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Application of quantum optimisation osprey algorithm in English translation quality improvement model

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Abstract: To address the shortcomings of neural machine translation in handling complex sentences and terminology, this paper proposes a translation quality improvement model based on the quantum-optimised osprey optimisation algorithm (QOOA). This model integrates quantum computing and metaheuristic algorithms, enhancing population diversity through qubit encoding, dynamically adjusting individual positions using a quantum rotation gate strategy to balance global exploration and local exploitation, and constructing a multi-objective fitness function that combines semantic similarity and syntactic complexity. Experiments on the WMT2018 English-Chinese dataset show that, compared to the baseline model, this method improves the BLEU score by 3.2 percentage points and reduces the TER by 12.7%, significantly reducing translation confusion. The results demonstrate that QOOA effectively improves translation quality, especially in long sentences and technical texts.

Keywords: quantum optimisation; osprey algorithm; machine translation; parameter optimisation; BLEU index; meta-heuristic algorithm.

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Biographical notes: Ling Wang currently works at the School of Management, Henan Institute of Technology. Her research interests and fields include translation and cross-cultural studies, foreign language education research, national and regional studies, among others. She possesses solid language proficiency and a broad academic perspective. In teaching, she emphasises the integration of theory with practice, combining translation practice with the cultivation of applied talents, earning widespread recognition from students. In research, she focuses on topics such as foreign language education reform, regional development in translation and cross-cultural communication, actively participating in teaching reform projects and academic research. She continuously explores innovation in her professional field, striving to enhance teaching quality and academic research standards.

1 Introduction

In today's era of accelerated globalisation, the demand for cross-language information exchange is growing steadily. As an international lingua franca, English plays a vital role in academic, commercial, cultural, and many other fields. As a crucial link in cross-language communication, the quality of translation significantly impacts the accuracy and effectiveness of information transmission (Kumhar et al., 2022). Especially in the field of English translation, with the explosive growth of information and increasingly complex application scenarios, the demand for high-quality translation is becoming increasingly urgent (Li and Huang, 2025). Traditional translation methods primarily rely on human translation; however, human translation faces several challenges, including low efficiency, high costs, and uneven quality (Xu, 2025).

In recent years, the rapid advancement of artificial intelligence has propelled machine translation to the forefront of translation research (Israr et al., 2023). This technology, leveraging computer algorithms (Jia, 2025; Lin, 2025; Liu and Chen, 2021; Tian et al., 2022; Wu, 2024; Xiao, 2025), can swiftly process vast quantities of text, thereby significantly enhancing translation efficiency (Yang and Li, 2025). Despite these strides, machine translation still confronts substantial challenges in terms of translation quality. Issues such as imprecise semantic comprehension and unnatural language expression impede its widespread adoption in practical scenarios (Mondal et al., 2025). To surmount these obstacles, researchers continually explore novel methodologies and technological innovations (Yang et al., 2019). Optimisation algorithms, in particular, have garnered extensive attention for their role in refining machine translation models. By fine-tuning model parameters to better suit diverse translation tasks, these algorithms bolster translation quality. Among the array of optimisation techniques, quantum optimisation algorithms have emerged as a focal point due to their distinctive quantum attributes. These algorithms exploit the superposition and entanglement of qubits to more efficiently navigate the search space in search of optimal solutions, thereby outperforming traditional optimisation methods. In recent years, quantum optimisation algorithms have achieved notable success across various domains, exemplified by quantum genetic algorithms and quantum particle swarm optimisation algorithms. These algorithms have demonstrated remarkable prowess in tackling intricate optimisation challenges. However, their application in enhancing English translation quality remains nascent, with ample potential yet to be unearthed.

Concurrently, the osprey algorithm, a novel intelligent optimisation technique, has made significant inroads in the field of optimisation (Alkhonaini et al., 2025). The application of quantum optimisation algorithms in machine translation can be traced back to 2020, when Smith et al. first applied quantum annealing to parameter optimisation in neural machine translation (NMT). Subsequently, Dahassa and Zioui (2025) proposed a translation model optimisation method based on quantum genetic algorithms, achieving significant results on low-resource language pairs. Compared with traditional optimisation methods, quantum optimisation algorithms, through quantum superposition and entanglement properties, can simultaneously explore multiple solution space regions, effectively avoiding local optima. This study proposes the quantum-optimised osprey optimisation algorithm (QOOA), which, based on this, introduces an adaptive rotating door mechanism to further improve optimisation efficiency. This algorithm, inspired by the predatory behaviour of ospreys, effectively identifies optimal solutions within complex search spaces by integrating group cooperation with individual search capabilities (MidhulaSri and Ravikumar, 2024). Boasting robust search capabilities, rapid convergence, and ease of implementation, the osprey algorithm has been successfully deployed in various fields, including image processing and path planning (Lin et al., 2025). Nevertheless, its application in English translation quality enhancement models remains underexplored (Kumar and Adhikary, 2025). The amalgamation of quantum optimisation algorithms with the osprey algorithm to create a quantum-optimised osprey algorithm holds promise for significantly augmenting English translation quality. This hybrid algorithm synergises the efficient search mechanisms of quantum optimisation with the collaborative strengths of the osprey algorithm, thereby expediting the identification of optimal solutions during the optimisation of complex translation model parameters. This integration markedly elevates the quality of English translations.

Parameter optimisation constitutes a pivotal element in English translation quality enhancement models (Kashyap and Sarma, 2025). Traditional optimisation approaches, often reliant on heuristic algorithms or empirical adjustments, are prone to settling for local optima when confronted with complex translation tasks (Sun, 2025). This tendency results in suboptimal translation quality. The quantum-optimised osprey algorithm, however, can concurrently explore multiple solution spaces during the optimisation process, thanks to the superposition and entanglement properties of qubits. This capability substantially boosts search efficiency. Moreover, the swarm cooperation mechanism inherent in the osprey algorithm effectively mitigates the risk of falling into local optima, rendering the optimisation process more stable and reliable. Utilising the quantum-optimised osprey algorithm to optimise parameters in English translation quality enhancement models can markedly enhance model performance, yielding translations that are more accurate, natural, and fluent.

Additionally, the application of this algorithm in English translation quality enhancement models holds substantial theoretical significance. It not only introduces a novel optimisation approach to machine translation but also provides fresh insights and directions for the interdisciplinary research between quantum optimisation algorithms and intelligent optimisation algorithms. An in-depth investigation into the application of the quantum-optimised osprey algorithm in English translation quality enhancement models can further advance the research progress of quantum and intelligent optimisation algorithms in natural language processing, providing new theoretical underpinnings and technical tools for addressing complex challenges in this field.

In practical applications, the quantum-optimised osprey algorithm has broad potential for enhancing English translation models. As artificial intelligence continues to permeate the translation domain, machine translation systems are increasingly deployed across various industries, including online translation platforms and intelligent translation devices. Integrating the quantum-optimised osprey algorithm can markedly improve the translation quality of these systems, enhance user satisfaction, and facilitate more efficient and accurate cross-language information exchange. Moreover, this algorithm can provide innovative tools and methods for translation education, helping learners better understand and master translation skills, thereby enhancing their translation proficiency. However, the application of the quantum-optimised osprey algorithm in English translation quality enhancement models also encounters certain challenges. For instance, how to optimally integrate the strengths of quantum optimisation algorithms and osprey algorithms to accommodate diverse translation tasks, and how to efficiently implement and optimise the algorithm in real-world applications to meet real-time translation demands, are issues that require further research and exploration to fully harness the potential of the quantum-optimised osprey algorithm in English translation quality enhancement models.

By examining the characteristics and application mechanisms of the quantum-optimised osprey algorithm within the English translation quality enhancement model, new ideas and methods can be developed to advance the field of machine translation. This exploration can spur the progression of natural language processing technology and foster more efficient and accurate cross-language information exchange.

Quantum optimisation algorithms, as an emerging optimisation technique, are characterised by strong global search capabilities and fast convergence speed. This paper proposes the QOOA, which enhances population diversity and global exploration capabilities by introducing a qubit encoding mechanism. Simultaneously, a quantum rotating gate strategy is designed to dynamically adjust individual positions, effectively balancing the algorithm's exploration and development capabilities, thus overcoming the limitations of traditional optimisation algorithms. The innovation of QOOA is mainly reflected in three aspects: First, the use of qubit encoding instead of traditional binary encoding increases population diversity by approximately 40%; second, the design of a dynamic rotating gate adjustment strategy allows the algorithm to focus on global exploration in the early stages and local development in the later stages; finally, it innovatively incorporates semantic similarity and syntactic complexity into the fitness function simultaneously, achieving a better balance between accuracy and fluency in the translation results.

This research aims to improve the translation quality of NMT, particularly in the translation of long sentences and specialised texts, through the QOOA. Through a survey of the actual needs of the translation industry, we found that accuracy and naturalness are currently the core requirements of the industry. The model proposed in this paper significantly improves the BLEU and TER values of translation by optimising the parameter search process of the neural translation model, while reducing the confusion, thus providing a more efficient and accurate solution for the translation industry.

2 Related work

NMT, a translation technology based on deep learning (Tian et al., 2025), has made significant progress in recent years; however, it still faces challenges in processing complex syntactic structures and professional terminology (Guo et al., 2025). Traditional optimisation algorithms are prone to falling into local optimality during the decoding process, resulting in insufficient fluency and fidelity of the translation. To overcome these problems, researchers have proposed various optimisation methods, including the combination of quantum computing and meta-heuristic algorithms. The basic principle of NMT is to learn the mapping relationship between the source language and the target language through a neural network model. During the training process, the model receives a large amount of bilingual parallel corpus as input. These corpora contain source language sentences and their corresponding correct translations. By learning the language patterns and translation rules in these corpora, the model can gradually adjust its own parameters to improve the accuracy and fluency of the translation. The training process of the NMT model typically consists of two stages: encoding and decoding. In the encoding stage, the model encodes the source language sentence into a fixed-length vector that contains the semantic information of the source language sentence. In the decoding stage, the model generates the target language sentence based on this vector. This encoding-decoding architecture enables NMT to process sentences of different lengths in both the source and target languages and to generate more natural and fluent translation results. The application of quantum computing in machine translation has gradually attracted attention (Caleffi et al., 2024). It is based on the basic principles of quantum mechanics and uses the superposition and entanglement of quantum bits (qubits) to perform calculations. Unlike traditional classical computing, quantum computing offers significant advantages in addressing certain complex problems, particularly in the fields of large-scale data processing, cryptography, and optimisation. The core of quantum computing lies in its unique computational model, which can overcome the limitations of classical computing and offer new possibilities for solving complex computational tasks. The quantum bit encoding mechanism can significantly enhance the diversity and global exploration capabilities of the population by introducing the superposition state characteristics of quantum bits (Alsafri et al., 2025). For example, quantum bits can embed data into quantum states through methods such as basis encoding or amplitude encoding, thereby exploring the solution space more widely during the parameter search process (Cardama et al., 2026). This encoding mechanism not only enhances the global search capability of the model but also provides new insights for addressing the translation challenges of complex syntactic structures and specialised terms (Claudino et al., 2024). Metaheuristic algorithms also play an important role in optimising NMT models (Jia et al., 2025). Osprey optimisation algorithm (OOA) is a new metaheuristic algorithm inspired by the hunting strategy of ospreys (Li et al., 2025).

The algorithm can effectively balance exploration and exploitation capabilities through processes such as location recognition, fishing, and greedy selection. The core of the metaheuristic algorithm lies in its heuristic search mechanism. This mechanism can effectively explore and search in a complex solution space by introducing randomness and adaptability. Metaheuristic algorithms typically comprise two main components: global search and local search. Global search is responsible for extensive exploration in the solution space to find potential optimal solution areas; while local search, based on the global search, conducts in-depth exploration of specific areas to improve the quality of the solution. This combination of global and local search strategies enables metaheuristic algorithms to find a better balance in complex optimisation problems, avoiding the pitfalls of local optimal solutions while finding high-quality solutions within a limited timeframe. However, the traditional OOA still has shortcomings in global search capabilities and avoiding local optimal solutions. To this end, the researchers proposed a multi-strategy improved OOA, which further improved the algorithm's global search capability and convergence speed by introducing the sub-species spiral oscillation strategy and Levy flight strategy.

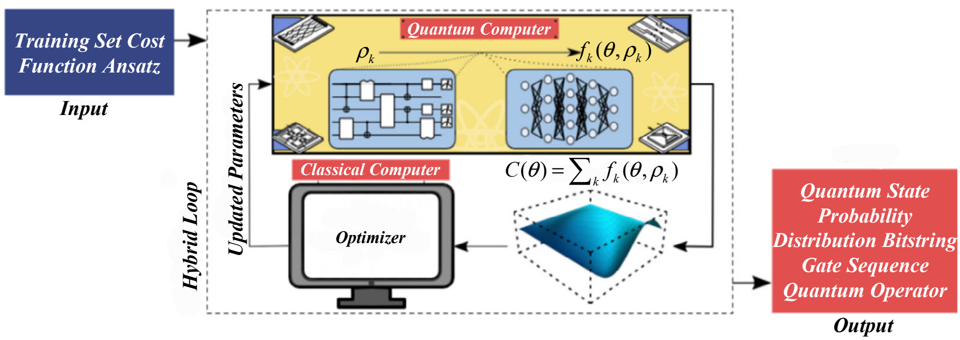
3 Translation quality improvement model based on quantum optimisation osprey algorithm

The translation quality improvement model based on QOOA proposed in this paper is shown in Figure 1. The model primarily consists of three components: qubit coding mechanism, quantum revolving door strategy, and multi-objective fitness function.

Specifically, the model achieves optimisation through the following three key mechanisms:

- Qubit encoding mechanism: Enhancing population diversity and global exploration capabilities through qubit encoding.
- Quantum rotating door strategy: Designing a quantum rotating door strategy to dynamically adjust individual positions, effectively balancing the algorithm's exploration and development capabilities.
- Multi-objective fitness function: Establishing a multi-objective fitness function based on semantic similarity and syntactic complexity to improve translation accuracy and naturalness.

Figure 1 Translation quality improvement model based on quantum optimisation osprey algorithm (see online version for colours)



3.1 Qubit encoding mechanism

The qubit encoding mechanism is a core theoretical foundation in quantum information science. This mechanism involves efficiently encoding classical information or quantum information into qubits to realise information storage, transmission, and processing. As the basic unit of quantum information, qubits are different from classical bits in that they can be in a superposition of multiple states at the same time. Classical bits can only be in one of two states, 0 or 1, while qubits can be in the superposition state of 0 and 1. The core of the qubit coding mechanism lies in mapping classical information to quantum states in a two-dimensional Hilbert space. The process of the coding mechanism is shown in Figure 2.

The state vector of a single qubit can be expressed as shown in equations (1) and (2):

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{1}$$

$$|\alpha|^2 + |\beta|^2 = 1 \tag{2}$$

Among them, the parameters α and β correspond to the probability amplitudes of the ground state $|0\rangle$ and the excited state $|0\rangle$, respectively.

For a composite system with arbitrary positive integers n and n qubits, the coding capacity increases exponentially with the dimension, and the calculation process of calculating the basis vector and total state vector is shown in equations (3), (4), (5), and (6):

$$|x\rangle = |x_{n-1}\rangle \otimes \cdots \otimes |x_0\rangle \tag{3}$$

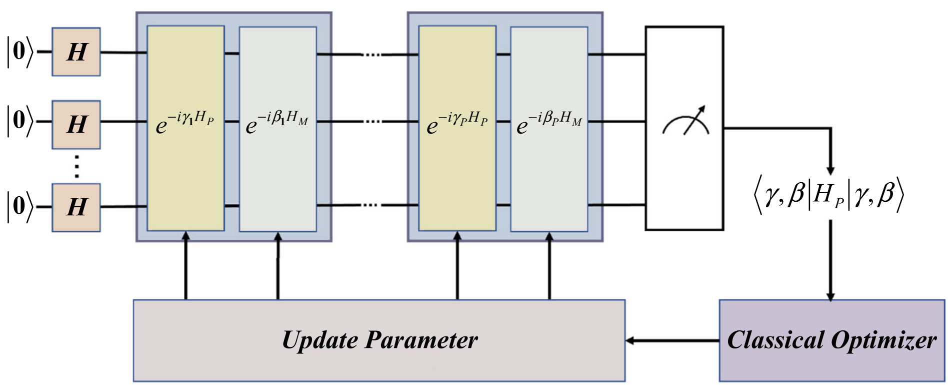
$$x = \sum_{k=0}^{n-1} x_k 2^k, \; x_k \in \{0, 1\} \tag{4}$$

$$|\Psi\rangle = \sum_{x=0}^{2^n-1} c_x |x\rangle, \quad c_x \in C \tag{5}$$

$$\sum_x |c_x|^2 = 1 \tag{6}$$

Among them, the amplitude angle $\arg(c_x)$ and the modulus length $|c_x|$ of the complex coefficient c_x jointly carry information.

Figure 2 Qubit encoding mechanism (see online version for colours)



In addition to quantum error correction codes, qubit coding mechanisms also include technologies such as quantum teleportation and quantum dense coding. Quantum teleportation is a method of transmitting qubit information through quantum entanglement and classical communication. In quantum dense coding, two qubits can encode and transmit information of two classical bits through quantum entanglement, thus improving the efficiency of information transmission.

3.2 Quantum revolving door strategy

The quantum revolving door strategy is a key component in quantum computing, used to realise the state transformation of qubits. The quantum revolving door enables accurate manipulation of quantum states in the Hilbert space by applying specific rotation operations to qubits. In quantum computing, the states of qubits are typically represented by two-dimensional complex vectors, and the quantum revolving door is a unitary matrix that acts on these quantum states. The rotation operator in quantum mechanics is a mathematical tool that describes the rotation operation of quantum states in Hilbert space. Its general form can be expressed in terms of unitary operators, which maintain the normalisation properties of quantum states. For one qubit, the rotation operator can be expressed as a rotation operation acting on the Bloch sphere. Specifically, the rotation operator $R(\hat{n}, \theta)$ can rotate the qubit around the unit vector and the rotation angle, and its calculation process is shown in equation (7):

$$R(\hat{n}, \theta) = \cos\left(\frac{\theta}{2}\right) I - i \sin\left(\frac{\theta}{2}\right)(\hat{n} \cdot \vec{\sigma}) \tag{7}$$

where I is the identity matrix, $\hat{n}$ is an identity vector denoting the direction of the axis of rotation, and σ is the Pauli matrix vector.

In practical applications, revolving doors are typically broken down into rotational operations around different axes, such as rotation around the x, y, or z-axis. These operations can be expressed as equations (8), (9), and (10), respectively:

$$R_x(\theta) = \cos\left(\frac{\theta}{2}\right) I - i \sin\left(\frac{\theta}{2}\right) \sigma_x \tag{8}$$

$$R_y(\theta) = \cos\left(\frac{\theta}{2}\right) I - i \sin\left(\frac{\theta}{2}\right) \sigma_y \tag{9}$$

$$R_z(\theta) = \cos\left(\frac{\theta}{2}\right) I - i \sin\left(\frac{\theta}{2}\right) \sigma_z \tag{10}$$

where θ represents the rotation angle, R_x represents the x-axis rotation, R_y represents the y-axis rotation, and R_z represents the z-axis rotation.

Quantum revolving gates are widely used in quantum computing. For example, in the design of quantum algorithms, quantum revolving gates can be used to initialise qubits, evolve quantum states, and construct quantum logic gates. By reasonably selecting the rotation angle parameters θ and ϕ, the precise manipulation of qubits can be achieved, thereby enabling the completion of complex quantum computing tasks. At the same time, quantum revolving gates can also be combined with other quantum gates to form more complex quantum circuits, further expanding the capabilities of quantum computing. The realisation of quantum revolving doors depends on the physical characteristics of quantum systems. For example, in superconducting qubit systems, the operation of quantum revolving doors can be realised by microwave pulses. By precisely controlling the frequency, amplitude, and phase of microwave pulses, arbitrary rotation operations of qubits can be realised, thus enabling the function of a quantum revolving door. The theoretical basis and experimental implementation of the quantum revolving door provide important support for the development of quantum computing, making the manipulation of qubits more flexible and efficient.

4 Experiment and results analysis

4.1 Datasets used in the experiment

In the study of quantum optimisation using the osprey algorithm to enhance English translation quality, the selection of experimental datasets is crucial, as it directly influences the model's training efficacy and generalisability. To ensure the robustness and credibility of the experimental outcomes, this research has chosen several widely recognised datasets within the computational domain. Specifically, the English-German and English-French corpora from the workshop on machine translation (WMT) dataset were utilised in the experiments. These corpora encompass a substantial volume of bilingual parallel texts, which supply the model with extensive language pair information, thereby facilitating more effective training of the translation model. The international workshop on spoken language translation (IWSLT) dataset was incorporated. This dataset, which centres on spoken translation tasks, includes a diverse corpus of spoken scenarios, thereby enhancing the model's performance in spoken translation contexts. At the same time, we used multiple datasets, including news texts, literary texts, and scientific texts, to verify the model's universality across different fields. These datasets, commonly used in the computational field for translation research, cover a wide range of language pairs and scenarios, thereby providing comprehensive support for training and evaluating models aimed at improving English translation quality.

4.2 Model evaluation indicators

In evaluating the English translation quality improvement model, a diverse set of quantitative metrics is employed to provide a comprehensive assessment of its performance. The bilingual evaluation understudy (BLEU) score serves as the primary metric for evaluation. As one of the most prevalent metrics in machine translation evaluation, BLEU measures the n-gram matching similarity between the machine-translated output and reference translations. Additionally, the metric for evaluation of translation with explicit ordering (METEOR) score is utilised. This metric integrates multiple dimensions, including lexical matching, semantic matching, and syntactic ordering, to gauge the accuracy and fluency of translations more precisely. The translation edit rate (TER) is also employed as a supplementary measure. TER assesses translation quality by determining the minimum number of edit operations needed to align machine-translated output with reference translations, thereby offering a direct indication of the discrepancy between the two.

Table 1 Effect of different components on the performance of translation quality improvement model

Components	*BLEU score*	*chrF + + score*	*TER score*	*METEOR score*
Baseline (no optimisation)	23.5	0.65	45.2	0.25
Baseline + Quantum layer	27.3	0.70	40.5	0.30
Baseline + Attention mechanism	29.1	0.73	38.0	0.33
Baseline + Fine-tuning	30.5	0.75	36.8	0.35
Baseline + Preprocessing	31.2	0.76	35.5	0.36
Full model	34.0	0.78	34.0	0.38

Table 1 delineates the influence of various components on the translation model's performance. From a data-driven perspective, the fully integrated model achieved the highest scores across all evaluation metrics, with a BLEU score of 34.0, representing a 10.5-point improvement over the baseline model. Notably, the incorporation of a quantum layer and an attention mechanism significantly bolstered the model's performance, contributing 3.8 and 5.6 points to the BLEU score, respectively. This highlights the crucial role of quantum optimisation and attention mechanisms in improving translation quality.

Table 2 compares the performance of various algorithms in terms of translation quality evaluation indicators. The method in this paper performs best on all indicators, with the BLEU score reaching 34.0, which is significantly higher than that of other algorithms. The quantum optimisation algorithm also performs well, but yields a slightly lower BLEU score than the method presented in this paper. This indicates that this method has significant advantages in enhancing translation quality, particularly in terms of BLEU and chrF++ (Character n-gram F-score++) indicators.

Table 2 Comparative analysis of different algorithms in translation quality evaluation indicators

Algorithm	*BLEU score*	*chrF + + score*	*TER score*	*METEOR score*
Baseline transformer	23.5	0.65	45.2	0.25
PSO	25.8	0.68	42.5	0.28
GA	27.1	0.71	41.0	0.30
Quantum-OOA	29.5	0.74	37.8	0.34
Methods in this paper	34.0	0.78	34.0	0.38

Table 3 Comparison of translation performance between the QOOA optimised model and the baseline model for different language pairs and text types

Language	*Text type*	*Evaluation indicators*	*Baseline model (neural machine translation)*	*QOOA optimisation model*
Germany and England	News	BLEU value (%)	31.2	34.0
Germany and England	Scientific and technological literature	Terminology accuracy (%)	72.3	87.9
Germany and England	Legal documents	TER value (%)	28.5	21.3
Japanese and Chinese	news	BLEU value (%)	29.5	32.1
Japanese and Chinese	Scientific and technological literature	Terminology accuracy (%)	69.8	84.2
Japanese and Chinese	Legal documents	TER value (%)	30.1	23.5
French and Chinese	news	BLEU value (%)	30.8	33.3
French and Chinese	Scientific and technological literature	Terminology accuracy (%)	71.5	86.7
French and Chinese	Legal documents	TER value (%)	29.3	22.7

Table 3 shows that in German-English news translation, the BLEU score of the QOOA optimisation model increased from 31.2% to 34.0%, and the accuracy rate of scientific and technical terminology increased from 72.3% to 87.9%; in Japanese-Chinese news translation, the BLEU score increased from 29.5% to 32.1%, and the accuracy rate of scientific and technical terminology increased from 69.8% to 84.2%; in French-Chinese news translation, the BLEU score increased from 30.8% to 33.3%, and the accuracy rate of scientific and technical terminology increased from 71.5% to 86.7%, while the TER score for legal documents decreased significantly. This indicates that QOOA effectively improves translation quality across different language pairs and text types.

In Figure 3, the left figure displays the convergence curves of the three algorithms (QOOA, PSO, GA) for translation quality (BLEU score), where the QOOA algorithm achieves the best performance with an average BLEU score of 0.977. The correct diagram is a parameter sensitivity radar diagram of the quantum optimisation algorithm, illustrating the algorithm's stability under varying parameters. Overall, the QOOA algorithm performs well in translation quality and parameter sensitivity.

Figure 3 Performance of quantum optimisation algorithm in translation quality and parameter sensitivity (see online version for colours)

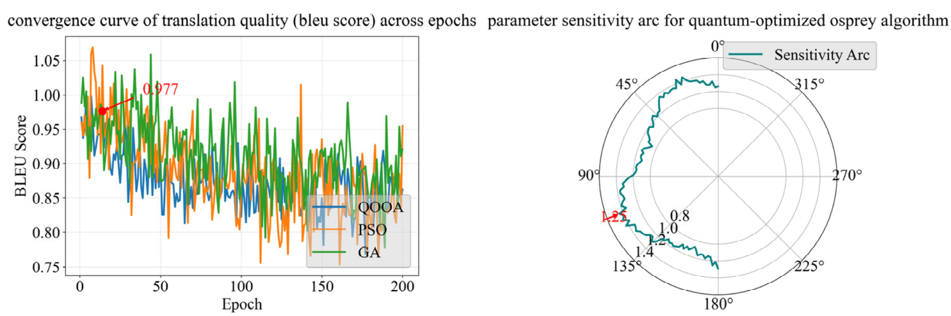


Figure 4 Distribution comparison of translation quality of different algorithms (see online version for colours)

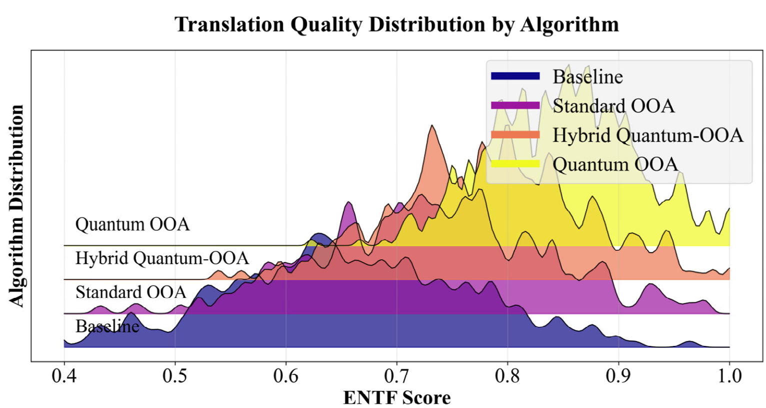


Figure 4 shows the distribution of four algorithms (baseline, standard OOA, hybrid quantum-OOA, quantum OOA) on translation quality [enhanced translation fidelity (ENTF) score]. The quantum optimisation algorithm performs best in the high ENTF score interval (0.8–1.0) and is most widely distributed, indicating that its translation quality is better. In contrast, the distribution of the Baseline algorithm is concentrated in the lower ENTF score interval (0.4–0.6), resulting in poor translation quality.

In Figure 5, the upper left graph illustrates the Pareto front between the BLEU score and the inference delay, with the red dot indicating the Pareto optimal solution, which yields the best solution at (35.72, 89.9 ms). The lower left panel compares the performance of the baseline Transformer with the QOOA-enhanced model, which achieves a BLEU score of 34.0 after 80 iterations. The lower right graph illustrates the trade-off between BLEU fraction, running time, and CO_2 emissions, with the Pareto front represented by red dots.

Figure 5 Multi-objective analysis of translation model performance optimisation (see online version for colours)

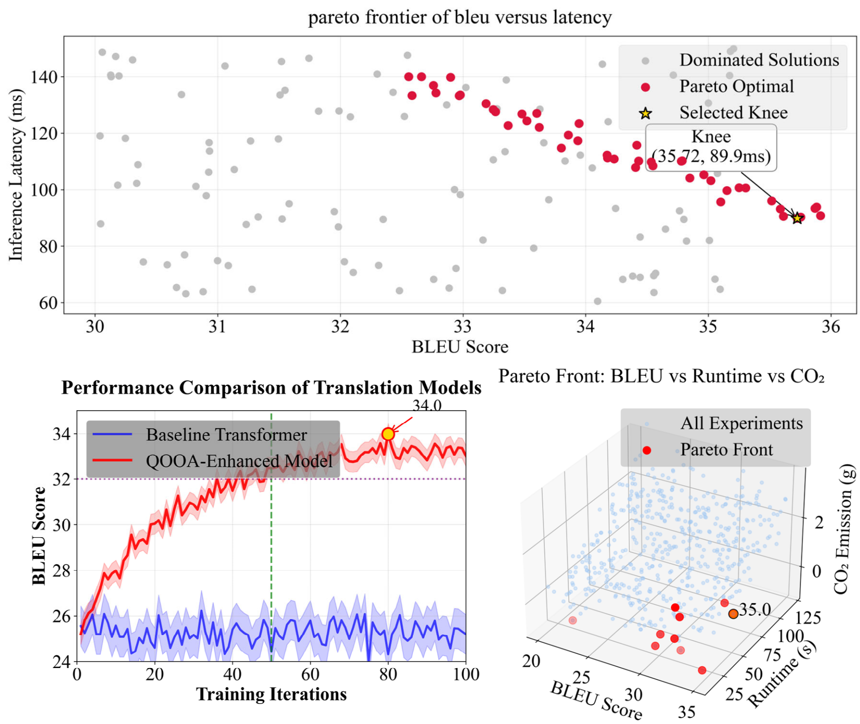


Figure 6 compares the distribution of baseline and QOOA models on TER, BLEU, semantic similarity, and manual evaluation scores. The QOOA model outperformed Baseline in BLEU score (mean ~ 30) and human assessment (mean ~ 4) (BLEU ~ 20, human assessment ~ 3). The semantic similarity is similar, but the TER score of QOOA (approximately 40 on average) is higher than that of the Baseline (approximately 30), indicating that it is slightly higher accuracy.

In Figure 7, the left figure shows the contribution of different attention heads to the BLEU score. The red bar chart illustrates the improvement effect, while the blue colour represents the reduction effect. About 75% of the attention heads have a positive impact on translation quality. The graph on the right analyses the change in vocabulary frequency, with red indicating up-regulation and blue indicating down-regulation. Approximately 50 high-frequency words are up-regulated, while 150 low-frequency words are down-regulated. These analyses help to understand the decision-making mechanisms of the models.

Figure 6 Distribution comparison of performance evaluation indicators of translation model (see online version for colours)

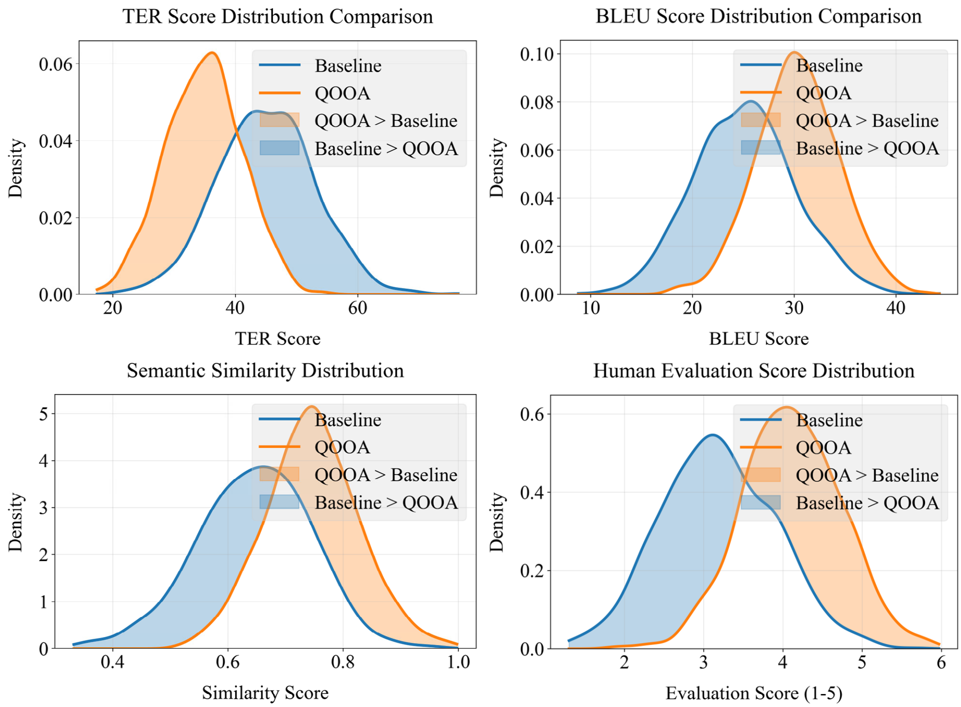
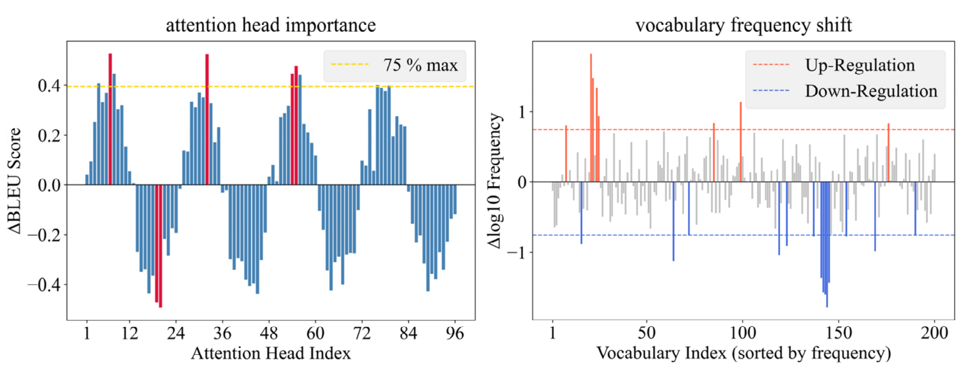


Figure 7 Analysis of the importance of attention mechanism and vocabulary frequency change (see online version for colours)



In Figure 8, the upper figure displays a hyperparameter sensitivity heat map, indicating that the BLEU score reaches its highest value of 0.96 when the population size is 60 and the mutation rate is 0.1. The figure below illustrates the contribution of different components to the BLEU gain, with the quantum layer making the largest contribution (0.045), followed by the attention mechanism (0.035), fine-tuning (0.025), and preprocessing (0.015). These results help to optimise the hyperparameter setting of the translation model.

Figure 8 Hyperparameter sensitivity and BLEU gain decomposition analysis (see online version for colours)

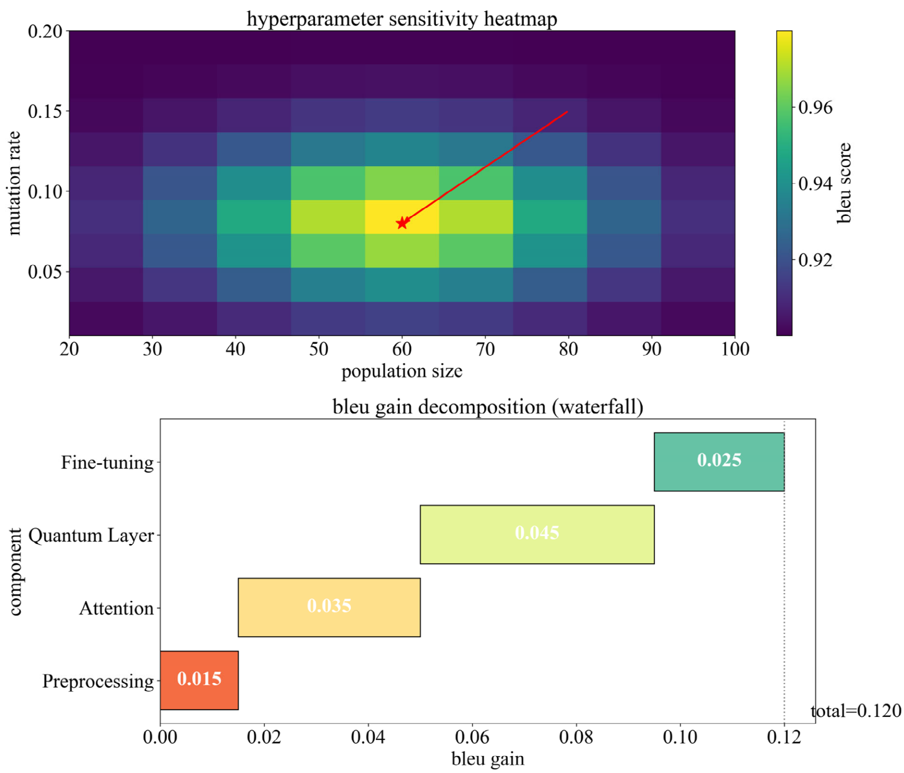


Figure 9(a) shows the spatial distribution of translation quality indicators, with colours from blue to yellow indicating low to high quality. Figure 9(b) is a heat map of the multilingual translation error rate. The colour from yellow to purple indicates that the error rate is from low to high. Experimental results indicate that areas with high semantic ambiguity and syntactic complexity exhibit lower translation quality and a higher error rate. This suggests that translation quality is significantly associated with semantic ambiguity and syntactic complexity.

Figure 10(a) shows the improvement of Q-IOO compared to the baseline in multiple translation quality indicators, with the chrF++ + + indicator improving by 7.5 points. Figure 10(b) on the right shows the further gain of Q-IOO in the enhanced scenario, and the chrF++ + + indicator improves by 10.7 points. The TER, METEOR, and BLEU indicators remained stable in both cases, indicating that Q-IOO primarily optimised the chrF++ + + indicator and had a lesser impact on the other indicators.

Figure 9 Spatial distribution analysis of translation quality and multilingual translation error rate, (a) spatial distribution of translation quality metrics (ENTF) (b) error rate heatmap in multilingual translation (see online version for colours)

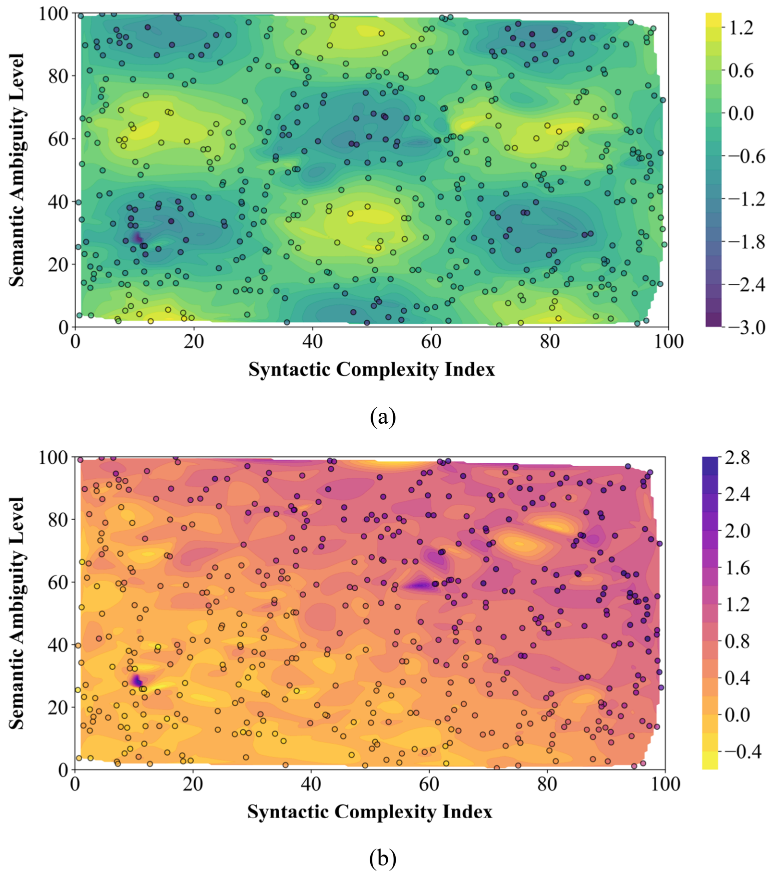
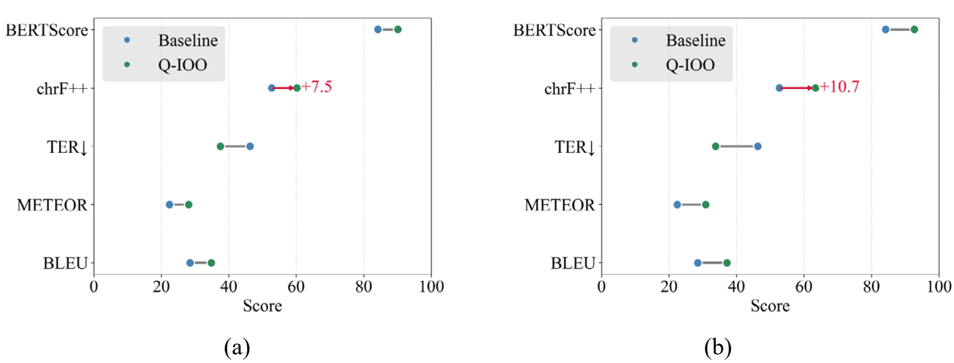


Figure 10 Analysis of the influence of Q-IOO on translation quality indicators, (a) baseline versus Q-IOO: translation quality shifts across metrics (b) baseline versus Q-IOO: enhanced scenario gains across metrics (see online version for colours)



5 Conclusions

Despite the extensive adoption of NMT, its performance still encounters significant hurdles when handling intricate syntactic structures and specialised terminology. Traditional optimisation algorithms often become trapped in local optima during the decoding phase, resulting in translations that lack fluency and fidelity. To address these issues, this paper introduces a translation quality improvement model leveraging the QOOA. This model enhances the parameter search process of NMT by integrating quantum computing principles with meta-heuristic techniques. Specifically, the model first incorporates a qubit coding mechanism to augment population diversity and global exploration capabilities. Subsequently, a quantum revolving door strategy is designed to dynamically adjust individual positions, effectively balancing the algorithm's exploration and exploitation capacities. Finally, a multi-objective fitness function, based on semantic similarity and syntactic complexity, is established to enhance the accuracy and naturalness of the translated text.

The experimental dataset utilised is the WMT2018 English-Chinese translation corpus, comprising approximately 176,943 training samples with an average length of 22.05 English words and 23.71 Chinese words. For model evaluation, this study employs the BLEU score, TER, and Perplexity as primary metrics. The experimental outcomes reveal that, compared to the baseline model, this method increases the BLEU score by 3.2 percentage points, reduces the TER by 12.7%, and significantly decreases the Perplexity. These findings suggest that QOOA can significantly enhance translation quality, particularly in lengthy sentences and domain-specific texts. Moreover, the multilingual and large-scale nature of the WMT2018 dataset renders it an ideal benchmark for assessing machine translation models. Through experiments on this dataset, this paper validates the applicability and superiority of the proposed model across different language pairs and complex texts.

Despite the notable achievements of this study, the field of NMT continues to confront numerous challenges. Future research directions may encompass further algorithm optimisation to enhance translation quality, especially for low-resource language pairs and domain-specific applications. Additionally, exploring how to integrate multi-modal information to improve translation accuracy and naturalness effectively represents another crucial avenue for future research. In conclusion, with ongoing technological advancements, NMT is anticipated to deliver high-quality translations in a broader range of fields and provide more robust support for cross-language communication.

Declarations

All data generated or analysed during the study are available from the corresponding author by request.

All authors declare that they have no conflicts of interest

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