Minimax Theory and its Applications

Volume 11 (2026), No. 2s, 369 to 376

Optimization of Translation Decisions Under Lexical and Semantic Uncertainty A Decision-Theoretic Framework With An Illustrative Case Study

Nilufar Khodjaeva[1], Yakuta Mamatova[2], Abdulla Xudayqulov[3], Ulugbek Yokubov[4], Sugdiyona Otamirzaeva[5], Guzal Umurova[6], Gulruy Donisheva[7]

[1]Associate Professor, Higher School of South Asian Languages and Literature, Tashkent State University of Oriental Studies, Tashkent, Uzbekistan. Email: nilufar_xodjayeva@tsuos.uz, https://orcid.org/0000-0002-9559-6681

[2]Professor, Department of Journalism and Uzbek Philology, National University of Uzbekistan, Tashkent, Uzbekistan. Email: ya_mamatova@mail.ru; yakutxonmamatova@gmail.com, https://orcid.org/0009-0002-6293-9606

[3]Associate Professor, Termez State University, Termez, Uzbekistan. Email: axudayqulov@tersu.uz; khudaykulovabdulla@gmail.com, https://orcid.org/0000-0001-6746-916X

[4]Lecturer in English for Specific Purposes, Department of Foreign Languages, Tashkent State University of Law, Tashkent, Uzbekistan. Email: u.yokubov@tsul.uz, https://orcid.org/0009-0004-3858-5240

[5]Lecturer in Teaching English to Speakers of Other Languages (TESOL), Department of Foreign Languages, Tashkent State University of Law, Tashkent, Uzbekistan. Email: s.otamirzayeva@tsul.uz, https://orcid.org/0000-0003-2952-1443

[6]Associate Professor, Department of Language Theory and Literary Studies, Faculty of Roman German Languages, Samarkand State Institute of Foreign Languages, Uzbekistan. Email: guzalumurova17@gmail.com, https://orcid.org/0009-0002-3756-3985

[7]Researcher, Jizzakh State Pedagogical University, Jizzakh, Uzbekistan. Email: pardaevagulroy@gmail.com, https://orcid.org/0009-0006-2219-0986

Abstract

Translation entails choices of meanings, lexical equivalents, and valid expressions in the target language. The choices become complex when multiple interpretations are possible for the source text or when the information provided by the translation tools is not certain. In this paper, we consider a decision theory framework for choosing translations in the face of uncertainty about lexis and semantics. Interpretations of the source are modeled as a finite number of semantic states, whereas choices of target language are modeled as possible actions. Translation choice starts by minimizing expected loss, followed by distributionally robust optimization when probabilities of interpretations are uncertain. Bounded set of ambiguous probabilities enables the decision-maker to manage the degree of conservatism. The model also encompasses a clarification procedure and document-level consistency constraint. A constructed two-sense example demonstrates how a direct equivalent, ambiguity-conserving translation, and clarification by humans can be optimal under varying degrees of uncertainty. These figures are indicative only, and no corpus-based experiments are made. The article ends with the presentation of a real-world test plan and consideration of the drawbacks of the semantic state inventory and probability calibration and automated measures of quality.

Keywords: Translation decisions, lexical ambiguity, semantic uncertainty, robust optimization, expected loss, clarification, semantic fidelity.

1. Translation as a choice with consequences

Translators not only find one word to substitute for another. Translators select from alternative expressions, some of which are different in terms of their level of specificity, register, syntactic form, and implication. One source word can be ambiguous, having several meanings in the dictionary. One sentence, constructed of

recognizable words, can be ambiguous due to lack of context, reference, and pragmatic meaning. Therefore, the selection of the correct target sentence is not enough if it implies a non-existent source interpretation.

In this work, two connected types of ambiguity are identified. Lexical ambiguity is associated with the selection of the target expression for the source expression, its alternatives, and terminology differences. Semantic ambiguity is the meaning of the source text in context. A translator can know which source meaning should be chosen but still be uncertain about which target expression to use. On the other hand, one can have a clear target expression but the meaning of the source text in context can still be unclear.

Disambiguation of word-sense is a considerable base for interpretation (Navigli, 2009). Multilingual knowledge bases like BabelNet relate language-based and conceptual knowledge between languages (Navigli & Ponzetto, 2010), and common evaluation measures for disambiguation promote better comparability of interpretation tools (Raganato et al., 2017). Knowledge bases can be used to produce evidences; however, it is not possible to remove the ambiguity of underspecified sources.

The problem being considered is that of how one should choose among alternative translations when there is uncertainty in the interpretation as well as in the consequences of making the wrong choice. The solution presented in this context takes into account decision-making under uncertainty. This model starts off with alternative interpretations of the source and goes on to evaluate the alternative translations based on them before taking a decision which incorporates an explicit uncertainty model. This can apply to human-assisted as well as machine translation(Alsamhan & Aldosari, 2025; Riadhusin et al., 2025).

2. Identify what is unknown before choosing an equivalent

2.1 A structured interpretation record

For a source segment x and its available context h, let

$$\mathcal{S}(x, h) = \{s_1, \dots, s_m\}$$

and let S be the set of possible semantic states. A state will denote an interpretation relevant to translation, but not always a dictionary meaning. It may include a word sense, a referent, or a desired relation between clauses. The states should be understandable for bilingual experts and sufficiently precise to separate translations with substantially different meanings.

Too detailed states can produce unreliable probabilities. Too wide states can hide serious errors. The inventory of the states should be compiled on the basis of the translation problem and validated through lexicons and translation examples. A special state “other interpretation,” which cannot be neglected, may be necessary when the inventory is incomplete, but the losses should be estimated separately.

2.2 Candidate actions need not have the same specificity

Let $\mathcal{T}(x, h) = \{t_1, \dots, t_K\}$contain the candidate translations in the target language. Candidate expressions may include a direct translation, a descriptive paraphrasing, or an ambiguous expression if the target language allows it. They can be generated by a human translator, a bilingual dictionary, or a translation system(Hooman & Fumani, 2017). They should all meet the same requirements before being optimized.

A candidate that preserves ambiguity is not always more favorable. Such a choice can be awkward, miss the necessary distinction, or even introduce a new ambiguity. An analogous case arises when the translation explanation is too lengthy to fit the subtitle or user interface space. Feasibility criteria need to disqualify non-conformable candidates rather than compensate for their violations with some minor penalty.

2.3 Sources of evidence and their limits

Contextual clues, terminology databases, document history, and domain knowledge can inform an estimated distribution $\hat{p}(s \mid x, h)$. Probabilities assigned to models cannot necessarily be considered as calibrated sense probabilities. Consensus among multiple translation systems may also arise from common training biases instead of evidence independent of each other.

Decoding based on minimum Bayes risk is loss-sensitive decision making with respect to translation selection (Kumar & Byrne, 2004). Loss-insensitive variants using neural metrics illustrate that an alternative with the maximum model probability does not have to be the best choice according to some quality measure (Freitag et

al., 2022). In the current framework, uncertain outcomes are explicitly stated in semantic space. This contrasts with techniques involving averaging of candidate similarities using reference translations sampled.

3. Specify the cost of a translation decision

3.1 A composite, state-dependent loss

For candidate t and state s, define

$$L(t,s) = \omega_M D_M(t,s) + \omega_L D_L(t,s) + \omega_F D_F(t) + \omega_C C(t),$$

where all components are nonnegative and the weights satisfy

$$\omega_M + \omega_L + \omega_F + \omega_C = 1.$$

D_M measures meaning distortion, including incorrect senses, changed relations, and omitted information. D_L measures inappropriate lexical realization within the intended meaning, such as inconsistent terminology or unsuitable register. D_F measures target-language awkwardness. C represents task-specific effort, length, or processing cost.

It is necessary to make the difference between meaning distortion and lexical mismatch evident in the annotation guidelines. In case an incorrect word sense was included in both components, this would lead to double punishment for one mistake. The reviewers need to assign each problem found by them according to the established taxonomy of errors.

Table 1: Decision components and a possible assessment basis

Component	Question for the reviewer	Assessment basis
Meaning distortion	Does the translation express the intended state?	Bilingual semantic assessment
Lexical mismatch	Is the chosen term appropriate within that meaning?	Glossary and register guidance
Fluency penalty	Is the expression natural in the target language?	Target-language assessment
Decision cost	Does the choice fit the task's resource limits?	Recorded length, time, or effort

3.2 Expected loss when probabilities are trusted

For a known interpretation distribution p, a rational selection rule is

$$t_{\mathrm{E}} \in \operatorname*{argmin}_{t \in \mathcal{T}} R(t;p), \qquad R(t;p) = \sum_{s \in \mathcal{S}} p_s \, L(t,s).$$

This criterion takes into account both the probability of the meanings and the consequences of a wrong choice of expressions. Choosing the most probable meaning and then translating it is optimal only on the assumption of strong loss conditions. If one mistake causes a significantly bigger consequence than another mistake, the choice based on expected loss will not necessarily be the same as the choice of most probable meaning.

Losses and weights should depend on the context of translation. An erroneous technical term can have a greater impact in a guidebook than in informal communication, while poor style in the latter will probably be more harmful than in the former.

Protecting decisions against uncertain interpretation probabilities

4.1 A bounded set of plausible distributions

When probabilities are uncertain, let

$$\mathcal{P}_\rho = \left\{ p \in \mathbb{R}^m : p_s \geq 0, \sum_s p_s = 1, \; \| \, p - \hat{p} \, \|_1 \leq \rho \right\}, \qquad 0 \leq \rho \leq 2.$$

The nominal estimate is $\hat{p}$ and ρ is the permitted deviation. The distributionally robust decision is

$$t_{\mathrm{R}} \in \operatorname*{argmin}_{t\in\mathcal{T}} \sup_{p\in\mathcal{P}_\rho} \sum_s p_s\, L(t,s).$$

The formulation is in line with principles of robust optimization and distributionally robust learning, while its interpretation is also related to decisions made with respect to several possible priors (Gilboa & Schmeidler, 1989; Bertsimas et al., 2011). This justifies the mathematical framework, but does not prove the usefulness of any particular semantic vocabulary and radius.

With $\rho = 0$, the rule reduces to nominal expected-loss selection. Increasing ρ expands the ambiguity set and cannot decrease a fixed candidate's robust loss. If the set covers the entire simplex, robust loss becomes $\max_s L(t,s)$. An intermediate radius can retain useful contextual information while protecting against moderate probability errors.

4.2 Computing robust loss for a fixed candidate

For a fixed t, the loss values are constants. Introducing nonnegative auxiliary variables u_s gives the linear program

$$\max_{p,u} \sum_s p_s\, L(t,s)$$

subject to

$$\sum_s p_s = 1, \qquad p_s \geq 0, \qquad u_s \geq 0,$$

$$p_s - \hat{p}_s \leq u_s, \qquad \hat{p}_s - p_s \leq u_s,$$

$$\sum_s u_s \leq \rho.$$

The solution to this problem for each candidate and choosing the one with minimum robust loss will yield an exact solution for the finite candidate set. The exactness depends on the loss values, states, and ambiguity set provided. It does not guarantee that the candidate list includes the optimal translation.

For two states, write $p_1 = q$ and $p_2 = 1 - q$. Since

$$\| p - \hat{p} \|_1 = 2|q - \hat{q}|,$$

the feasible interval is

$$q \in [\max(0, \hat{q} - \rho/2),\ \min(1, \hat{q} + \rho/2)].$$

Expected loss is linear in q, so the worst case occurs at an interval endpoint. This permits a simple analytical illustration.

4.3 Choosing the radius without claiming a guarantee

The value of the radius can be determined on the training data which consists of meanings that have been separately assessed. The method that could be applied for doing this is to find the minimum radius that allows meeting a given tolerance on semantic errors subject to a certain quality bound.

The radius defined in this way is a model parameter. It is not a confidence region since its coverage has not been calculated or justified in any way. Even in case of wrong probabilities being used, it can only partly overcome this problem. It cannot address omitted interpretations or incorrectly estimated losses.

4. When asking for context is the better action

Clarification can be included as an action a_Q when the workflow permits interaction. Under the idealized assumption that clarification reveals the correct state, its state-dependent loss is

$$L(a_Q, s) = c_Q + \min_{t \in \mathcal{T}} L(t, s),$$

where c_Q is the cost of asking and processing the answer. Robust selection can compare this action directly with immediate translations.

Perfect revelation is often unrealistic. If a clarification response r has likelihood $P(r \mid s)$, a more general risk is

$$R_Q(p) = c_Q + \sum_r \min_{t \in \mathcal{T}} \sum_s p_s P(r \mid s) L(t, s).$$

The expression presupposes that selection of a translation is possible based on observation of r, as well as that the response model is known. In case the response model is unknown, the uncertainty set should include the response model too. This clarification is worthwhile only if it is profitable from the perspective of the expected decrease of the loss due to decision making.

An alternative possible action is human review, but it cannot automatically imply zero loss in semantic sense. Human beings may err, and time limitations might prohibit the review. The important thing is to distinguish between asking the author of the source document for clarifications and asking other translators to analyze the same fragment of information.

5. Illustrative decision analysis

6.1 Two meanings and three translations

Consider a hypothetical ambiguous segment with two plausible meanings s_1 and s_2. Candidate t_1 commits to the first meaning, t_2 commits to the second, and t_3 uses a broader expression that is moderately acceptable under either meaning. These are abstract alternatives rather than claimed translations of a particular language pair.

Assume $\hat{q} = 0.75$. Table 2 supplies constructed composite losses on an arbitrary normalized scale. These are neither human measurements nor corpus findings.

Table 2: Assumed loss matrix and calculated decision scores

Action	Loss under state 1	Loss under state 2	Nominal loss	Robust loss, radius 0.60
Direct choice t1	0.05	0.85	0.250	0.490
Direct choice t2	0.80	0.10	0.625	0.800
Broader choice t3	0.32	0.38	0.335	0.353
Ideal clarification	0.29	0.34	0.303	0.318

The clarification row assumes $c_Q = 0.24$ and perfect revelation. Its losses are $0.24 + 0.05$ and $0.24 + 0.10$ respectively. Including it is conditional on clarification being feasible.

6.2 Nominal selection and robust selection

At the nominal distribution,

$$R(t_1; \hat{p}) = 0.75(0.05) + 0.25(0.85) = 0.250.$$

Thus, immediate nominal selection chooses t_1, including when ideal clarification is available. For $\rho = 0.60$, the feasible interval is $q \in [0.45,1]$. The candidate risk functions are

$$R(t_1; q) = 0.85 - 0.80q, \quad R(t_2; q) = 0.10 + 0.70q, \quad R(t_3; q) = 0.38 - 0.06q.$$

Their largest interval values are 0.490, 0.800, and 0.353. Without clarification, robust selection therefore chooses t_3. Its nominal loss is higher than that of t_1, showing the cost of protection against an incorrect probability estimate.

For ideal clarification,

$$R_Q(q) = 0.34 - 0.05q,$$

having an interval width of 0.3175. Selection of robustness depends on whether clarification is present or not. It also depends on the cost and accuracy associated with it; it is not proof that clarification improves translation.

6.3 How much uncertainty changes the decision

Before interval clipping becomes relevant to the lower endpoint, the robust losses of t_1 and t_3 are

$$R_\rho(t_1) = 0.250 + 0.40\rho, \qquad R_\rho(t_3) = 0.335 + 0.03\rho.$$

They become equal at

$$\rho^\star = \frac{0.335 - 0.250}{0.40 - 0.03} \approx 0.230.$$

This threshold concerns the two immediate alternatives. When clarification is available, its robust loss is $0.3025 + 0.025\rho$ in the same range, and it overtakes t_1 at $\rho = 0.140$. The availability of an information-gathering action therefore changes the decision boundary.

The computations illustrate the behavior of the model. They do not prove a preference for any radius, accuracy measurement, or superiority of wide expressions over narrow translation.

6. Extending the decision to a whole document

Independent segment decisions can produce inconsistent terminology. Let t_i be the translation selected for segment i of a document with N segments. A simple extension is

$$\min_{t_1,\dots,t_N} \left\{ \sum_{i=1}^{N} \sup_{p_i \in \mathcal{P}_i} \sum_{s} p_{i,s}\, L_i(t_i, s) + \gamma \sum_{(i,j)\in\mathcal{E}} I_{ij}\left(t_i, t_j\right) \right\}.$$

The set E relates events which must be considered together. The consistency cost I_ij is incurred when the two events of the same concept employ inconsistent vocabulary. This does not mean penalizing different versions of a word with different meanings, where the latter are polysemous.

This is the sum of the individual worst-case risk assuming individually variable marginal distributions, also known as a rectangular uncertainty. It could be an overly conservative measure when meanings in the documents are highly dependent on each other. This is because joint probability distribution could reflect the interdependence better.

However, it increases the elicitation and computation costs. A feasible approach would be the use of hard glossary constraints for the mandatory vocabulary and soft cost functionals for the preferred styles. Then after the choice at the document level, bilingual verification of consistency is needed.

7. Empirical validation and practical boundaries

8.1 An evaluation that separates meaning from fluency

In any subsequent experiment, source fragments should be selected with known types of ambiguity, adequate context of the documents, and several potential translation options. Plausible translations and losses should be collected by bilinguals following specific instructions. Unresolved ambiguity should be left as such rather than being forced into an unnatural single answer.

The comparison should involve the most probable candidate, nominal choice based on expected loss, robust selection at various development-driven radii, and selection with clarifications when possible. All approaches should receive the same set of candidates and context. Otherwise, improvements in candidate generation may be confused with the decision optimization process.

COMET and uncertainty-aware translation evaluation can contribute to the evaluation process but evaluation score uncertainty is different from the uncertainty related to the source meaning(Glushkova et al., 2021; Rei et al., 2020). BLEU (Papineni et al., 2002), chrF (Popović, 2015), and BLEURT (Sellam et al., 2020)

complement each other by providing an alternative view of the quality of translation. Their scores should not be used in the loss directly without proper scaling and alignment with semantic mistakes.

Expert judgment with sufficient contextual information is very important for fluent translations with different meanings (Freitag et al., 2021). It is necessary to record the metrics configuration for reproducibility (Post, 2018). The primary metrics may include wrong sense translation, severity weighted semantic loss, clarification request rate, and reviewer's time. Fluency and document consistency should be reported separately.

8.2 Reliability, resource inequality, and falsifiable claims

Loss annotations must report agreement, disagreement resolutions, and uncertainties. Bootstrapping confidence intervals at the document level can account for correlated segments. Probability calibration should be tested separately from translation quality. Perturbation tests on the context or a new domain can reveal whether robustness persists despite perturbations to the nominal estimates.

Resource inequality across languages might have implications for sense inventories, candidate quality, and metric reliability (Joshi et al., 2020). Consequently, success in well-resourced language pairs cannot be taken to carry over without modification. A good experiment will divide the examples according to language pair, domain, and type of ambiguity, and give the number in each group.

The main claim is that robust selection minimizes semantic errors in the face of probability misspecification, at an acceptable cost to nominal quality and effort. This claim can fail if loss estimates are inaccurate, if the ambiguity set is ill-suited, or if all the candidates share a semantic error. An empirical paper must report these results and not just an inference from the optimization problem.

8. Conclusion

Lexical and semantic translation under uncertainty may be formulated as a problem of choosing among actions that are evaluated using possible interpretations of the source. Minimization of expected loss is an appropriate formulation whenever interpretation probabilities are known to be reliable. Bounded ambiguity set generalizes the choice procedure to the case of uncertain probabilities and quantifies conservatism.

The numeric example shows how various decisions are made under nominal choice, robust immediate choice, and robust choice with clarification. Terminology consistency for the whole document is introduced in addition to the choice procedure; assumptions underlying independence of uncertainty sets are discussed. This approach provides a basis for future corpus research; however, its practical relevance is limited by candidate representation, evidence weighting, losses, and bilingual context.

References

1. Alsamhan, A., & Aldosari, F. H. (2025). AI-Enabled Translation Assistance for Preserving Meaning in Cross-Language Communication. *International Journal of English and Education, 14*(4), 109-117. https://doi.org/10.67050/IJEE/V14I4/IJEE254014

2. Bertsimas, D., Brown, D. B., & Caramanis, C. (2011). Theory and applications of robust optimization. *SIAM review*, *53*(3), 464-501. https://doi.org/10.1137/080734510

3. Freitag, M., Foster, G., Grangier, D., Ratnakar, V., Tan, Q., & Macherey, W. (2021). Experts, errors, and context: A large-scale study of human evaluation for machine translation. *Transactions of the Association for Computational Linguistics*, *9*, 1460-1474. https://doi.org/10.1162/tacl_a_00437

4. Freitag, M., Grangier, D., Tan, Q., & Liang, B. (2022). High quality rather than high model probability: Minimum Bayes risk decoding with neural metrics. *Transactions of the Association for Computational Linguistics*, *10*, 811-825. https://doi.org/10.1162/tacl_a_00491

5. Gilboa, I., & Schmeidler, D. (1989). Maxmin expected utility with non-unique prior. *Journal of mathematical economics*, *18*(2), 141-153. https://doi.org/10.1016/0304-4068(89)90018-9

6. Glushkova, T., Zerva, C., Rei, R., & Martins, A. F. (2021, November). Uncertainty-aware machine translation evaluation. In *Findings of the Association for Computational Linguistics: EMNLP 2021* (pp. 3920-3938). https://doi.org/10.18653/v1/2021.findings-emnlp.330

7. Hooman, A. M., & Fumani, M. R. F. Q. (2017). An Investigation into the Application of Strategies Used for Translation of Persian Jaam-e Jam TV Series Subtitles from Persian into English Based on Baker's (1992) Model. *International Academic Journal of Humanities, 4*(1), 89–105

8. Joshi, P., Santy, S., Budhiraja, A., Bali, K., & Choudhury, M. (2020, July). The state and fate of linguistic diversity and inclusion in the NLP world. In *Proceedings of the 58th annual meeting of the association for computational linguistics* (pp. 6282-6293). https://doi.org/10.18653/v1/2020.acl-main.560

9. Kumar, S., & Byrne, B. (2004). Minimum bayes-risk decoding for statistical machine translation. In *Proceedings of the human language technology conference of the North American chapter of the association for computational linguistics: HLT-NAACL 2004* (pp. 169-176).

10. Navigli, R. (2009). Word sense disambiguation: A survey. *ACM computing surveys (CSUR)*, *41*(2), 1-69. https://doi.org/10.1145/1459352.1459355

11. Navigli, R., & Ponzetto, S. P. (2010, July). BabelNet: Building a very large multilingual semantic network. In *Proceedings of the 48th annual meeting of the association for computational linguistics* (pp. 216-225).

12. Papineni, K., Roukos, S., Ward, T., & Zhu, W. J. (2002, July). Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics* (pp. 311-318). https://doi.org/10.3115/1073083.1073135

13. Popović, M. (2015, September). chrF: character n-gram F-score for automatic MT evaluation. In *Proceedings of the tenth workshop on statistical machine translation* (pp. 392-395). https://doi.org/10.18653/v1/W15-3049

14. Post, M. (2018, October). A call for clarity in reporting BLEU scores. In *Proceedings of the third conference on machine translation: Research papers* (pp. 186-191). https://doi.org/10.18653/v1/W18-6319

15. Raganato, A., Camacho-Collados, J., & Navigli, R. (2017, April). Word sense disambiguation: A unified evaluation framework and empirical comparison. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers* (pp. 99-110).

16. Rei, R., Stewart, C., Farinha, A. C., & Lavie, A. (2020, November). COMET: A neural framework for MT evaluation. In *Proceedings of the 2020 conference on empirical methods in natural language processing (emnlp)* (pp. 2685-2702). https://doi.org/10.18653/v1/2020.emnlp-main.213

17. Riadhusin, R., Radhakrishnan, R., Rajendren, D. J., Rakhmanovich, I. U., Lal, N. D., & Anand, U. (2025). Adaptive Language Translation in Multinational Info Service Platforms. *Indian Journal of Information Sources and Services, 15*(2), 124–129. https://doi.org/10.51983/ijiss-2025.IJISS.15.2.17

18. Sellam, T., Das, D., & Parikh, A. (2020, July). BLEURT: Learning robust metrics for text generation. In *Proceedings of the 58th annual meeting of the association for computational linguistics* (pp. 7881-7892). https://doi.org/10.18653/v1/2020.acl-main.704

19. Dusi, P. (2026). Adaptive Time–Frequency Signal Decomposition Using Deep Learning for Intelligent Spectral Analytics. *Transactions on Advanced Signal Processing and Analytics*, *1*(1), 7-13.

20. Hyunjae, L., & Sungho, J. (2026). Machine Learning-Enabled Fault Prediction and Adaptive Testing Framework for Reliable VLSI System Design. *Progress in AI-Accelerated VLSI Systems*, *1*(3), 36-46.

21. Hyunjae, L., & Sungho, J. (2026). Real-Time Spectral–Statistical Fusion Framework for Scalable Big Data Analytics in Distributed Sensor Networks. *Transactions on Advanced Signal Processing and Analytics*, *1*(3), 16-23.