5. Zhu, Y., & Agrawal, G. (2012). Resource provisioning with budget constraints for adaptive applications in cloud environments. IEEE Transactions on Services Computing, 5(4), 497–511. https://doi.org/10.1109/TSC.2011.34
6. Microsoft. (2023). Windows Server documentation. Microsoft Learn. https://learn.microsoft.com/windows-server/

**DOI 10.70286/EOSS-23.02.2026.003.157-159**

# RELIABILITY-ADAPTIVE FUSION FOR STREAMING MULTIMODAL TIME SERIES IN DECISION SUPPORT SYSTEMS

**Uzun Illia**
Postgraduate student
**Lobachev Mykhaylo**
Ph.D, Professor
Institute of Artificial Intelligence and Robotics
National University «Odessa Polytechnic», Ukraine

**Abstract.** Streaming forecasting models based on multimodal data must remain robust when individual modalities undergo temporary degradation [1, 2]. This paper investigates Reliability-Adaptive Dynamic Fusion (RADF), a method that adjusts fusion weights in real-time based on calibrated reliability signals [4]. We present a stress-testing protocol involving alternating missingness and scale shifts and report practical findings from controlled benchmarks and real-world domains (Energy, Crypto) in a prequential setting [6]. Results show that RADF reduces Mean Absolute Error (MAE) by up to 93% in severe stress scenarios compared to naive fusion, while maintaining optimal performance in clean regimes via a “safety gate” mechanism.

**Keywords:** machine learning; data analysis; information systems; decision support systems; time series; streaming forecasting; multimodal learning; data fusion; reliability estimation; robustness; missing data; concept drift.

Multimodal forecasting offers the potential for higher accuracy but also introduces the risk of performance collapse if one source degrades. Naive fusion strategies (e.g., early fusion or equal averaging) propagate noise from degraded channels to the final prediction. We propose Reliability-Adaptive Dynamic Fusion (RADF) to mitigate this by explicitly weighting modalities by their estimated reliability.

**RADF Method and Stress Protocol.** RADF computes dynamic weights $w_t^{(m)} \propto w_0^{(m)} \cdot r_t^{(m)}$, where $w_0$ is a base weight and $r_t$ is the online reliability score. A key feature is the clean-safety gate: when all modalities are reliable, RADF locks weights to the optimal static configuration $w_0$, ensuring no performance loss in normal conditions. We tested RADF under an "alternating stress" protocol ($T = 8000$) where Modality 1 and Modality 2 degrade sequentially (missingness $p = 0.7$, scale shifts).

**Empirical Results.** In controlled experiments with alternating missingness, RADF achieved **MAE 0.64 ± 0.11**, significantly outperforming Early Fusion (0.68 ± 0.08) and approaching the theoretical oracle performance. More importantly, in applied domains with severe degradation ($p = 0.90$ missingness in one modality), the benefits were drastic:

– **UCI Appliances Energy**: RADF reduced MAE from 0.4015 (Naive) to **0.2608** (-35%);

– **BTC/USD**: RADF reduced MAE from 0.3453 (Naive) to **0.0239** (-93%).

In the BTC/USD case, the naive model failed catastrophically due to noise propagation, while RADF effectively "switched off" the degraded channel, relying on the stable modality.

Table 1. Robustness comparison (MAE) under severe degradation.

| Domain | Method | MAE (Stress) | MAE (Clean) |
|---|---|---|---|
| Energy | Naive Fusion | 0.4015 | 0.3427 |
| | **RADF (Ours)** | **0.2608** | **0.2781** |
| BTC/USD | Naive Fusion | 0.3453 | 0.0222 |
| | **RADF (Ours)** | **0.0239** | **0.0221** |

These findings confirm that reliability-based weighting is a practical necessity for deployment in uncontrolled environments. The «safety gate» ensures that this robustness does not come at the cost of accuracy during normal operation.

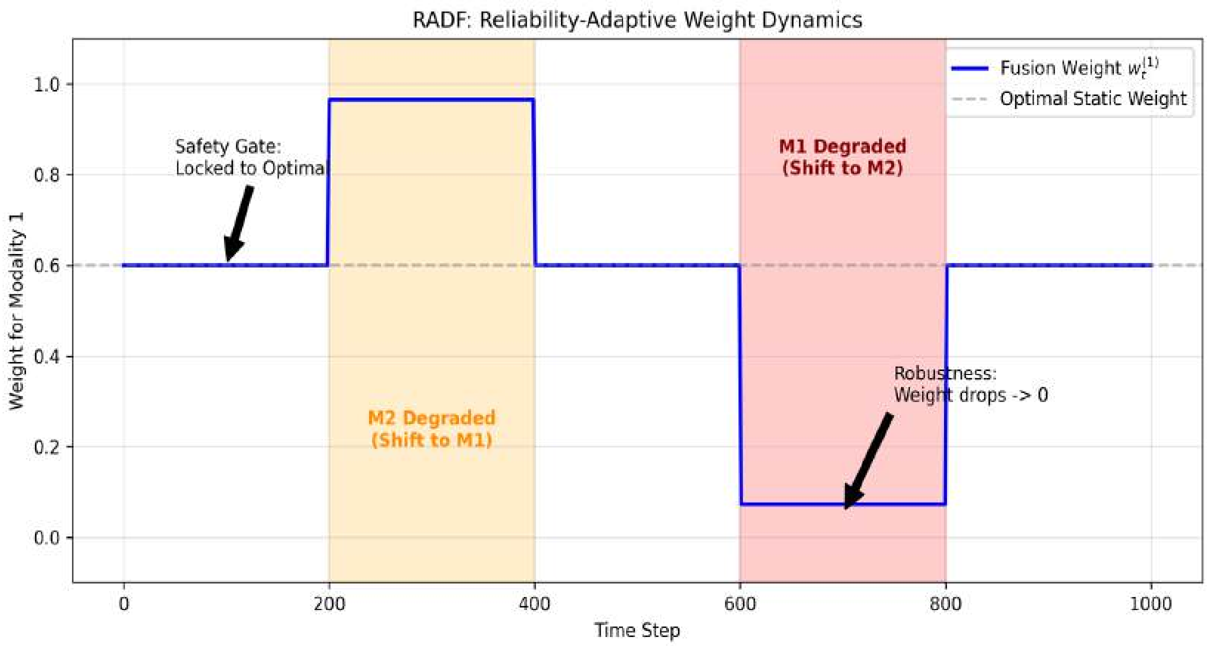


Figure 1. RADF weight dynamics: weights automatically shift away from the degraded modality (red zones) and return to baseline in clean segments.

**References**

1. Baltrušaitis, T., Ahuja, C., & Morency, L.-P. (2019). Multimodal machine learning: A survey and taxonomy. IEEE Transactions on Pattern Analysis and Machine Intelligence, 41(2), 423–443. https://doi.org/10.1109/TPAMI.2018.2798607
2. Lahat, D., Adali, T., & Jutten, C. (2015). Multimodal data fusion: An overview of methods, challenges, and prospects. Proceedings of the IEEE, 103(9), 1449–1477. https://doi.org/10.1109/JPROC.2015.2460697
3. Gama, J., Žliobaitė, I., Bifet, A., Pechenizkiy, M., & Bouchachia, A. (2014). A survey on concept drift adaptation. ACM Computing Surveys, 46(4), Article 44. https://doi.org/10.1145/2523813
4. Guo, C., Pleiss, G., Sun, Y., & Weinberger, K. Q. (2017). On calibration of modern neural networks. In Proceedings of the 34th International Conference on Machine Learning (Vol. 70, pp. 1321–1330). PMLR. https://proceedings.mlr.press/v70/guo17a.html
5. Fawcett, T. (2006). An introduction to ROC analysis. Pattern Recognition Letters, 27(8), 861–874. https://doi.org/10.1016/j.patrec.2005.10.010
6. Dawid, A. P. (1984). Statistical theory: The prequential approach. Journal of the Royal Statistical Society. Series A (General), 147(2), 278–292. https://doi.org/10.2307/2981683

**DOI 10.70286/EOSS-23.02.2026.004.159-164**

# HIGH-PERFORMANCE PROCESSING AND STREAMING ARCHITECTURE FOR MULTIMODAL NEURO-MOTOR SIGNAL ANALYSIS

**Bishchak Dmytro**
PhD Student
Department of Software Engineering
Ternopil Ivan Puluj National Technical University, Ukraine

**Abstract.** This paper presents performance-focused addition to multimodal neuro-motor analysis software that integrates electroencephalography (EEG) and motor deviation signals (ΔR). While traditional diagnostic approaches rely on static session-based evaluation, this work introduces computational complexity evaluation of core analytical modules, a scalable serverless cloud architecture for streaming biomedical data signals, and a transition from static indicators to time-resolved dynamic diagnostic parameters.