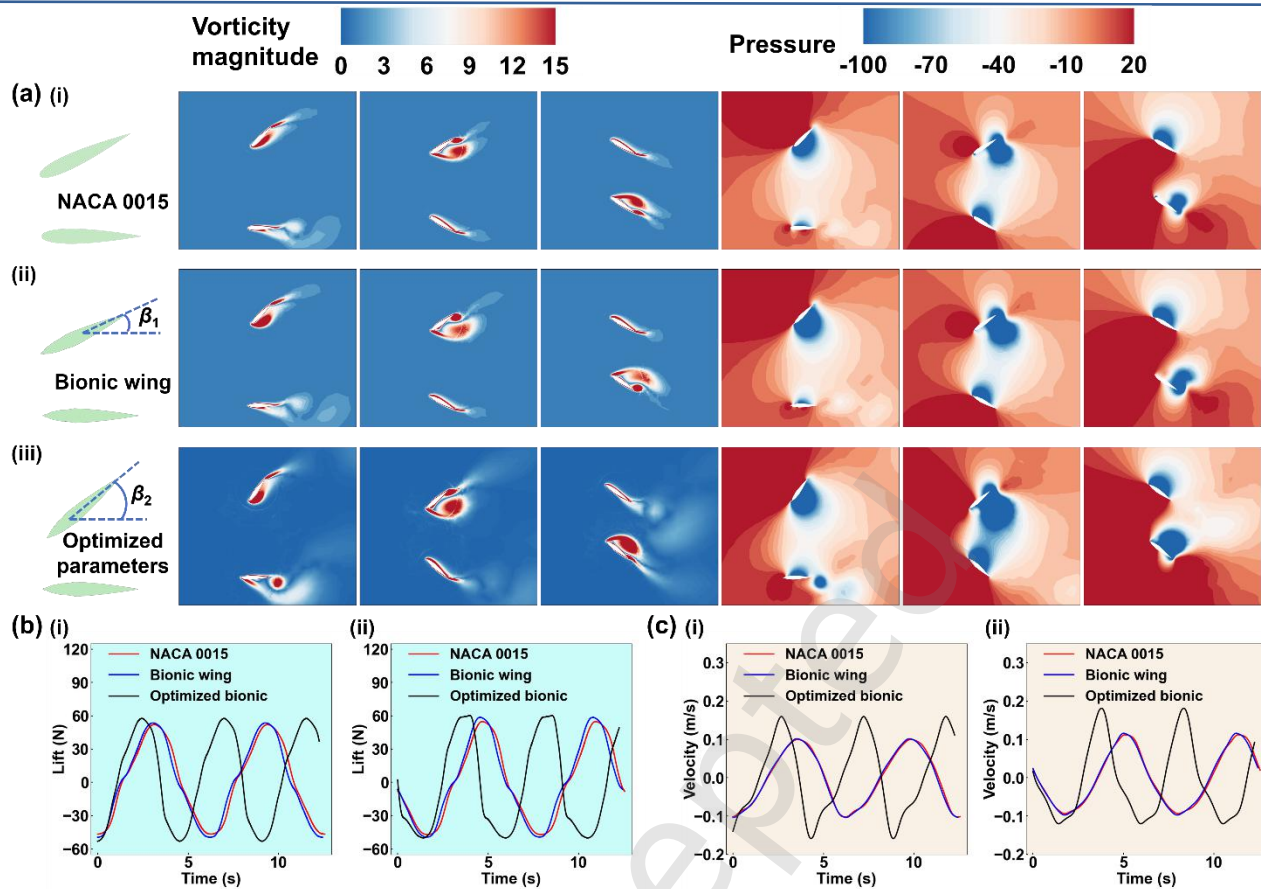


Fig. 3. CFD simulation results of the flapping foils. a) Contour plots of the flow field: (i) original NACA 0015 airfoil, (ii) biomimetic airfoil, and (iii) optimized biomimetic airfoil. b) Time-dependent lift coefficients of the three flapping foils. c) Flapping velocities of the three configurations.

2.4 Parameter optimization of the TENG unit

The selection of triboelectric materials with opposite polarities plays a critical role in determining the electrical output performance of the TENG. Figure 4a compares the output characteristics of FEP, PTFE, and ETFE over a range of rotational speeds. The results indicate that at relatively low rotational speeds, FEP and ETFE exhibit comparable performance. However, as the rotational speed increases, ETFE delivers superior output voltage and current compared with both FEP and PTFE. This improvement can be attributed to the stronger triboelectric polarity generated at the ETFE-electrode interface, which enhances the electrostatic induction process during rotation.

In addition, the length of the dielectric film is a key factor influencing the output performance of the TENG. Figure 4b presents the energy output of TENG devices with different film lengths (45 mm, 55 mm, and 65 mm) under varying rotational speeds. At low rotational speeds, the differences in output voltage and current among the three configurations are minimal. As the rotational speed increases, the TENG with a film length of 65 mm exhibits a pronounced enhancement in output performance. This behavior arises because the increasing rotational speed generates stronger centrifugal forces, which promote progressive coverage of the copper electrode surface by the dielectric film and thereby enlarge the effective contact area. However, when the rotational speed exceeds 130 rpm, the output voltage

and current of the 65 mm configuration approach saturation. At this stage, the dielectric film already fully covers the electrode surface, and further increases in rotational speed no longer significantly enlarge the effective contact area. As a result, the output voltage and current tend to stabilize. The output current shown in Figure 4b(ii) follows a similar trend. Detailed data are provided in Figure S7 in the ESM.

Figure 4c illustrates the output performance of the TENG with three different dielectric film thicknesses (0.05 mm, 0.15 mm, and 0.25 mm) under varying rotational speeds. The results reveal a non-monotonic dependence of the TENG output on film thickness, with performance initially increasing and then decreasing as the thickness increases. Specifically, the TENG with a film thickness of 0.05 mm exhibits relatively superior performance at low rotational speeds. However, as the rotational speed increases, the output improvement becomes gradual. This phenomenon is mainly attributed to the relatively low rigidity of the thin dielectric film. Under high rotational speeds, the film tends to undergo deformation, resulting in unstable contact with the positive electrode and fluctuations in the effective contact area. In contrast, thicker films possess higher rigidity but maintain a relatively small and less adaptable contact area with the electrode surface, which also limits the output performance. Consequently, the intermediate thickness of 0.15 mm provides a better balance between flexibility and structural stability, enabling a nearly linear increase in output voltage and current with increasing rotational speed.

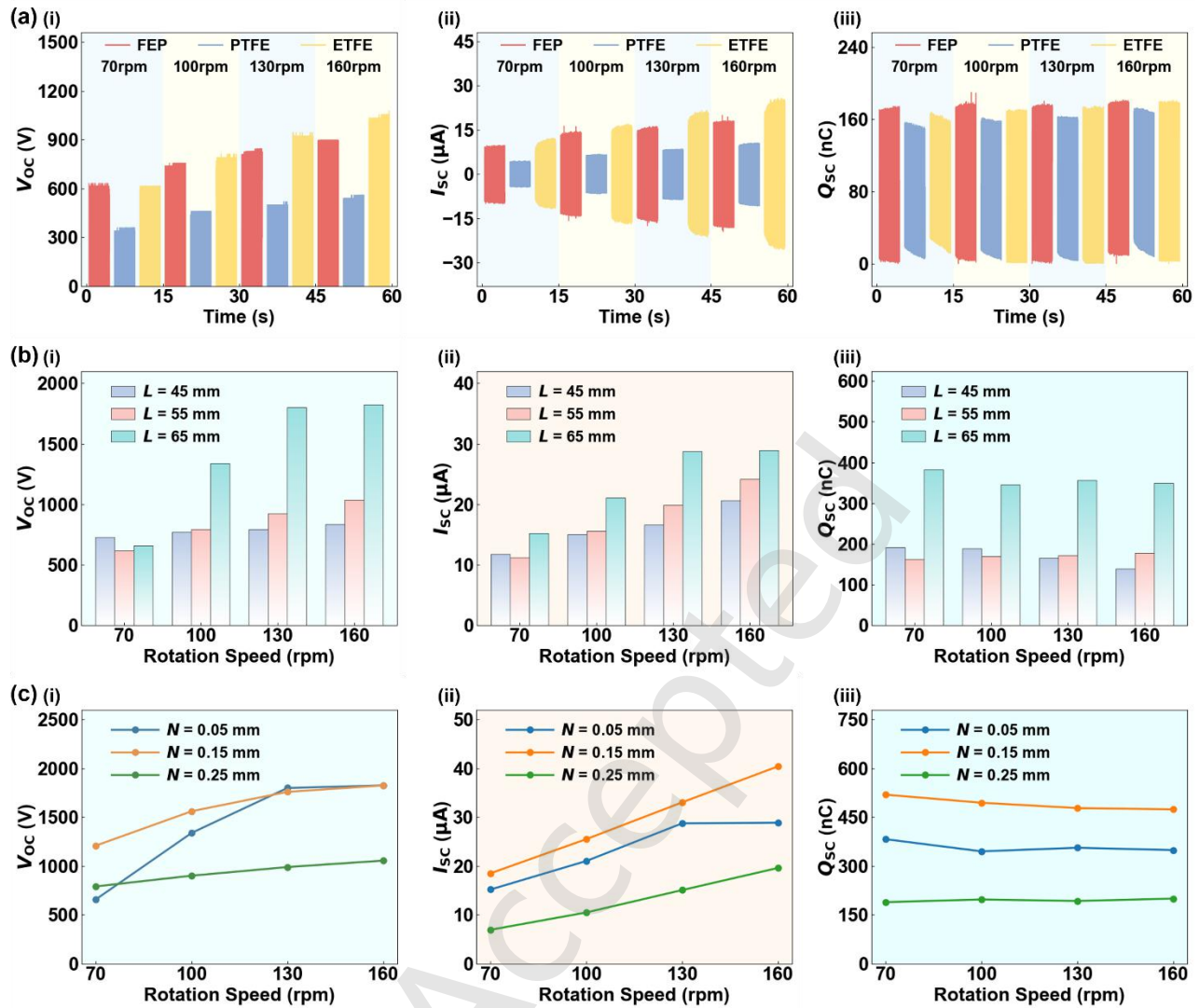


Fig. 4. Output performance of the TENG. a) Power output of the TENG with different triboelectric materials. b) Power output of the TENG with different film lengths. c) Power output of the TENG with different film thicknesses.

2.5 Application of the GS-TENG

Figure 5a presents the application workflow of the GS-TENG. Irregular water flow in the environment is first harvested by the GS-TENG and subsequently converted into usable electrical energy through a power management circuit, as illustrated in Figure S8 in the ESM. The durability performance of the TENG unit is shown in Figure S9 in the ESM, where the device retains 85.59% of its initial output after approximately 10 h of continuous operation at 130 rpm, demonstrating good operational stability.

The working mechanism of the energy storage-release system is depicted in Figure 5b(i), where a pawl-ratchet mechanism enables periodic switching between the energy storage and release modes. As shown in Figure 5b(ii), the incorporation of this mechanism significantly enhances the capacitor charging rate, achieving an improvement of 71.7%.

Figure 5c illustrates the output power as a function of external load resistance. According to $P=I^2R$, the TENG reaches a peak power of 46.65 mW and a maximum power density of 29.32 W m^{-3} at an optimal load resistance of 100 M Ω . The capacitor charging performance of the GS-TENG is shown in Figure 5d(i), where a 2200 μF capacitor is charged

to 3 V after 22 energy storage-release cycles via the power management circuit. Furthermore, Figure 5d(ii) compares the peak power density of the GS-TENG with those reported in previous studies, demonstrating its superior performance relative to existing energy-harvesting devices.

To further validate its practical applicability, application-level demonstrations are conducted. As shown in Figure 5e, the GS-TENG is capable of charging a 2200 μF capacitor to 3 V within 1080 s, thereby powering a water temperature sensor. As demonstrated in Video S2, this result highlights its potential for applications in agricultural production and ecological monitoring.

Finally, utilizing natural water flow in an outdoor open-channel environment, the GS-TENG successfully powers a wireless water level sensor, enabling real-time water level warning, as shown in Figure 5f and Video S3. These results demonstrate that the GS-TENG can effectively harvest hydrokinetic energy to power small-scale Internet of Things devices, thereby enabling self-powered water-environment monitoring. This approach eliminates the need for transmission lines and disposable batteries, significantly reducing system complexity and operational costs.

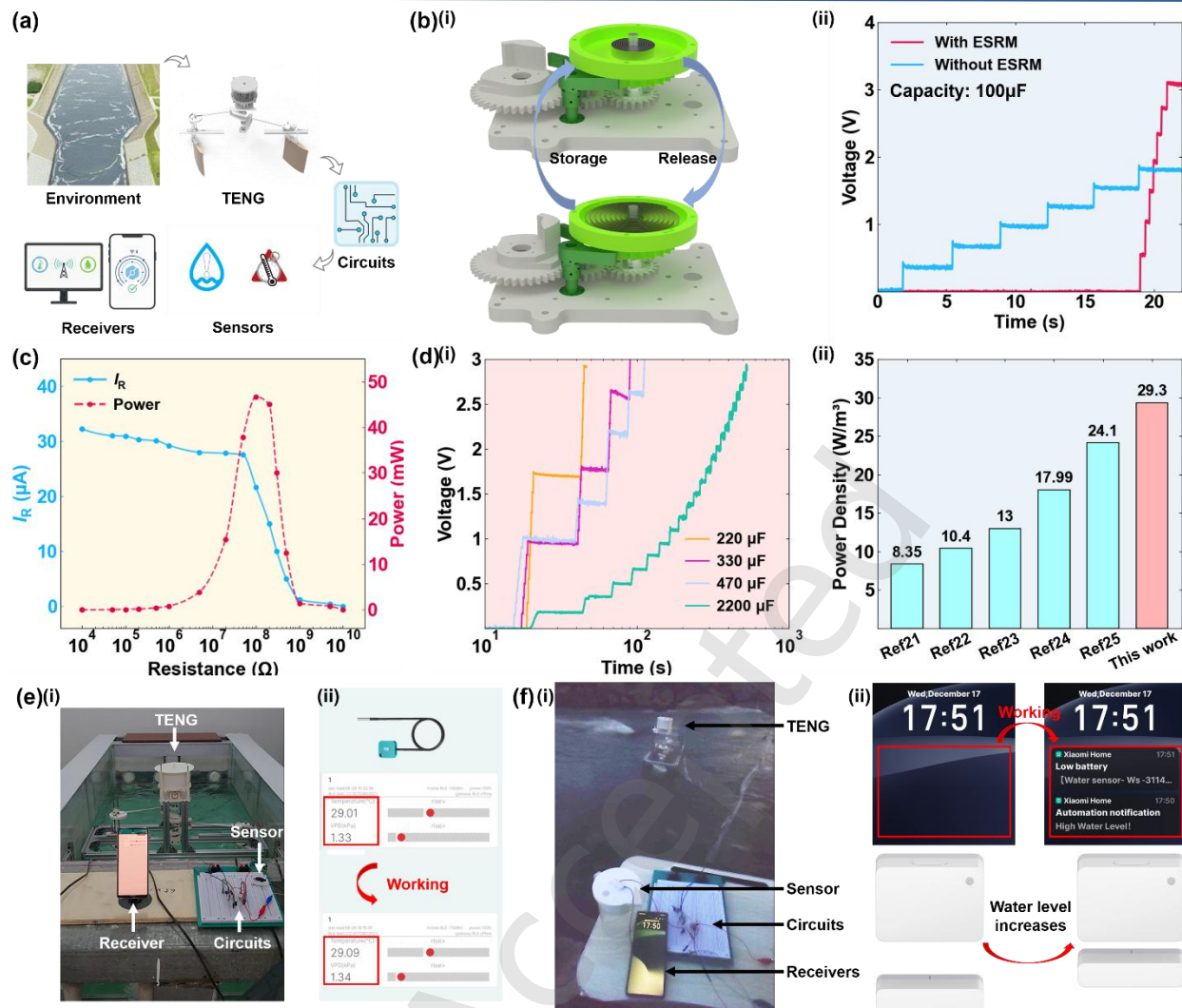


Fig. 5. Application of the GS-TENG in water-flow environments. a) Working workflow of the GS-TENG. b) (i) Energy storage mode and release modes; (ii) comparison of capacitor charging rates with and without the energy storage-release mechanism. c) Effect of load resistance on the output performance of the TENG. d) (i) Capacitor charging rate of the GS-TENG; (ii) performance comparison with previously reported studies. e) Self-powered water temperature sensing. f) Self-powered wireless water level monitoring in a real-world environment.

3 Conclusion

In this work, a novel gray shark-inspired triboelectric nanogenerator (GS-TENG) is proposed for efficient hydrokinetic energy harvesting and self-powered sensing. Inspired by the streamlined morphology of the gray shark, a biomimetic hydrofoil structure is designed to enhance hydrodynamic performance and regulate vortex dynamics, thereby improving energy harvesting efficiency under low-flow conditions. Furthermore, a deep-learning-assisted optimization framework is developed to determine the key structural parameters of the biomimetic hydrofoil. Computational fluid dynamics (CFD) simulations indicate that the optimized biomimetic hydrofoil achieves a 92.4% enhancement in average power compared with the conventional NACA 0015 airfoil. In addition, an energy storage-release mechanism is incorporated to convert low-frequency and irregular flow excitations into high-frequency mechanical motion, effectively achieving frequency up-conversion and matching the operational characteristics of the TENG under unsteady flow conditions. This strategy enhances the electrical output performance by 71.7%, delivering a peak power of 46.65 mW and a maximum power

density of 29.32 W m^{-3} .

Finally, both laboratory and real-world open-channel experiments demonstrate that the GS-TENG can continuously harvest hydrokinetic energy and reliably power water temperature and water level sensors. These results highlight its strong potential for stable energy harvesting in aquatic environments and for enabling self-powered water-environment monitoring systems.

4 Experimental Section

4.1 Fabrication of the GS-TENG

The GS-TENG consists of a pair of biomimetic hydrofoils, a transmission mechanism, an energy storage-release unit, and a TENG generator.

The biomimetic hydrofoils have a maximum chord length of 200 mm and a wingspan of 200 mm. The entire structure is fabricated via three-dimensional (3D) printing (E3, Raise, China) using polylactic acid (PLA) as the printing material.

The transmission mechanism is designed based on a crank-slider configuration and is also manufactured 3D printing. All components of the energy storage-release mechanism are fabricated using the same 3D printing process.

For the TENG unit, ethylene tetrafluoroethylene (ETFE) film (length: 65 mm, width: 70 mm, thickness: 0.15 mm) is used as the negative triboelectric material, while nylon serves as the positive triboelectric material, which is attached to the surface of a copper foil.

The TENG consists of 20 sector-shaped electrodes, where every 10 electrodes form one electrical group. All electrodes are mounted on a circular substrate with an outer diameter of 160 mm and an inner diameter of 150 mm.

4.2 Electrical measurement and water tank

An electrometer (6514, Keithley, USA) is utilized to measure the ISC and QSC. An oscillograph (DS2202A, RIGOL, China) is utilized to measure the VOC, and the relevant data are stored in LabVIEW software. In the laboratory, water pumps (AQ12000DP, Huitian, China) are serviced as power sources.

The experimental water tank has dimensions of 2.1 m × 1.1 m, and the water depth during testing was maintained at 0.4 m.

Electronic Supplementary Material: Supplementary material (please provide the brief detail of the ESM) is available in the online version of this article at <https://doi.org/10.26599/NR.2026.94908973>.

Data availability

All data needed to support the conclusions in the paper are presented in the manuscript and/or the Electronic Supplementary Material. Additional data related to this paper may be requested from the corresponding author upon request.

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Declaration of competing interest

All the contributing authors report no conflict of interests in this work.

Author contribution statement

Guang Qian: Investigation, Writing - Original Draft, Validation. Jinzhi Zhu: Conceptualization, Investigation, Writing - Original Draft. Lu Dong: Investigation, Validation. Yinhu Qiao: Validation, resources. Xuejing Sun: Conceptualization, resources, writing - review & editing, supervision. Jianyang Zhu: Conceptualization, resources, writing - review & editing, supervision. Tinghai Cheng: Conceptualization, Writing - review & editing, supervision. All the authors have approved the final manuscript."

Informed consent

Not applicable.

Ethics statement

Not applicable.

Use of AI statement

None.

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Electronic Supplementary Material

Deep-learning-assisted design of a gray shark-inspired bionic triboelectric nanogenerator for water-flow energy harvesting

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Supplementary Figures:

Fig. S1. Prototype of GS-TENG.

Fig. S2. General geometry employed for parameter definition.

Fig. S3. Flow chart of the interaction between the deep learning model and the CFD simulations.

Fig. S4. Interpretability analysis of the CNN model

Fig. S5. The computational domain and boundary conditions.

Fig. S6. Computation flow chart of fluid-structure interaction.

Fig. S7. Parameter optimization for TENG.

Fig. S8. Power management circuit of the GS-TENG.

Fig. S9. TENG durability test.

Tab. S1. Comparison of optimization results.

Supplementary Videos:

Video S1. Flow field structure variation.

Video S2. Self-powered water temperature monitoring.

Video S3. Wireless self-powered water level alarms.

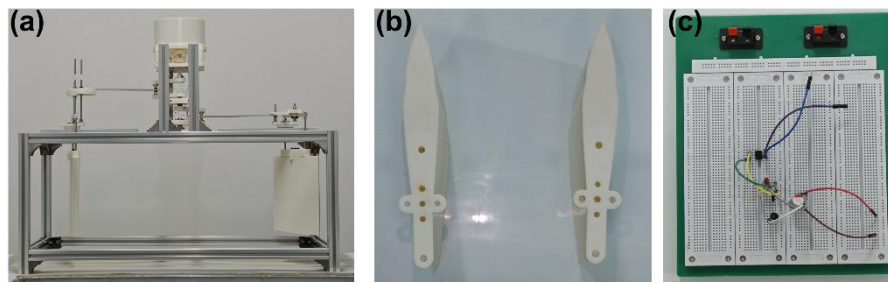


Fig. S1. Prototype of GS-TENG. a) Overall Structure design. b) Physical drawing of the wings. c) Physical diagram of the power management circuit.

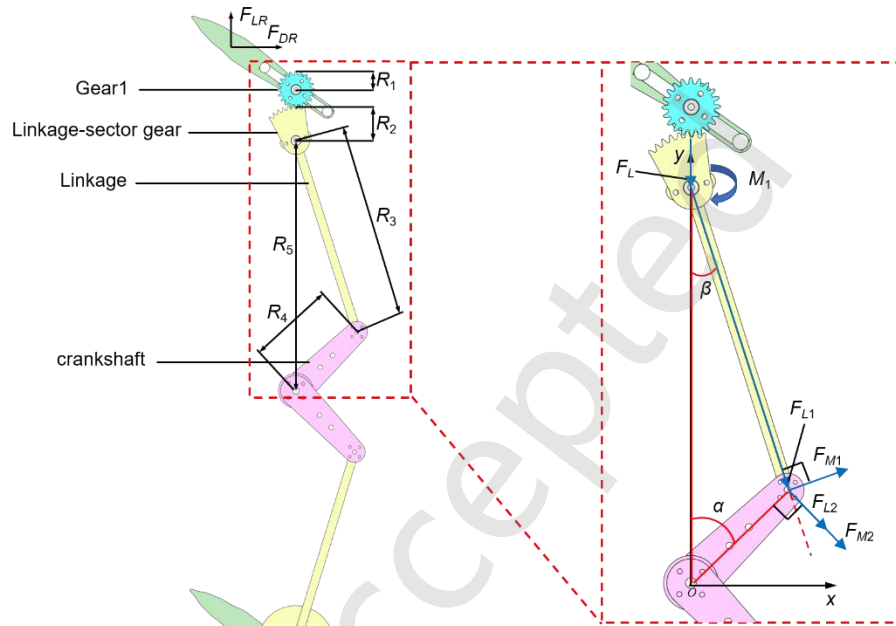


Fig. S2. General geometry employed for parameter definition

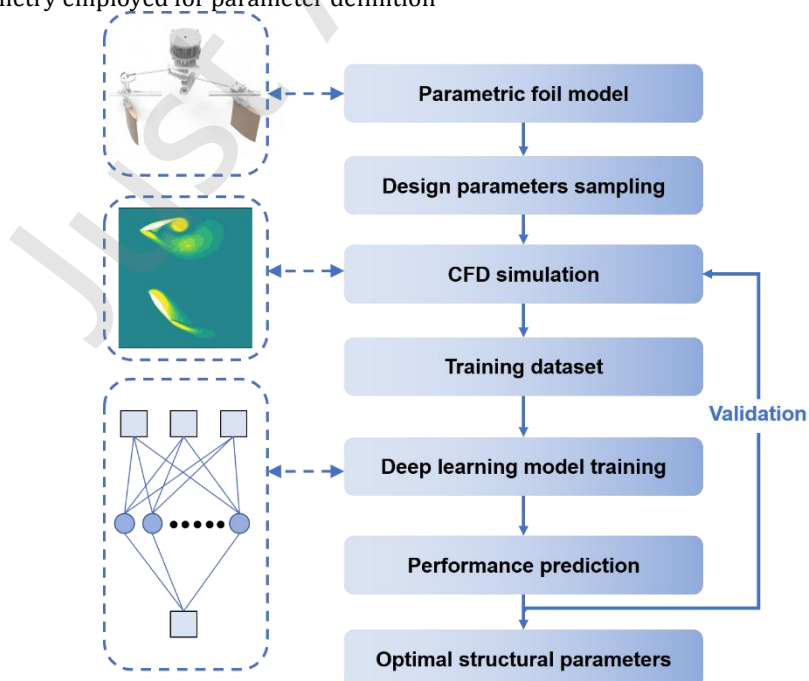


Fig. S3. Flow chart of the interaction between the deep learning model and the CFD simulations.

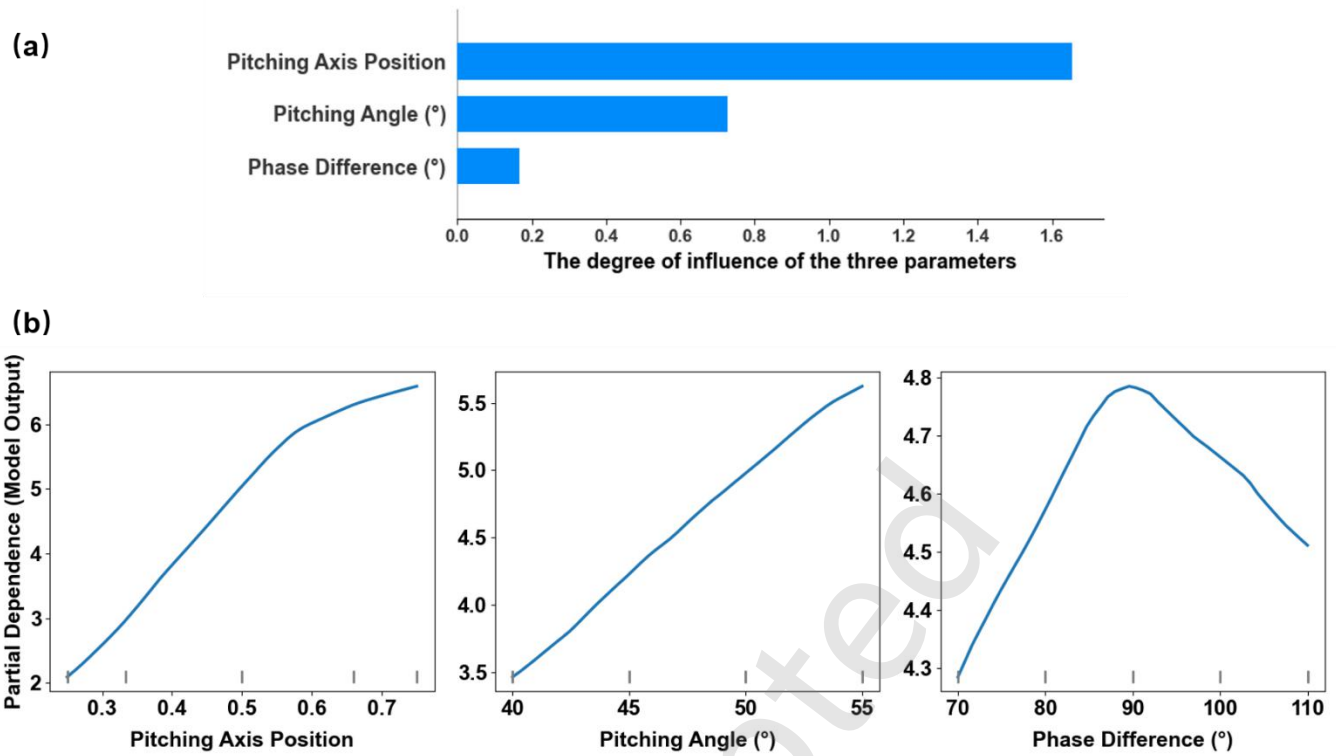


Fig. S4. Interpretability analysis of the CNN model a) Global SHAP feature-importance ranking b) Dependence plots of the three parameters.

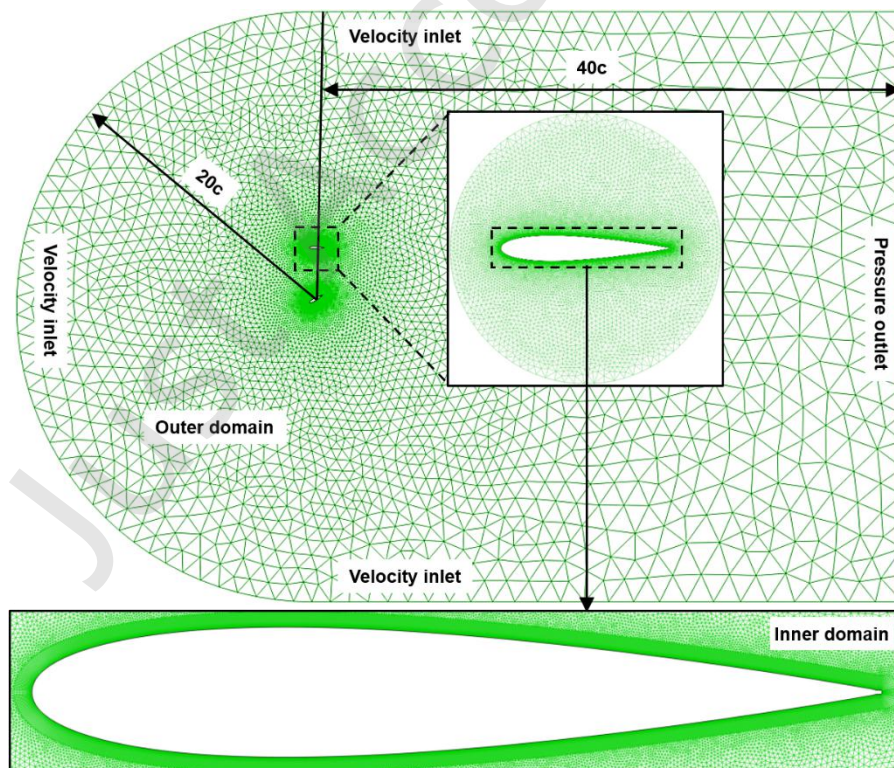


Fig. S5. The computational domain and boundary conditions

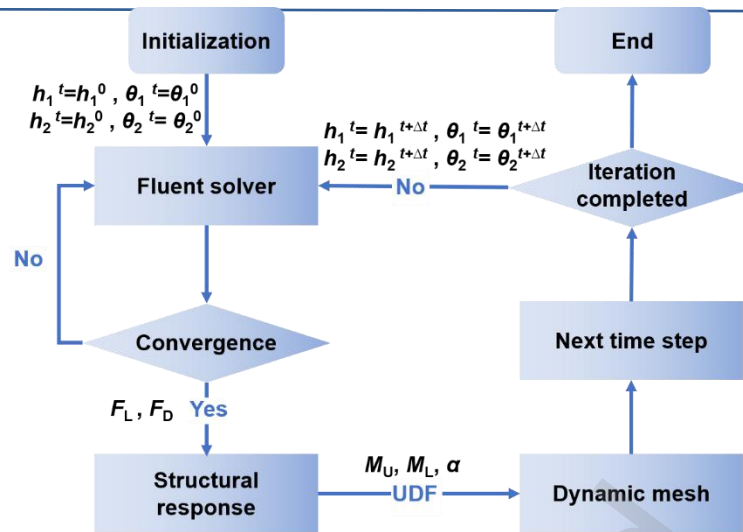


Fig. S6. Computation flow chart of fluid-structure interaction.

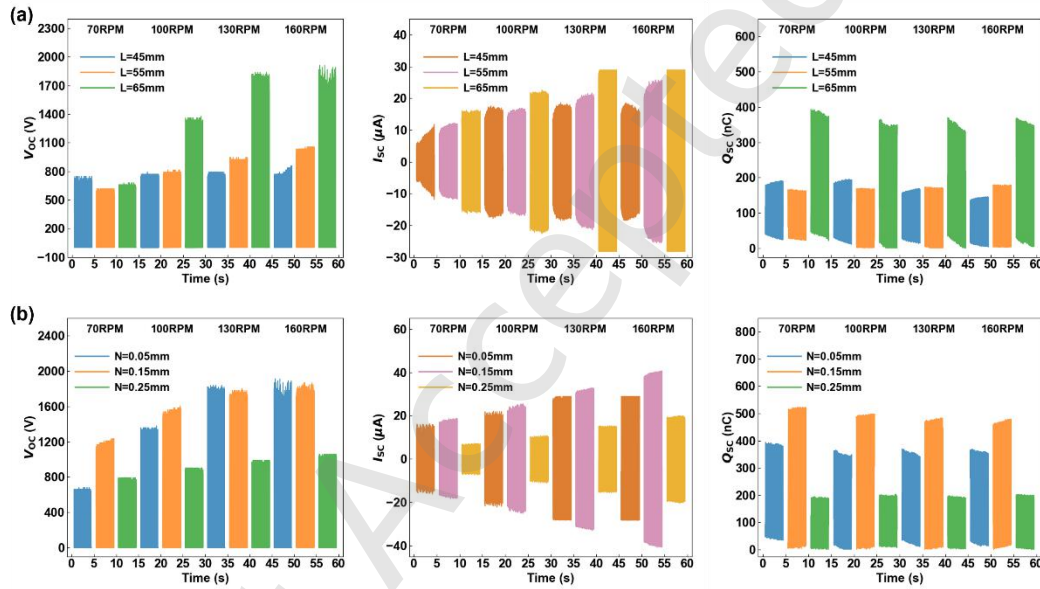


Fig. S7. Parameter optimization for TENG. a) Electrical performance parameters of TENG with different length. b) Electrical performance parameters of TENG with different thickness.

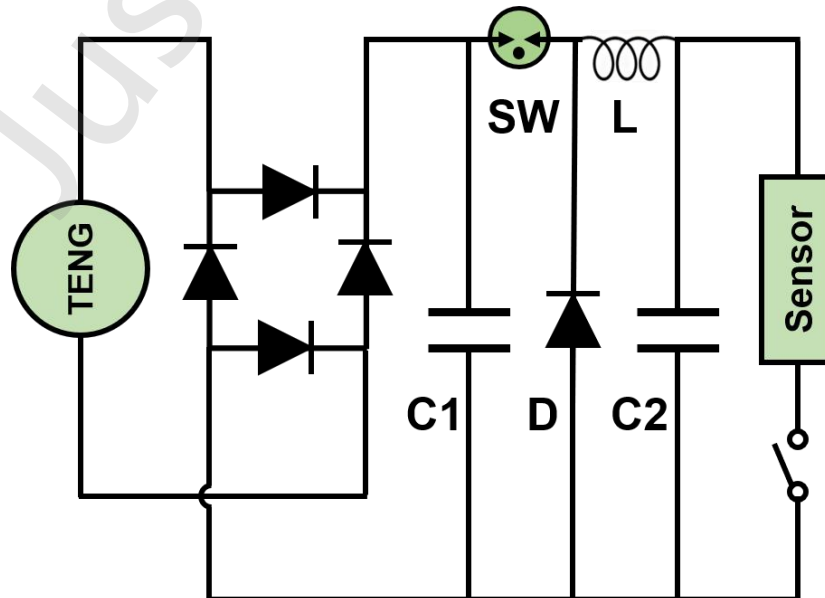


Fig. S8. Power management circuit of the GS-TENG.

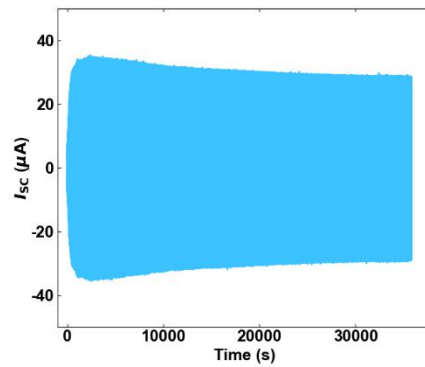


Fig. S9. TENG durability test.

Method	Optimized parameter combination	CFD validation results
First-order response surface	0.75-55°-110°	8.4513
Second-order response surface	0.75-55°-100°	8.8918
Third-order response surface	0.75-55°-98°	8.9223
Fourth -order response surface	0.70-55°-95°	8.9635
CNN	0.75-55°-96°	8.9751

Tab. S1. Comparison of optimization results.

Supporting Notes

Figure S2 illustrates the geometric schematic of the flapping wings. Gear1 is fixed to the flapping wings, with its radius designated as R_1 . The linkage sector gear and the linkage are constructed as an integrated unit, where the radius of the linkage sector gear is defined as R_2 , and the length of the linkage is specified as R_3 . The length from the connection point between crankshaft and the linkage is denoted as R_4 , while the distance from crankshaft to the rotation center of the linkage-sector gear is marked as R_5 . The angle formed between R_3 and R_5 is identified as β , and the angle between R_4 and R_5 is labeled as α . An orthogonal coordinate system is established, with its origin positioned at the rotation axis of crankshaft.

The lift and drag forces acting on any point of the flapping wings are denoted as F_{LR} and F_{DR} , respectively. By integrating over the points on the flapping wings, the total lift force F_L , drag force F_D , and torque M of the flapping wings are obtained. The effective component of the lift force F_L acting on the linkage is defined as F_{L1} , which is aligned parallel to R_3 . The component of F_{L1} transmitted to crankshaft is designated as F_{L2} . The torque M transmitted to the linkage-sector gear is represented as M_1 . The force F_{M1} , which is transmitted from M_1 to crankshaft through the linkage, is perpendicular to R_3 . The component of F_{M1} transmitted to crankshaft is identified as F_{M2} . The specific expressions are given as follows:

$$M_1 = M \frac{R_2}{R_1} \quad (1)$$

$$F_{M1} = \frac{M_1}{R_3} \quad (2)$$

$$F_{M2} = F_{M1} \cos(\beta + \alpha) \quad (3)$$

$$F_{L1} = F_L \cos \beta \quad (4)$$

$$F_{L2} = F_{L1} \cos(\pi - \beta - \alpha) \quad (5)$$

$$M_U = F_L \cos \beta \cos(\pi - \beta - \alpha) R_4 + M \frac{R_2 R_4}{R_1 R_3} \cos(\beta + \alpha) \quad (6)$$

Where M_U represents the total torque acting on the crankshaft.

A geometric relationship is established between the R_5 , α and β :

$$R_4 \cos \alpha + R_3 \cos \beta = R_5 \quad (7)$$

$$R_4 \sin \alpha = R_3 \sin \beta \quad (8)$$

Since gear1 and the linkage-sector gear are engaged in meshing, the pitching displacement θ_d of the flapping wings is related to β . The heaving displacement h of the flapping wings is R_5 . The specific expressions are given as follows:

$$\theta_d = \frac{R_2}{R_1} \beta \quad (9)$$

$$h = R_5 \quad (10)$$

The moment transmitted to crankshaft by the other flapping wings is derived through an identical process and is denoted as M_L . Consequently, the total torque exerted on Crankshaft is expressed as $M_U + M_L$. The dynamical equations of a rigid body, established in accordance with Newton's laws of motion, are given by:

$$J\alpha + C\dot{\alpha} + K\alpha = M_U + M_L \quad (11)$$

where M_U and M_L denotes the torque acting on the crankshaft; J indicates the equivalent moment of inertia; C denotes the equivalent rotational damping coefficient; K represents the equivalent torsional stiffness. α is defined as the rotational angle of the crankshaft, $\dot{\alpha}$ is defined as the angle velocity of the crankshaft, $\ddot{\alpha}$ denotes the angular acceleration of crankshaft.

The time derivative terms are discretized using the central difference method, which is specifically expressed as follows:

$$\alpha' = \frac{\alpha^{t+\Delta t} - \alpha^{t-\Delta t}}{2\Delta t}, \alpha'' = \frac{\alpha^{t+\Delta t} + \alpha^{t-\Delta t} - 2\alpha^t}{\Delta t^2} \quad (12)$$

where Δt represents the time step for iteration, while, $\alpha^{t+\Delta t}$, α^t and $\alpha^{t-\Delta t}$ denote the displacements at the next, current, and previous time steps, respectively.

By substituting Equation (12) into Equation (11), the rotational displacement of the crankshaft is obtained as:

$$\alpha^{t+\Delta t} = \frac{2(2 - \frac{K}{J}\Delta t^2)}{2 + \frac{C}{J}\Delta t} \alpha^t + \frac{\frac{C}{J}\Delta t - 2}{2 + \frac{C}{J}\Delta t} \alpha^{t-\Delta t} + \frac{2\Delta t^2(M'_U + M'_L)}{J(2 + \frac{C}{J}\Delta t)} \quad (13)$$

By substituting Equation (13) into Equations (7), (8), (9) and (10), the passive heaving and pitching displacements of the flapping wings are derived as:

$$\theta^{t+\Delta t} = \frac{R_2}{R_1} \arcsin \left[\frac{R_4}{R_3} \sin \left(\frac{2(2 - \frac{K}{J}\Delta t^2)}{2 + \frac{C}{J}\Delta t} \alpha^t + \frac{\frac{C}{J}\Delta t - 2}{2 + \frac{C}{J}\Delta t} \alpha^{t-\Delta t} + \frac{2\Delta t^2(M'_U + M'_L)}{J(2 + \frac{C}{J}\Delta t)} \right) \right] \quad (14)$$

$$h^{t+\Delta t} = R_4 \cos \left[\frac{2(2 - \frac{K}{J}\Delta t^2)}{2 + \frac{C}{J}\Delta t} \alpha^t + \frac{\frac{C}{J}\Delta t - 2}{2 + \frac{C}{J}\Delta t} \alpha^{t-\Delta t} + \frac{2\Delta t^2(M'_U + M'_L)}{J(2 + \frac{C}{J}\Delta t)} \right] + R_3 \cos \left[\arcsin \left[\frac{R_4}{R_3} \sin \left(\frac{2(2 - \frac{K}{J}\Delta t^2)}{2 + \frac{C}{J}\Delta t} \alpha^t + \frac{\frac{C}{J}\Delta t - 2}{2 + \frac{C}{J}\Delta t} \alpha^{t-\Delta t} + \frac{2\Delta t^2(M'_U + M'_L)}{J(2 + \frac{C}{J}\Delta t)} \right) \right] \right] \quad (15)$$

Supplementary Method

1. Model size (lightweight architecture).

A one-dimensional convolutional neural network (CNN) was used to model the relationship between the input feature sequences and the target variable. The model was implemented using the TensorFlow backend through the Keras API. Each sample consisted of three input features, which were reshaped into a tensor of size (samples, 3, 1) to enable one-dimensional convolution operations. The CNN architecture consisted of:

A MaxPooling1D layer with a pooling size of 2

A second Conv1D layer with conv2_filters filters and kernel size 2 with ReLU activation

A GlobalMaxPooling1D layer to aggregate temporal features into a fixed-length representation

A fully connected Dense layer with dense_neurons neurons and ReLU activation

A final Dense output layer with a single neuron for regression

To mitigate overfitting, L2 regularization was applied to the dense layer with a regularization coefficient l2_reg.

The implemented model contains 1,145 trainable parameters, corresponding to approximately 4.6 kB in FP32 precision, confirming that the architecture is highly lightweight compared with typical deep learning models.

2. Computational complexity.

Given that the entire model contains 1,145 trainable parameters (~4.6 kB in FP32) and requires only $\sim 2.1 \times 10^3$ FLOPs per inference, the proposed CNN architecture is computationally lightweight and well suited for small datasets and real-time prediction scenarios.

3. Training dataset.

The dataset consisted of 100 experimental samples. Each sample contained three input features describing the experimental conditions and one corresponding output value used as the regression target. These labeled samples were used to train and evaluate the CNN model.

Just Accepted