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Comparative Analysis of LSTM and GBR for BLDC Motor Speed Estimation Under Noisy Conditions

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Abstract Estimation of BLDC motor speed plays a critical role in enhancing the efficiency and reliability of electric motors, particularly with the complexities of real-world operating conditions. In this work, we applied the techniques Long Short-Term Memory (LSTM) networks and Gradient Boosting Regressors (GBR) for estimating motor speed in environments characterized by noise and unpredictable changes. The dataset was generated from a numerical simulation of the BLDC motor dynamic model (Linix 45ZWN24-40), implemented in MATLAB/Simulink. This simulation-based approach was adopted to allow controlled introduction of Gaussian noise and abrupt torque transitions, enabling systematic evaluation of model robustness before future physical implementation. The input features consist of voltage, load torque, and motor parameters (B, L_s) varied across scenarios to represent real-world parameter uncertainty. The simulations conducted with the LSTM model resulted in a mean squared error (MSE) of 2580.12 and an R-squared value of 0.95. In contrast, the Gradient Boosting Regressor (GBR) achieved an MSE of 3150.87 and an R-squared value of 0.93. While GBR requires less time for training, LSTM consistently provided higher accuracy, particularly during the rapid variations in torque. This systematic comparison of two machine learning models offers practical insights for engineers tasked with developing motor control systems in unpredictable and dynamic environments.

Keywords Neural networks, Machine learning, Long Short-Term Memory (LSTM), Pattern recognition, Gradient Boosting Regressor (GBR), Time-series analysis

AMS 2010 subject classifications 68T05, 62M10, 93C40

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1. Introduction

Accurate motor speed estimation is critical for enhancing the performance, efficiency, and reliability of electrical motors, which are key components in renewable energy systems, electric vehicles, and industrial automation. As industries increasingly prioritize sustainability and energy efficiency, the demand for resilient and adaptable motor control mechanisms in real-world environments has grown significantly [1, 2]. Traditional methods, relying on simplified mathematical models, often fall short in capturing the complexities of real-world conditions, such as non-linear behaviors, noise, and dynamic variations. This gap highlights the need for innovative approaches through which these challenges can be effectively addressed [3, 4].

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Machine learning (ML) has emerged as a transformative tool to overcome the limitations of traditional techniques. Long Short-Term Memory (LSTM) networks, known for their ability to process sequential data and capture temporal dependencies, have shown substantial promise in dynamic systems where real-time adaptability is essential [5, 6]. Similarly, ensemble models such as Gradient Boosting Regressors (GBR) have proven effective at modeling non-linear relationships and offer computational efficiency in relatively stable conditions [7, 8]. Whether used alone or in hybrid models, these techniques have significant potential to advance motor speed estimation, especially in noisy environments, under fluctuating workloads, and with energy constraints [9, 10, 11].

Recent studies have made notable progress in this area. A hybrid machine learning approach using Nonlinear Autoregressive Neural Networks with Exogenous Inputs (NARX-NN) was proposed for precise speed and torque modeling of BLDC motors, achieving robust predictions suitable for real-time integration [32]. Transformer-based in-context learning has been explored for zero-shot speed estimation of BLDC motors, demonstrating strong generalization capabilities without retraining [33]. ANN-based sensorless speed detection methods have also been developed with promising results [34, 38]. In the broader context of state estimation, hybrid estimators combining machine learning with Extended Kalman Filters (EKF) have demonstrated superior accuracy and robustness compared to either approach alone [35]. Furthermore, deep learning-based controllers and supervised learning approaches have shown significant improvements in BLDC motor speed regulation and real-time control [36, 37].

Despite these advances, there remain notable challenges in applying these models to motor speed estimation under real-world operational conditions. Much of the existing research evaluates these models independently, overlooking the potential benefits of systematic comparison under identical conditions and the challenges posed by noisy data and environmental fluctuations [12, 13, 14]. Recent studies emphasize the need for hybrid approaches that combine the adaptability of LSTMs with the computational efficiency of ensemble models, offering a promising path forward for robust motor diagnostics and state estimation [15, 16, 17]. Furthermore, the lack of noise-resistant frameworks and validation across diverse operational conditions remains a critical issue [18, 19].

This study aims to address these challenges by comparing the performance of LSTM and GBR models in motor speed estimation. By focusing on their noise resilience, adaptability to dynamic conditions, and computational feasibility, this work offers valuable insights into the design of energy-efficient and adaptable motor control systems. These findings are relevant for meeting the increasing demands of real-time industrial and automotive applications. For example, hybrid ML approaches, combining LSTM networks with ensemble methods [20, 21] have shown significant promise in improving both adaptability and computational efficiency in dynamic environments. Additionally, noise-resistant frameworks aim to resolve longstanding challenges in deploying machine learning systems for motor diagnostics under real-world conditions, ensuring higher accuracy and reliability even in fluctuating environments [22, 23].

Another key area of focus is the optimization of energy-efficient algorithms for motor speed estimation [24]. Recent studies have emphasized the importance of adaptive networks and evolutionary optimization techniques that can dynamically adjust to varying workloads and operational constraints. These methods not only improve system performance but also align with broader sustainability goals in industrial systems.

This study builds on these advancements by providing a systematic comparison of LSTM and GBR models, highlighting their respective strengths and limitations under noisy and dynamic conditions [25]. The findings contribute to the development of next-generation smart motor systems that are both efficient and adaptive, advancing the state of the art in industrial automation.

The remainder of this paper is structured as follows. Section 2 presents the materials and methods employed in this study, including dataset generation, preprocessing, and machine learning techniques. Section 3 reports the experimental results and their implications. Finally, Section 4 concludes the paper with key findings and recommendations.

2. Materials and Methods

2.1. Dataset Generation and Preprocessing

The Brushless DC (BLDC) motor using in this article is a Linix 45ZWN24-40 motor and the experimental setup was constructed at the Electrotechnical Laboratory of the National Polytechnic School of Constantine in Algeria as shown in Figure 1. The parameters of this motor are given as follows: the rated speed is 4000 RPM, the rated torque is 0.0924 Nm, the rated power is 40 W, the continuous current is 2.34 A and the number of pole pairs is 2.

The dataset used in this study was generated from a numerical simulation of the BLDC motor dynamic model described by Equation (1), implemented in MATLAB/Simulink. This simulation-based approach was deliberately chosen to allow controlled introduction of noise and dynamic torque events, enabling systematic evaluation of model robustness before future physical implementation.

The equation of the speed is given in (1) as

$$\frac{dw_r}{dt} = \frac{T_e - T_l - B \cdot w_r}{J} \tag{1}$$

Where:
w_r: Rotor speed,
J: Rotor inertia,
B: Damping constant,
T_e: Electromagnetic torque,
T_l: Load torque
The electromagnetic torque is given in (2) as:

$$T_{em} = \frac{e_a \cdot i_a + e_b \cdot i_b + e_c \cdot i_c}{w_r} \tag{2}$$

Where:
e_a,e_b and e_c: Back-emf of voltage of the three phases a, b and c.
i_a,i_b and i_c: Currents of the three phases a, b and c.
Gaussian noise ($\epsilon \sim \mathcal{N}(0, \sigma^2)$) was defined to simulate sensor inaccuracies, resulting in a noisy motor speed as in (3):

$$\omega'(t) = \omega(t) + \epsilon \tag{3}$$

To enhance realism, abrupt torque transitions were added at $t = 0.4s$ and $t = 0.6s$, creating dynamic speed variations. The dataset was sampled at 1 kHz over one-second intervals and included features such as time, voltage, and load torque. The damping coefficient (B) and stator inductance (L_s) were also included as input features; while these values remain constant within each simulation run, they were systematically varied across training scenarios (with perturbations of $\pm 10\%$ around nominal values) to represent real-world parameter uncertainty due to manufacturing tolerances and operating condition changes. This variation enables the models to learn robust speed estimation across a range of motor parameter configurations. It should be noted that Back-EMF was deliberately excluded from the input features, since it is directly proportional to rotor speed ($e \propto \omega_r$); including it would create a trivial prediction problem where the target variable is essentially provided as input. For preprocessing, a sliding window approach was applied to convert the data into a supervised learning format. Each input sequence consisted of 10 time steps (X), with the target being the motor speed at the next time step ($y = w'(t+1)$). Features were normalized to enhance training efficiency using (4) :

$$x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \tag{4}$$

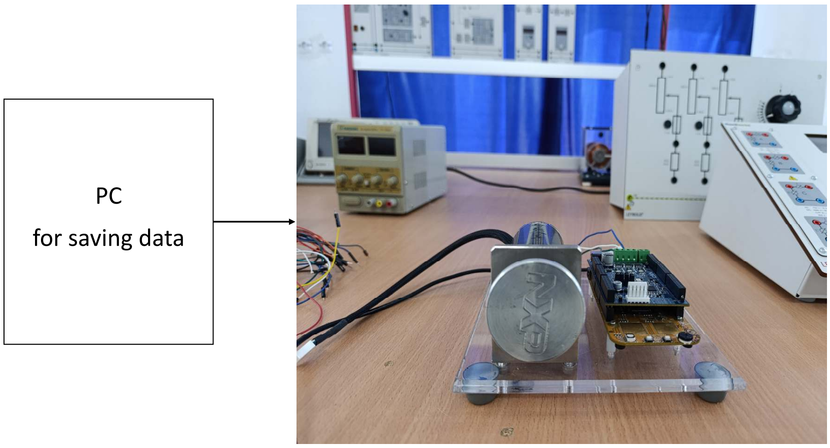

Figure 1. Experimental setup of the BLDC motor

2.2. Machine Learning Methods

Long Short-Term Memory (LSTM) Networks: The LSTM model was specifically designed for time-series predictions [26]. It featured:

• Input Layer: Processes sequences of 10 time steps.

• Hidden Layers: Two LSTM layers, each with 50 memory cells, ReLU activations, and a dropout rate of 20% to reduce overfitting.

• Output Layer: A single neuron predicting motor speed at the next time step.

The gating mechanisms that enable LSTM's temporal modeling are defined in (5) :

$$\begin{aligned} f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)\,, \\ C_t &= f_t \odot C_{t-1} + i_t \odot \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \end{aligned} \tag{5}$$

where f_t,i_t, and o_t represent the forget, input, and output gates, respectively. The model was trained using the Adam optimizer with a learning rate (α) of 0.001 to minimize the Mean Squared Error (MSE). A validation split of 10% was used during training to monitor for overfitting.

Gradient Boosting Regressors (GBR): GBR models were implemented for efficient non-linear regression as in Figure 2 [27]. The algorithm built an ensemble of 200 decision trees with:

• Tree Depth: Limited to 4 to control complexity,

• Learning Rate: Set at 0.1 to balance convergence speed and accuracy,

• Objective: Minimizing residuals at each iteration.

The GBR algorithm iteratively updates predictions in (6) as:

$$\hat{y}_i^{(m)} = \hat{y}_i^{(m-1)} + \eta \cdot h_m(x_i) \tag{6}$$

where $h_m(x_i)$ represents the weak learner trained on residuals $r_i^{(m-1)} = y_i - \hat{y}_i^{(m-1)}$ and η controls the contribution of each learner.

Figure 2 illustrates the relationships between the input features (torque, voltage, damping coefficient, stator inductance) and the two models (GBR and LSTM), ultimately estimating the motor speed $(\omega(t))$.

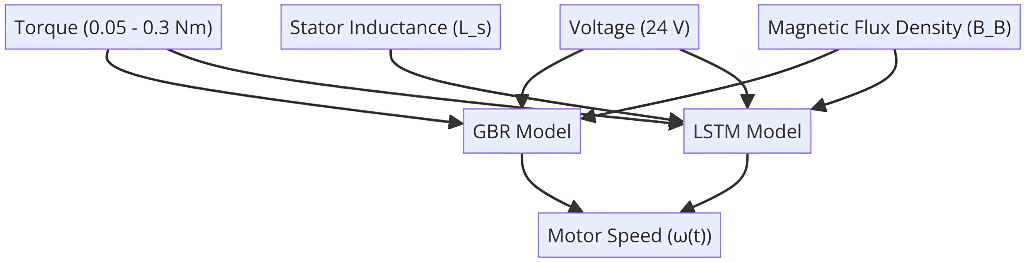

Figure 2. Diagram of Motor Speed Estimation Using GBR and LSTM Models with Input Features [27]

2.3. *Hyperparameter Selection*

Table 1 summarizes the hyperparameters used for each model. For the LSTM model, the architecture and learning rate were selected based on preliminary experiments using a 10% validation split from the training data, monitoring validation loss to avoid overfitting. For the GBR model, the number of estimators, maximum depth, and learning rate were chosen to balance prediction accuracy and computational cost, following established recommendations in the literature [2, 8]. The selected values were validated through training convergence analysis and cross-comparison of results across multiple configurations.

Table 1. Hyperparameters used for LSTM and GBR models

Model	**Hyperparameter**	**Value**
LSTM	Memory cells (per layer)	50
	Number of LSTM layers	2
	Activation function	ReLU
	Dropout rate	0.2
	Learning rate (α)	0.001
	Optimizer	Adam
	Epochs	50
	Batch size	32
	Validation split	10%
GBR	Number of estimators	200
	Maximum depth	4
	Learning rate (η)	0.1

Computational Setup:

All experiments were conducted on an HP i5 (6th generation) PC with 8 GB RAM. MATLAB was used to generate the dataset, while model training and evaluation were performed using Python (TensorFlow for LSTM and scikit-learn for GBR).

2.4. *Evaluation Metrics*

The models were evaluated using comprehensive metrics [28, 29, 30, 31] :

• Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{7}$$

• Root Mean Squared Error (RMSE):

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \tag{8}$$

• Mean Absolute Percentage Error (MAPE):

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{9}$$

• Explained Variance Score (EVS):

$$\mathrm{EVS} = 1 - \frac{\mathrm{Var}(y-\hat{y})}{\mathrm{Var}(y)} \tag{10}$$

• Signal-to-Noise Ratio (SNR):

$$\mathrm{SNR} = 10\log_{10}\left(\frac{\mathrm{Var}(y)}{\mathrm{Var}(y-\hat{y})}\right) \tag{11}$$

3. Results and Discussions

This study evaluated the performance of Long Short-Term Memory (LSTM) networks and Gradient Boosting Regressor (GBR) for motor speed estimation under dynamic and noisy conditions. The comparison was conducted using multiple statistical metrics to ensure a comprehensive assessment.

Table 2. Performance comparison of LSTM and GBR models for BLDC motor speed estimation

Model	**MSE**	**RMSE**	**MAPE (%)**	**R^2**	**SNR (dB)**
LSTM	2580.12	50.79	5.12	0.95	20.45
GBR	3150.87	56.12	6.78	0.93	18.32

As illustrated in Table 2 and Figure 4, LSTM consistently outperformed GBR across all five key performance indicators. The LSTM model achieved an MSE of 2580.12, RMSE of 50.79, and MAPE of 5.12%, demonstrating superior accuracy in speed estimation. In contrast, GBR exhibited larger errors with an MSE of 3150.87, RMSE of 56.12, and MAPE of 6.78%. Furthermore, LSTM's R^2 value of 0.95 and SNR of 20.45 dB surpassed GBR's corresponding values of 0.93 and 18.32 dB, indicating LSTM's enhanced capability to capture temporal dependencies while effectively reducing noise interference.

The temporal tracking capabilities of both models reveal distinct behavioral patterns. Figure 4 demonstrates LSTM's ability to effectively track real-time motor speed variations, particularly during rapid transitions observed at t = 0.4 s and t = 0.6 s. This responsiveness highlights LSTM's strength in learning complex temporal patterns inherent in time-series data. More specifically, the internal gating mechanisms of the LSTM architecture play a key role: the forget gate selectively retains relevant past information, the input gate incorporates new dynamic information during transitions, and the output gate regulates the final prediction. These mechanisms enable LSTM to maintain a continuous internal memory of the motor's dynamic trajectory, making it particularly effective at capturing rapid state changes. Conversely, Figure 3 shows that while GBR maintains adequate performance under steady-state conditions, it exhibits limitations during fast transitions, displaying step-like behavior characteristic of its tree-based, piecewise constant prediction nature. Since each decision tree in the GBR ensemble partitions the feature space into discrete regions with constant output values, the model inherently produces discontinuous predictions during rapid transitions, resulting in the staircase-like artifacts visible in Figure 3. These observations align with the higher error metrics recorded for GBR in dynamic operating scenarios.

Training efficiency presents a notable trade-off between the two approaches. GBR demonstrated significantly faster convergence, requiring only 15–20 seconds over 200 iterations to minimize training loss. This rapid convergence stems from its ensemble-based architecture, which optimizes residuals sequentially. In comparison, LSTM required approximately 600 seconds over 50 epochs to achieve convergence. While this represents a considerably longer training period, the iterative learning process is essential for LSTM to effectively model complex temporal dependencies and noise patterns.

The findings reveal complementary strengths between the two models. LSTM excels in applications requiring high accuracy for time-varying dynamics in noisy environments, though at the cost of increased computational demands. GBR offers advantages in resource-constrained scenarios where faster convergence and lower computational overhead are priorities, albeit with reduced accuracy in capturing rapid temporal transitions. The selection between these models should therefore be guided by the specific requirements of the motor control application, balancing accuracy needs against available computational resources.

Several promising avenues emerge from this comparative study. First, optimizing the LSTM architecture to reduce computational burden without sacrificing accuracy remains a critical objective. Second, both models should be validated across a broader range of motor systems and operating conditions to establish their generalizability. Third, validation on physical experimental data constitutes an important next step to confirm the findings obtained in this simulation-based study. Finally, exploring hybrid frameworks that leverage the complementary strengths of both approaches—such as combining LSTM's temporal modeling capabilities with GBR's computational efficiency, or using accurate speed estimates as input for a second-stage parameter identification algorithm (e.g., Recursive Least Squares) to estimate physical motor parameters such as inertia (J) and damping (B)—represents a particularly promising direction for advancing motor speed estimation methodologies.

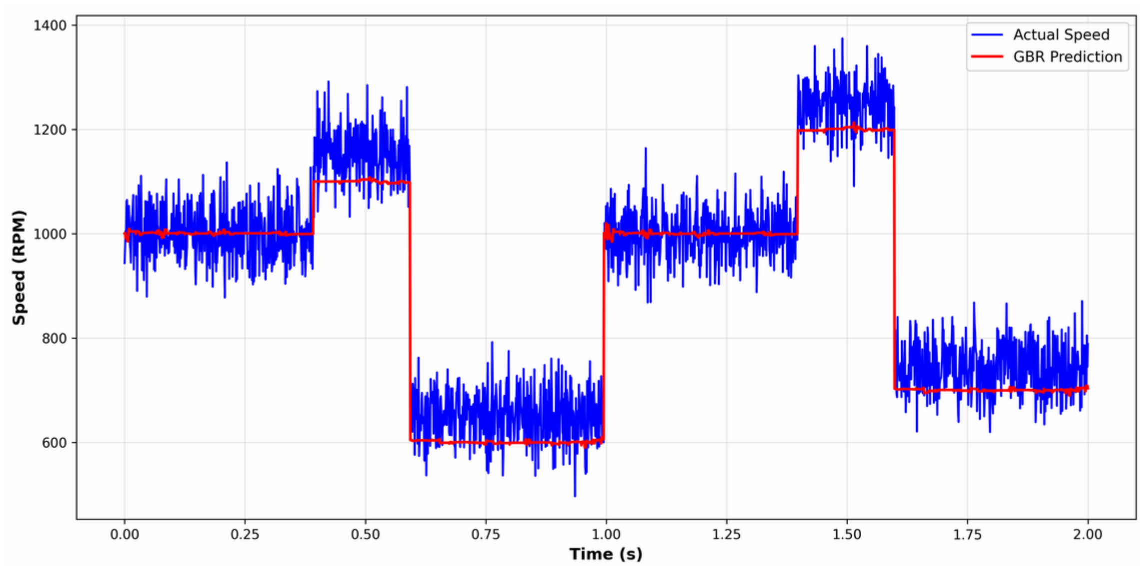

Figure 3. GBR prediction of motor speed.

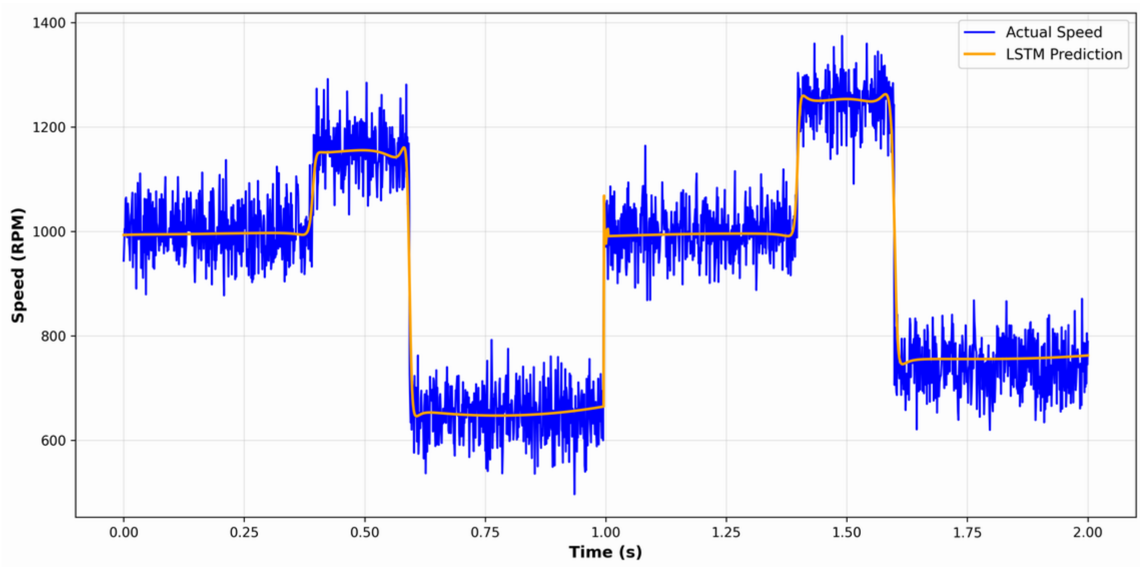

Figure 4. LSTM prediction of motor speed.

4. Conclusion

The presented paper studies the application of LSTM and GBR methods in the context of motor speed estimation in dynamic noisy environments. It uses a dataset that was generated from a numerical simulation of the BLDC motor dynamic model to resemble realistic scenarios, which emphasizes the advantages and shortcomings of each method.

The results highlight LSTM's superiority in problems where adaptability to changing environments is needed, with great prediction accuracy and resilience to noise. However, its longer training time results in significant computational costs, although its capability to capture temporal dependencies is especially effective for tracking sudden changes in motor speeds.

On the other hand, GBR can work quite well in steady-state conditions with increased training speed and less operational training cost. While its tree-based nature limits smooth prediction during rapid transitions, it remains very effective for structured datasets and nonlinear approximations, making it a strong choice for resource-constrained environments.

These findings provide insights for engineers and researchers who are developing motor control systems. In future work, validation on physical experimental data is an important next step. Furthermore, extending this framework to a two-stage approach—where speed estimates serve as input for identifying physical motor parameters (J, B) via Recursive Least Squares—would bridge speed estimation with full parameter identification. Additionally, LSTM architectures can be optimized to keep the computational cost low and still achieve high accuracy. Also, improvements on feature engineering methods for GBR may make it more effective in modeling dynamics over time. This will help underpin the development of adaptive, energy-efficient solutions for reliable motor control across a variety of motor types and environmental conditions.

Data Availability : Data supporting the findings of this study are available upon request from the corresponding author.

Author contributions : All authors have accepted responsibility for the entire content of this manuscript and approved its submission.

Conflicts of interest

The authors declare that there is no conflict of interest.

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