Journal of Languages & Translation
P-ISSN: 2716-9359 E-ISSN: 2773-3505
Volume 05 Issue 02 July 2025 pp.271-286

Translating "*Inside the Box*": A Paradigm Shift to Neural Machine Translation

Asma ALOUI[1]
M'Hamed Bougara University of Boumerdes, Algeria
a.aloui@univ-boumerdes.dz
0009-0008-1928-0539

Received *26/11/2024* ***Accepted*** *29/05/2025* ***Published*** *01/07/2025*

Abstract
At a time when artificial intelligence (AI) comes of age, machine translation; otherwise commonly referred to as MT, gains momentum. The present paper sheds light on two prominent yet divergent approaches in the realm of machine translation; *i.e.*, statistical machine translation (SMT) and neural machine translation (NMT); the latter being the descendant of the former. The paper focuses on neural machine translation, being the most recent and most enhanced of the two approaches, and aims at providing a critical analysis of machine translation output as opposed to that of a human reference by probing the translation strategies deployed by three online translation tools that are free to use by translation professionals and translation students alike; namely, Google Translate, Yandex Translate, and Reverso Translation. It is worth mentioning; at this point, that the aforementioned online translation tools, unlike other ones, support Arabic in their language database, which caters to the needs of translation agents seeking language transfer involving Arabic as a source and/or target language. In order to examine the efficiency of these translation tools in terms of specialized translation, the corpus that has been chosen includes passages from three different text genres; political, economic, and judicial. The findings suggest that online translation tools prove to be efficient in translating sentences with short and simple structures with minimal interpretation scope. The findings also suggest that online translation tools help perform corpus-based translation tasks. Nevertheless, human judgment and supervision as well as editing are still required to ensure correctness, efficiency, and reliability especially in regards to cultural idiosyncrasies.

Keywords: Artificial Intelligence; Neural Machine Translation; Source Input; Statistical Machine Translation; Target Output.

[1] Corresponding author: a.aloui@univ-boumerdes.dz/ Asma ALOUI

Introduction

Machine translation is a flourishing field of research nowadays. New approaches and paradigms are created on a regular basis to cope with the ever expanding nature of computer technologies. Artificial intelligence powered translation tools are a living proof of the marriage between computer sciences and translation/language sciences. The sections ahead will provide a brief review of machine translation, its history, and current approaches. Three neural machine translation tools are chosen for analysis to examine their efficiency in terms of specialized translation compared to a human reference. Despite the technological advances in the field of artificial intelligence in general and machine translation in particular, many people are still skeptical about the output of machine translation and would, more often than not, opt for a human translator. The problem of 'trust' and reliability here stems from the fact that artificial intelligence lacks the facility of human judgment; mainly in regards to extraliguistic elements such as social, cultural, and ideological nuances that could only be understood and interpreted by a seasoned human translator. This study aims at introducing the concept of neural machine translation as part of the latest developments in the realm of machine translation, Furthermore, it seeks to examine the reliability of machine translation output by conducting a descriptive critical analysis of three common online translation tools that use NMT.

I. Literature Review

1. Machine Translation: Setting the Record Straight

When reading about the field of machine translation, one might encounter several terms referring to the matter such as machine-aided translation and machine translation. However, these terms are incorrectly used in an interchangeable manner; therefore, it is rather important to distinguish between them and set the record straight. Machine-aided translation or machine-assisted translation (MAT), computer-aided translation or computer-assisted translation (CAT), machine-aided human translation or machine-assisted human translation (MAHT), and computer-aided human translation or computer-assisted human translation (CAHT) are all terms used to designate the process of translation whereby human translators use computers as an aid to perform translation tasks. This implies that human translators perform most of the translation task and only resort to computers for assistance in smaller portions of the task, as is indicated by the adjectives aided or assisted. In contrast, the term automatic translation or machine translation, commonly abbreviated as MT, signifies that the process of translation can be fully automated; *i.e.*, performed by computers without human intervention. (Sager, 1994; Shuttleworth & Cowie, 1997)

Although one form (MAT, CAT, MAHT, CAHT) is considered partially-automated and the other (MT) fully-automated, human agency is still present in the process of translation, but to varying degrees. Whereas in the crossbred form of translation (human>machine), the human translator is the active agent in the process of translation as he actively performs the task of translation himself/herself with the assistance of a machine, in the automated form of translation (machine>human), he/she is the initiating agent of the process of translation undertaken by the machine. The human translator's role here is to verify and edit the output of the machine to insure the correctness and adequacy of the transfer between source and target languages.

2. Natural Language vs. Artificial Language

Sager (1994) differentiates between natural language and artificial language in that natural languages are human languages that share similar features like phonetics and grammar due to historic or geographic closeness, while artificial languages, which can be derived from natural languages, are computer languages divided according to the community of users. As the author puts it, "… natural languages are grouped into historical families and geographically distributed, artificial language, even though many are derived from a natural language, are used

in different patterns by diverse user groups." (p.34)
While artificial language can be derived from natural language, the former adds certain useful features to the latter (Sager, 1994); for instance:

- specific references;
- economy of expression;
- accommodation to the community of users.

The interesting thing about machine translation is that it performs transfer from one natural language to another, yet the translation process involves artificial language taking the forms of coding and decoding performed by an automated system.
Shuttleworth and Cowie (1997) disregard the stereotype which considers machine translation as inefficient for they believe the ultimate goal for machine translation is not to produce an output that is as perfect as the one produced by a human translator; but rather, to perform translation tasks at higher speed and lower costs, all while producing an output that can still be edited by a human translator.

3. Machine Translation in Retrospect

The idea of mechanical dictionaries dates all the way back to the 17th century when the principle of a universal language that gathers equivalent ideas from different languages in a shared symbol system was suggested by René Descartes (Okpor, 2014). In the thirties of the 20th century, George Artsouni issued a patent for a storage device that functions as a multilingual dictionary in nowadays terms, then a few years later, Peter Smirnov-Troyanskii issued another patent for a three-phase editing mechanical translation, which one could argue is almost exactly the same concept as the transfer approach in linguistic knowledge architecture explained in the upcoming sections of this paper. (Zughoul & Abu-Alshaar, 2005, p.1024)

The early traces of a machine that performs multilingual translations can be found in a memorandum written by Warren Weaver to the Rockefeller Foundation back in the year 1949. This memorandum triggered research in machine translation in the early fifties and led to the creation of several research groups in Europe and America. Despite the initial enthusiasm for this concept, it was soon met with harsh skepticism whereby the idea of a fully-automated high-quality machine translation (FAHQMT) output was disregarded and thought to be impossible for the machine does not have the general knowledge humans have about the world; and hence, lacks human interpretation skills and is incapable of spotting the correct suitable meaning in different situations and contexts. Subsequently, governments cut off funds for research in this field as it was deemed unfruitful. (Arnold *et al.*, 1997, pp.12-13) A beacon of hope resurfaced in the following decade as the Mormon Church funded some groups in order to work on Bible translation leading; thus, to the creation of machine translation systems like WEIDNER, ALPS, and METEO. (Arnold *et al.*, 1997, p.14)

In the seventies, machine translation started to gain huge momentum as different machine translation systems were bought and enhanced in different parts of the world like Europe, America and Japan. Funds were granted to research and development groups with the aim of creating sophisticated designs of machine translation systems. With the evolution of information technology and computers, and with the propagation of globalization and the proliferation of multinational companies in need of translation services, machine translation spurred more research in the eighties, leading to yet greater advances in the field, especially since it joined forces with other fields like linguistics, computer science, and artificial intelligence. (Zughoul & Abu-Alshaar, 2005, p.1025)

Developments have been in full fling ever since which resulted in machine translation being established as a research field (Arnold *et al.*, 1997, p.14), as well as a functional translation option for individual or corporate translation seekers. One of these major developments was marked by the shift from grammar-based and rule-based machine translation to statistical machine translation in the nineties (Zughoul & Abu-Alshaar, 2005, p.1027); and then, from statistical machine translation to neural machine translation in the twenties of the 21st century. These two approached are discussed separately in the sections following machine translation engines and paradigms.

4. Inside the Box: Machine Translation Engines and Paradigms

Machine translation, *ab initio*, used a basic system called transformer architecture. Later on, a more advanced MT system was developed; it is called Linguistic Knowledge (LK) and it includes two approaches: interlingual approach and transfer approach (Arnold *et al.*, 1994, p.2)
As stated above, machine translation engines are classified according to their architecture into:

4.1. Direct or Transformer Architecture

This MT system transforms source language which is called 'input' directly into target language which is referred to as 'output' by replacing source words with their target equivalents with reference to the bilingual dictionary. These words are later re-ordered according to the target language system. (Arnold *et al.*, 1994, p.59)

4.2. Indirect or Linguistic Knowledge Architecture

This architecture prioritizes extensive linguistic knowledge in both the source language and the target language equally. Each language has its own independent grammar so as to insure an individual and deep representation of each language; and as such, yield higher quality translations. (Arnold *et al.*, 1994, pp.66-67). This system uses two approaches:

4.2.1. Interlingual Approach

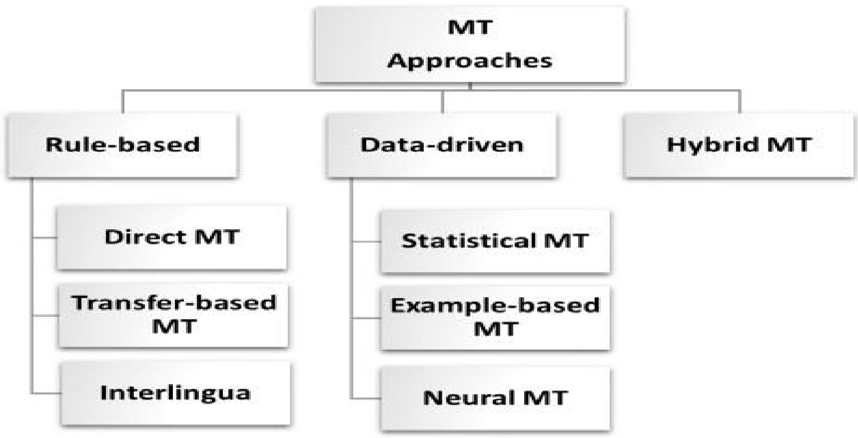
Translation here goes through two phases; the first, is parsing input sentences into abstract interlingual representations; and the second, is producing output sentences based on those interlingual representations.

4.2.2. Transfer Approach

Translation goes through three phases; in the first, parsers analyze input sentences into representations with source language interface structures (analysis phase) and turn them into underlying representations with target language interface structures (transfer phase), these representations will then be used by generators to produce output sentences with target language interface structures (synthesis phase).

On a similar note, Ameur *et al.*, (2020), in their study about Arabic machine translation, distinguish between three paradigms in machine translation which are **rule-based**, **data-driven**, and **hybrid machine translation**. The first approach groups direct and indirect machine translation (discussed above), the second involves example-based machine translation, statistical machine translation, and neural machine translation (discussed below), and last but not least, the third includes hybrid rule-based machine translation and hybrid data-driven machine translation. The following figure illustrates this taxonomy.

Figure 1: Taxonomy of machine translation paradigms



Source: (Ameur et al., 2020, p.7)

5. Statistical Machine Translation

Statistical machine translation (SMT) is a data-driven machine translation approach that uses large volumes of bilingual data to find the closest target equivalent for an input. Statistical machine translation systems learn to translate by analyzing the statistical relationships between original texts and their existing human translations. https://machinetranslate.org/statistical-machine-translation

Since SMT is based on the analysis of bilingual text corpora which could generate many probable translation results. The initial SMT model; as explained by Okpor (2014), is based on Bayes Theorem which is a mathematical formula for calculating probability whereby the translation with the highest probability is given the highest score by the system.

The probability is calculated as shown below where P stands for probability, S for source sentence, and T for candidate translation (Hearne & Way, 2011)

Figure 2: Calculating probability

$$P(T|S) = \frac{P(S|T) \quad * \quad P(T)}{P(S)}$$

Source: (Ebadat, 2009, p.3)

SMT is based on a three-component system:

5.1. Language Model

The language model ensures a grammatically correct output. It is based upon the monolingual data of the output language. It filters the best possible translation choices based on the translation language; and hence, helps in the overall fluency and naturalness of the output. https://machinetranslate.org/statistical-machine-translation

5.2. Translation Model

The translation model ensures the production of a target hypothesis corresponding to the source sentence. It consists in a table of aligned phrases; called n-grams, and their translation. The translation model predicts candidate translations for specific input texts; and hence, it helps in the overall adequacy since it focuses on the meaning of the source. https://machinetranslate.org/statistical-machine-translation

5.3. Decoder

A decoder is based on a searching algorithm. Its role is to find a translation with maximum probability among all possible translations (Ebadat, 2009).
Using the decoder, and in order to maximize P(T|S) to find the best translation, the following equation is suggested:

Figure 3: Equation for maximum probability

$$\hat{T} = argmax_T(P(T|S)) \quad = argmax_T(P(S|T) \quad * \quad P(T))$$

Source: (Ebadat, 2009, p.3)

SMT uses different approaches to generate output like word-based translation which operates on a word-by-word basis; phrase-based translation which operates on a sequence of words basis; syntax-based translation which operates on a syntactic units basis; and lastly, hierarchical phrase-based translation which operates on a combination of phrase-based and syntax-based approaches. https://machinetranslate.org/statistical-machine-translation
Despite the innovation that was brought to the MT world with SMT, it still suffered certain shortcomings that hindered its performance. Some of these challenges include but are not restricted to cost inefficiency, time consumption, magnitude of parallel database, unpredictability of errors, and inefficiency with language pairs that have different phonetic systems and grammatical structures like Arabic and English. https://machinetranslate.org/statistical-machine-translation

6. Neural Machine Translation

Neural machine translation (NMT) is also a data-driven machine translation approach. It is a relatively new approach to machine translation; it appeared nearly a decade ago at the time of writing, and it uses a single large tuned neural network to transform source input into target output for maximized performance, instead of using separate components as was the case of previous SMT models. (Bahdanau *et al.*, 2016, p.1) The concept of neural networks was used in natural language processing (NLP), then was soon introduced into machine translation systems, and more specifically to traditional SMT systems. The breakthrough was to use a single large neural network that can directly turn source input into target output. (Koehn, 2017b; Stahlberg, 2020).

Despite its short lifespan, NMT is developing on a day-to-day basis and at mind-blowing speed due to state-of-the art technology and high competitiveness. Koehn (2017b) stated that NMT is currently outperforming SMT in terms of performance, research, and academic contributions. He also predicts that NMT will improve significantly in the years to come by overcoming current obstacles and limitations. According to Bahdanau *et al.* (2016), the majority of NMT systems use an encoder-decoder framework whereby the **encoder** reads and analyzes the input sentence into a fixed-length vector, and the **decoder** uses the sequence representation or the encoded vector to produce a translation.
A vector, as reported from the machine translation website https://machinetranslate.org/vector, is a unique fixed-size list of numbers where each number is referred to as a coordinate. Each coordinate represents a certain aspect of the word or the phrase. Vectors can encode meaning, speech parts, grammatical structures, and word relationships. They can also spot similarities between two sentences and identify inaccurate output translations. An example of a vector is shown below.

cat = [0.049, 0.121, 0.503, 0.888]

However, fixed-size vectors are incapable of coping with the big bulk of data from long sentences; therefore, it is crucial to use an **attention mechanism** that focuses on and learns to align between specific relevant input data. https://machinetranslate.org/neural-machine-translation

Accordingly, the architecture of NMT comprises three main components (Wu *et al.*, 2016, p.1):

Table 1: NMT architecture and components

Recurrent Neural Networks (RNNs)	1. Encoder
	2. Decoder
Coping mechanism	3. Attention Mechanism

Source: (Wu *et al.*, 2016, p.1)

Being a fairly young approach, NMT faces certain other challenges (Koehn & Knowles, 2017; Wu *et al.*, 2016) which include the following:

- Adequacy can be jeopardized due to current inefficiency in out-of-domain content;
- Low performance in low resource settings;
- Low quality in translating very long sentences;
- Risk of divergence from the word alignment model;
- Slow training and inference speed;
- Inability to cover all part of a source input.

Going back to the main issue of the encoder-decoder model, this latter uses fixed-length vectors to process all the data related to the source input, which will hinder the neural network when dealing with very long sentences. As a solution, Bahdanau *et al.* (2016) suggest a version of the encoder-decoder approach that uses a **variable-length vector** instead of a fixed-length vector. This would not only enable the neural network to process source data of long sentences, but also produce better quality and more accurate output translations. As the authors put it;

> … we introduce an extension to the encoder–decoder model which learns to align and translate jointly. Each time the proposed model generates a word in a translation, it (soft-)searches for a set of positions in a source sentence where the most relevant information is concentrated. The model then predicts a target word based on the context vectors associated with these source positions and all the previous generated target words. (p.1)

Likewise, Wu *et al.* (2016) suggest a similar three-component NMT model consisting of encoder network, decoder network and attention network. The model proved to be overall more effective than other NMT competitor models, and is said to have a 60% reduction in translation errors compared to traditional MT systems. The design, which was developed at Google and called Google Neural Machine Translation GNMT, suggests solutions for current NMT problems as listed in the table below.

Table 2: GNMT solutions for NMT issues

NMT Issue	GNMT Solution
Memory/Capacity	Long short-term memory for recurrent neural networks LSTM RNNs
Parallelism	Connecting bottom layer of decoder network to top layer of encoder network
Inference time	low-precision arithmetic plus Google's Tensor Processing Unit
Rare words	sub-word units or 'wordpieces'
Long sentences	Beam search technique length normalization procedure

Source: Wu *et al.* (2016)

6.1. Google Translate

Google Translate is an active free online translation service owned and developed by Google. It was launched in 2006 and was initially a statistical machine translation service, then nearly a decade later; in 2016, it switched to neural machine translation. This service translates an estimated 100 billion words per day and provides translations for different modes of expression like text, speech, text in image, handwritten texts, and transcriptions. Google Translate is available in website interface and mobile application versions and supports a 133 languages on its language database, including Arabic, for which it provides transliteration in equivalent Latin alphabet phonetics, as well as voice input and text-to-speech options.
Google Translate uses neural machine translation and performs deep learning and interlingual machine translation whereby the semantics of a sentence are encoded in order to provide better quality translations.
Despite the advances it witnessed, Google Translate is still incapable of guessing the adequate meaning of polysemic words, it often produces literal translations with no sense, and it lacks accuracy compared to human translation. https://en.wikipedia.org/wiki/Google_Translate

6.2. Yandex Translate

Yandex is an active free web service owned and developed by Yandex; a Russian multinational technology company that offers different products and services in the internet world. Yandex Translate is a translation service launched in 2011, it used statistical machine translation at first, then switched to a hybrid mode combining both statistical and neural machine translation in 2017. It supports up to 98 languages on its language database, including Arabic; however, unlike Google Translate, Yandex Translate does not provide Latin transliteration nor text-to-speech options for Arabic in the web interface, but rather on mobile application. It uses optical character recognition technology which enables it to perform photo-to-text translation. Yandex Translate is available in web interface and mobile application versions. It comes in a free version as well as a paid version mainly used for localization services. Similarly to Google Translate, Yandex Translate produces literal translations in most cases, does not manage polysemic words well, and lacks accuracy compared to a human translator. https://en.wikipedia.org/wiki/Yandex_Translate

6.3. Reverso Translation

Reverso is an active French company that provides various language and translation services like neural machine translation, contextual dictionaries, grammar, conjugation and spelling. It was launched in 1998, included a bilingual dictionary service in 2013, an English-learning service through subtitled movies in 2016, and a mobile application with translation and language acquisition services in 2018. In the website interface, Reverso supports about 26 languages on its language database including Arabic for which it provides, like Google Translate, Latin transliteration along with text-to-speech option. Other options include a virtual keyboard, a copy translation button, a spelling and grammar checker, as well as a newly-added feature called 'Rephrase' which suggests paraphrases for the source text. Although the parallel text alignment may produce blatant literal translations, as is the case for most machine translation tools, Reverso provides an "Examples in context" section below the bilingual translation section whereby examples are provided in several contexts and are translated, not word for word, but by meaning. https://en.wikipedia.org/wiki/Reverso_(language_tools)

When seeking the translation of the expression 'It is raining cats and dogs'; an English idioms meaning it is raining heavily, both Google Translate and Yandex Translate provide literal Arabic translation (إنها تمطر القطط والكلاب); however, in addition to the literal transfer that Reverso does; which produces the same literal expression as the other two translation tools, it also provides a list of contextualized examples where one can see the Arabic translation (إنها تمطر بغزارة) which is the most adequate provided equivalent for the English idiom.

II.Methodology

This study attempts to compare the output of the three chosen online translation tools; Google Translate, Yandex Translate, and Reverso Translation, as opposed to the output of a human translator, then analyzing the findings. The source language of these texts is English and the target language is Arabic. The input texts, references, and output texts will be displayed in a table for better visualization. The corpus of this study consists in text passages from three different genres; political, economic, and judicial. The purpose behind choosing such a miscellaneous corpus is to examine the efficiency of AI-powered translation tools in terms of specialized translation, especially in the above-mentioned fields which are of utmost significance in a human society. Respectively, the first sample is taken from a text about Arab normalization with the Zionist entity. The second sample is taken from a text about OPEC organization, and the third sample is taken from a text about counsel conduct. The human-translated versions will be used as references.

1. Corpus Analysis

1.1. Sample 1

The following table illustrates the first corpus sample. MTT here stands for machine translation tool. Only a few examples from the sample are chosen for analysis.

Table 3: Sample 1 (political source input, reference, and MMT output)

Political	Source Input	Reference
Sample 1	We know that the refugee issue is complex and multifaceted in nature. It demands a holistic approach in addressing both the immediate needs and underlying causes. We agree that refugees, often vulnerable and in need of protection, face hostile receptions, bias and trauma. Border closures, pushbacks and restrictive policies erode and undermine the cornerstone principle of international protection. It is therefore imperative that we reinforce protection mechanisms and uphold international refugee principles and norms and, in particular, the principle of non-refoulement.	نحن ندرك أن مسألة اللاجئين مسألة معقدة ومتعددة الأوجه في طابعها. وتتطلب نهجا كليا في تلبية الاحتياجات الفورية ومعالجة الأسباب الكامنة المتسببة فيها. نحن متفقون على أن اللاجئين، وغالبا ما يعانون من الوهن وبحاجة إلى الحماية، يلاقون استقبالا عدائيا وتحيزا وصدمات نفسية. إن إغلاق الحدود وعمليات الصد والسياسات التقييدية تقوض المبدأ الأساسي للحماية الدولية وتضعفه. وبناء عليه، من الأهمية بمكان أن نرسخ آليات الحماية ونحافظ على المبادئ والمعايير الدولية للاجئين، مع التركيز بشكل خاص على مبدأ عدم الإعادة القسرية.
MTT	**MTT Output**	
Google	نحن نعلم أن قضية اللاجئين معقدة ومتعددة الأوجه في الطبيعة. ويتطلب نهجا شموليا في معالجة كل من الاحتياجات الفورية والأساسية الأسباب. نحن نتفق على أن اللاجئين، غالبًا ما يكونون ضعفاء وفي حاجة إلى الحماية، يواجهون الاستقبالات العدائية والتحيز والصدمات. إغلاق الحدود وعمليات الصد والتقييد السياسات تؤدي إلى تآكل المبدأ الأساسي وتقويضه للحماية الدولية. ولذلك فمن الضروري أن نعزز آليات الحماية وندعمها المبادئ والأعراف الدولية المتعلقة باللاجئين، في وعلى وجه الخصوص، مبدأ عدم الإعادة القسرية	
Yandex	نحن نعلم أن قضية اللاجئين معقدة و متعدد الأوجه في الطبيعة. يتطلب نهجا شاملا في تلبية كل من الاحتياجات الفورية والأساسية الأسباب. نحن نتفق على أن اللاجئين ، الذين غالبا ما يكونون ضعفاء وفي حاجة إلى الحماية ، مواجهة حفلات	

	الاستقبال العدائية ، التحيز والصدمة. إغلاق الحدود ، ودفع ظهورهم وتقييدية السياسات تقوض وتقوض مبدأ حجر الزاوية الحماية الدولية. لذلك من الضروري أن نعزز آليات الحماية وأن نتمسك بها ثانيا-المبادئ والقواعد الدولية المتعلقة باللاجئين ، على وجه الخصوص ، مبدأ عدم الإعادة القسرية
Reverso	نحن نعلم أن قضية اللاجئين معقدة ومتعددة الأوجه في طبيعتها. يتطلب نهجا شاملا في معالجة الاحتياجات الفورية والأساسية على السواء الأسباب. نحن نتفق على أن اللاجئين، المعرضين للخطر في كثير من الأحيان في حاجة إلى الحماية، مواجهة الاستقبالات العدائية، التحيز والصدمات النفسية. إغلاق الحدود والتراجع والتقييد تقوض وتقوض مبدأ حجر الزاوية الحماية الدولية. لذلك من الضروري تعزيز آليات الحماية والتمسك بها والمبادئ والقواعد الدولية المتعلقة باللاجئين ولا سيما مبدأ عدم الإعادة القسرية

Source: UN digital library

At first glance, and compared to the reference, one could notice that all three MTTs rendered the political terminology adequately. Example terms like (refugees, closures, international protection, principle of non-refoulement) were translated respectively by all three tools as (اللاجئين، إغلاق الحدود، الحماية الدولية، عدم الإعادة القسرية). The term restrictive policies; however, was rendered by Google and Yandex as (التقييد السياسات) and (تقييدية السياسات) respectively. Both versions are incorrectly rendered because they produced literal translations following the structures of the English text and reversed the order of the two words in Arabic. Unlike English language where the adjective is placed before the noun (for example: beautiful landscape), Arabic language places the noun before the adjective (same example: منظر خلاب). The human reference rendered the term correctly as (السياسات التقييدية) following the correct structure in Arabic language.

Terminology is an important element in any given text for it defines its genre and sets the tone and style of writing; therefore, finding the adequate equivalent is not only crucial within the translation process, but also in terms of political and ideological considerations, particularly in delicate matters.

The first sentence of the source input finishes with the phrase (in nature) referring to the complexity of the issue of refugees. The translator rendered it with the Arabic phrase (في طابعها) which is considered as an adequate equivalent that showcases the richness of Arabic language in terms of vocabulary. While both Google and Yandex produced the same output (في الطبيعة); a literal translation of the input, Reverso produced a similar version with the same words but with a slightly different structure (في طبيعتها) by adding (ها) to (طبيعة) to refer back to the feminine Arabic noun (مشكلة) making the sentence; thus, more cohesive.

In the input sentence (It demands a holistic approach in addressing both the immediate needs and underlying causes) rendered by the translator as (وتتطلب نهجا كليا في تلبية الاحتياجات الفورية ومعالجة الأسباب الكامنة المتسببة فيها) the gerund (addressing) was used for both nouns (needs) and (causes) since the English verb (to address) can be deployed in both contexts of catering to someone's needs and finding solutions to a particular problem. However in the reference, the translator used two different nouns (تلبية) and (معالجة) to go with (الاحتياجات) and (الأسباب) respectively, creating; hence, the collocations (تلبية الاحتياجات) and (معالجة الأسباب). The use of amplification technique here is evidence of the translator's experience and mastery of translation techniques as well as their knowledge of Arabic language structures and ways of expression which tend to employ collocations and different adjectives for different nouns for more clarity and meticulousness. Google and Reverso here used one noun (معالجة) and Yandex opted for (تلبية) which resulted in an unclear and incoherent output since these nouns go only with one context each; i.e., it is correct to say in Arabic: معالجة الأسباب but it is wrong to say معالجة الحاجات similarly, it is correct to say تلبية الحاجات but it is wrong to say تلبية الأسباب In the same sentence, and in the same way, the translator added the adjective phrase (المتسببة فيها) to the noun (الأسباب) for a clearer and more fluent expression while the three MTTs added none. The translator also produced a more adequate translation by using the adjective (الكامنة) to render the adjective (underlying), whereas all three MTTs produced the adjective (الأساسية) which is in reality a translation of basic, main, principle, etc. rather than underlying. Furthermore, Google and Yandex made the same mistake of inverting the word order again by saying (الأساسية الأسباب) instead of (الأسباب الأساسية), and this effected both meaning and style negatively, in addition to the initial wrong choice of words. Not too far behind is Reverso's output (الأساسية على السواء الأسباب) where the phrase (على السواء) was inserted between the also inverted words (الأساسية الأسباب) which resulted in a meaningless and non-fluent expression.

In another example from this political passage, the reference (... يلاقون استقبالا عدائيا وتحيزا وصدمات نفسية) was the translation of the input sentence (…face hostile receptions, bias and trauma). The translator here rendered the sentence adequately using correct wording and correct structures in Arabic. Google's output (... يواجهون الاستقبالات العدائية والتحيز والصدمات) was the closest to the reference and the most adequate of the three MTTs versions. This version starts with the verb (يواجهون) referring to the subject (اللاجئين) in the beginning of the sentence. Grammatically speaking, Google produced the correct structure when rendering this complex sentence. On the other hand, Yandex and Reverso were lost in translation and used a noun (مواجهة) instead of a verb due to the length and complexity of the sentence, which resulted in poor language and poor translation. One can also notice that the version of Yandex produced nonsense output in the phrase (مواجهة حفلات الاستقبال العدائية) which; if translated to English literally, would mean (face hostile reception parties). Here, the message is completely altered and the meaning is lost. This is considered a fatal mistake in the translation business for it may have severe repercussions.

1.2. Sample 2

The following table illustrates the second corpus sample. Only a few examples from the sample are chosen for analysis.

Table 4: Sample 2 (economic source input, reference, and MMT output)

Economic	Source Input	Reference
Sample 2	The Extraordinary Conference of the Organization of the Petroleum Exporting Countries (OPEC) has reviewed the oil market outlook, including overall demand/supply projections for the year 2009, in particular the first and second quarters. The Conference highlighted that crude oil volumes entering the market remain well in excess of actual demand: this is clearly demonstrated by the fact that crude stocks in the Organization for Economic Co-operation and Development countries (OECD) are well above their five-year average and are expected to continue to rise.	استعرض المؤتمر الاستثنائي لمنظمة البلدان المصدرة للنفط أوبك توقعات السوق النفطية، بما فيها التقديرات الشاملة لسوق للعرض والطلب لسنة 2009، لاسيما في الربعين الأول و الثاني. وقد أشار المؤتمر إلى أن كميات النفط الخام التي تدخل السوق لا تزال في زيادة عن الطلب الفعلي، وهذا يثبت بوضوح حقيقة أن مخزونات النفط الخام في بلدان منظمة التعاون الاقتصادي والتنمية (أوسيد) كانت أعلى من متوسطها بخمس سنوات، و يُتوقع أن تستمر في الارتفاع.
MTT	**MTT Output**	
	استعرض المؤتمر الاستثنائي لمنظمة البلدان المصدرة للنفط (أوبك) توقعات سوق النفط، بما في ذلك توقعات	

Google	الطلب/العرض الإجمالية لعام 2009، ولا سيما الربعين الأول والثاني. وشدد المؤتمر على أن كميات النفط الخام التي تدخل السوق لا تزال تتجاوز بكثير الطلب الفعلي: ويتجلى ذلك بوضوح في حقيقة أن مخزونات النفط الخام في بلدان منظمة التعاون الاقتصادي والتنمية (OECD) أعلى بكثير من متوسطها خلال خمس سنوات. ومن المتوقع أن يستمر في الارتفاع
Yandex	وقد استعرض المؤتمر الاستثنائي لمنظمة البلدان المصدرة للنفط (أوبك) توقعات سوق النفط ، بما في ذلك التوقعات الإجمالية للطلب/العرض لعام 2009 ، ولا سيما الربعين الأول والثاني. وأبرز المؤتمر أن أحجام النفط الخام التي تدخل السوق لا تزال تتجاوز الطلب الفعلي: ويتجلى ذلك بوضوح في حقيقة أن مخزونات النفط الخام في منظمة التعاون الاقتصادي والتنمية (منظمة التعاون الاقتصادي والتنمية) أعلى بكثير من متوسطها في خمس سنوات ومن المتوقع أن تستمر في الارتفاع
Reverso	استعرض المؤتمر الاستثنائي لمنظمة البلدان المصدرة للنفط توقعات أسواق النفط، بما في ذلك التوقعات الإجمالية للطلب/العرض لعام 2009، ولا سيما الربعين الأول والثاني. وأبرز المؤتمر أن أحجام النفط الخام التي تدخل السوق لا تزال تتجاوز بكثير الطلب الفعلي: ويتضح ذلك بوضوح من حقيقة أن مخزونات النفط الخام في بلدان منظمة التعاون والتنمية في الميدان الاقتصادي أعلى بكثير من متوسطها في السنوات الخمس ومن المتوقع أن تستمر في الارتفاع

Source: opec.org

The economic terms used this passage like (Conference of the Organization of the Petroleum Exporting Countries, oil market, demand/supply projections, quarters, stocks) were translated adequately by the reference as well as the three MTTs as (منظمة البلدان المصدرة للنفط، سوق النفط، توقعات الطلب/العرض، الربع، مخزونات). The other organization called Organization for Economic Co-operation and Development countries (OECD) was rendered as (منظمة التعاون الاقتصادي و التنمية (أوسيد)by the reference. The human translator here respected the conventional translation method of organizations' names by providing the full equivalent in the target language in addition to the Arabic transliteration of the English acronym for more precision and clarity. Google produced the output (منظمة التعاون الاقتصادي والتنمية) but the acronym (OECD) was left in Latin letter and it was misplaced in the sentence because it did not follow the full name directly, but came before it in a random place in the sentence. Yandex produced the output (منظمة التعاون الاقتصادي والتنمية) then repeated this full name between brackets instead of the acronym. Reverso produced the output (منظمة التعاون والتنمية في الميدان الاقتصادي) which is not the correct equivalent for the organization, but rather an interpretation of it. This output also came without the Arabic transliteration of the English acronym.

In the source input, the word (outlook) was paired with (oil market) resulting in the phrase (oil market outlook). It was rendered in the reference as (توقعات السوق النفطية); and likewise, Google, Yandex and Reverso opted for the same output (توقعات سوق النفط), with a little exception from Reverso by having the word 'market' come in the plural form in Arabic (توقعات <u>أسواق</u> النفط). The word (projections) was used in the following phrase (including overall supply/demand projections) and was translated in the reference by a new equivalent word (تقديرات), while Google, Yandex, and Reverso repeated the same equivalent word as in the previous phrase (توقعات). The adjective (overall) was rendered by the translator as (الشاملة) and as (الإجمالية) by the three MTTs. As for word order, Google produced the structure (توقعات الطلب/العرض الإجمالية) which is more correct and eloquent in Arabic language because it placed (الطلب/العرض) between the noun (التوقعات) and the adjective (الإجمالية). Yandex and Reverso; similarly to the reference, both produced the structure

(التوقعات الإجمالية للطلب/العرض) by placing the adjective (الإجمالية) right after the noun (التوقعات) then adding (حرف الجر لـ-) to (الطلب/العرض). This could be considered more of a structure calque from the English phrase (overall projections of supply/demand); but rather, the structure used in the source input is (overall supply/demand projections). The difference is that both English structures are deemed equally correct; however, in Arabic the first structure is considered more correct and eloquent.
The input phrase (this is clearly demonstrated by), which is in the passive voice structure, was transferred by the translator as (وهذا يُثبت بوضوح) in the active voice structure. The verb (demonstrate) here was translated into Arabic with a verb that is equivalent to the verb (prove), then was followed by (الجار والمجرور بوضوح) as the translation for the adverb (clearly). One could argue that (بوضوح) could be skipped to avoid redundancy since the Arabic verb (يُثبت) already alludes the idea of visible evidence or proof. The adverb (clearly) was collectively rendered by all three MTTs as (بوضوح); however, the verb (demonstrate) was rendered by Google and Yandex as (يتجلى), and by Reverso as (يتضح). Google's and Yandex's outputs for this verb could be considered as a collocation when paired with (بوضوح); resulting thus, in a more eloquent phrase (يتجلى بوضوح), whereas Reverso's output (يتضح بوضوح) is redundant and rather poorly phrased.

1.3. Sample 3

The following table illustrates the third corpus sample. Only a few examples from the sample are chosen for analysis.

Table 5: Sample 3 (judicial source input, reference, and MMT output)

Judicial	Source Input	Reference
Sample 3	Counsel shall be respectful and courteous in his or her relations with the Chamber, the Prosecutor and the members of the Office of the Prosecutor, the Registrar and the members of the Registry, the client, opposing counsel, accused persons, victims, witnesses and any other person involved in the proceedings.	على المحامين الالتزام بالاحترام واللباقة في علاقاتهم مع دائرة المحكمة والمدعي العام وأعضاء مكتب المدعي العام والمسجل وأعضاء قلم المحكمة وموكليهم ومحامي الادعاء والمتهمين والضحايا والشهود وأي شخص آخر يشارك في الإجراءات القضائية
MTT	**MTT Output**	
Google	يجب أن يكون المحامي محترماً ومهذباً في علاقاته مع الدائرة والمدعي العام وأعضاء مكتب المدعي العام والمسجل وأعضاء قلم المحكمة والموكل والمحامي المعارض والمتهمين والضحايا والشهود وأي شخص آخر. شخص آخر مشارك في الإجراءات	
Yandex	ويكون المحامي محترما ومهذبا في علاقاته مع الدائرة والمدعي العام وأعضاء مكتب المدعي العام والمسجل وأعضاء قلم المحكمة والموكل والمحامي المعارض والمتهمين والمجني عليهم والشهود وأي شخص آخر يشارك في الإجراءات	
Reverso	يكون المحامي محترما ومهذبا في علاقاته مع الدائرة والمدعي العام وأعضاء مكتب المدعي العام والمسجل وأعضاء قلم المحكمة والموكل والمحامي المعارض والمتهمين والمجني عليهم والشهود وأي شخص آخر يشارك في الإجراءات	

Source: code of professional conduct for counsel

The example about to be analyzed in this sample pertains to judicial terms which were, roughly speaking, rendered in nearly the same way by the reference and the three MTTs. The terms (Counsel, Prosecutor, Registrar, Registry, client, witnesses) were rendered respectively as (المحامين، المدعي العام، المسجل، قلم المحكمة، موكلين، الشهود) by the translator as well as Google, Yandex, and Reverso. The only difference here is that the terms (المحامين، الموكلين) came in the plural form in the reference, whereas in the singular form in the three MTTs (المحامي، الموكل). Using a plural form in Arabic when talking about a singular item or individual is a common practice by Arabic speakers in cases of generalized descriptions. This is reminiscent of a cultural reference inherent in the Arab world whereby the concept of family, unity, and collectivism is key to Arab individuals. The chosen MTTs used a sort of a form calque as they all copied the singular form of English. The singular form in English language is reflective of the individualistic ideology in the culture of the Western world. This proves that translation process is not a mere transfer of words and expressions; but rather, a matter of "making intelligible an entire culture" in the words of Anthony Burgess. Understanding the language nuances that are intrinsic to a certain culture or ideology could be considered as the 'X factor' missing in MT systems. The term (Chamber) rendered as (دائرة المحكمة) in the reference, was translated as (الدائرة) in the versions of Google, Yandex, and Reverso. The versions of the MTTs could create a sort of confusion in meaning if placed outside of context. The translator used addition technique by adding the word (المحكمة) to the word (دائرة) for more context precision and meaning clarity. The term (opposing counsel) was correctly rendered in the reference as (محامي الادعاء); however, it was rendered as (المحامي المعارض) by the three MTTs which is more of a literal translation since (opposing) was translated as (المعارض) instead of (الادعاء). The term (victims) was rendered in the reference and also by Google as (الضحايا), whereas both Yandex and Reverso produced the output (المجني عليهم). Although the equivalent (الضحايا) is correct, yet in this case, the second version produced by Yandex and Reverso is more appropriate to the legal context than the first version produced by the human translator and by Google. By adding the adjective (القضائية) to the noun (الإجراءات), the translator produced the reference (الإجراءات القضائية) for the term (proceedings) which was translated collectively by all MTTs as (الإجراءات). The translator's version is once again more contextually accurate.

Another example in this sample is the use of affirmative structure in English with an imperative tone when describing the duties of a counsel (Counsel shall be respectful and courteous) which was altered to an imperative structure in the reference as (على المحامين الالتزام) and by Google as (يجب أن يكون المحامي). Although Google's version is correct and well-structured, the translator's version is more articulate and eloquent for the translator incorporated the noun (الالتزام) to refer to the counsel's obligations, and used (حرف الجر على) at the beginning of the sentence without the verb (يجب) before it; resulting hence, in a more smoothly-flowing sentence to native Arabic speakers. Yandex and Reverso produced a descriptive affirmative structure (يكون المحامي) which is grammatically correct, yet lacks the obligation tone and misses the eloquence flow.

On another note, using the structure (الالتزام بالاحترام واللباقة) in the reference exhibits the translator's knowledge of and experience with legal jargon which tends to use more nouns (الالتزام، الاحترام، اللباقة) than adjectives and verbs (يجب، يكون، محترما، مهذبا) as was the case of Google, Yandex, and Reverso.

III. Results and Discussion

Roughly speaking, the chosen MTTs were successful in rendering terminology of various fields; political, economic, and judicial. This is due to the fact that NMT, a machine translation approach adopted by all three tools, uses advanced technology and a large database that enables it to perform translation tasks more efficiently by producing accurate meaning and cohesive structures in most cases.

The aspect that could be problematic sometimes is the translation of culture-specific items and references, because culture and ideology nuances are not a matter of mere linguistic transfer, but a process of Hermeneutic and extra-linguistic interpretation. Despite the current advances in this field, MT still needs improvements to reach the level of human translators in regards to such matters. Human judgment is capable of filling in the blanks that an automated system fails to recognize; hence, painting the whole picture with all colors and shapes and giving it life.

Another issue with MT is the translation of long sentences with complex structures like the example (We agree that refugees, often vulnerable and in need of protection, face hostile receptions, bias and trauma) which was correctly and adequately rendered in the reference. However, one of MTTs fell into the trap of incorrect meaning and non-cohesive sentences producing; thus, inadequate target output.

Redundancy can be a re-occurring mistakes in MT output. The example in question was the input phrase (this is clearly demonstrated by) which was rendered as (يتجلى بوضوح) by Google and Yandex, but as (يتضح بوضوح) by Reverso. In some cases, certain MTTs perform better than other MTTs regardless of the reference.

Addition technique was frequently used in the reference. The added words contributed to the creation of a more contextualized translation and a smoother eloquence flow in Arabic. The addition of the adjective (القضائية) to the noun (الإجراءات) is a good example of this strategy.

In most cases, the reference was more accurate and eloquent than the output produced by Google, Yandex, and Reverso. However, there were some rare instances where the MT versions were more accurate and eloquent as in the case of the term (victims) which was translated in the reference as (الضحايا) and as (المجني عليهم) by Yandex and Reverso. The MT output here is better suited for the legal and judicial context and terminology.

Conclusion

The present study shed light on a very promising aspect of modern time translation; one which is performed by an automated system called NMT. The study's significance is twofold as it contributes to both academic and professional realms of translation. Academically, the study examines the translation strategies deployed by NMT systems and compares them to those used by a human reference to pinpoint convergence and divergence between machine performance and human performance. Professionally, the study provides a detailed descriptive and critical analysis of machine translation output in order to explore the efficiency and reliability of NMT systems in terms of specialized translation. The choice of a wide spectrum of text genres; i.e., political, economic and judicial, is reflective of the texts that are in high demand in professional translation contexts. The correct and accurate translation of the terminology in these fields poses challenges to even the most seasoned translators, let alone machine translation tools. Therefore, the integration of technology-based translation tools combined with human expertise would result in an enhanced hybrid output, and would assist human translators with voluminous translation tasks. As it is unjust to expect a machine translation system to outperform a seasoned human translator, it is also unfair to dismiss the noticeable progress made in MT field and put all the burden on human translators. If used wisely, technology can be of great assistance to humans, and no party has to cancel the other, for each is essential to the development of the field of Translation Studies in general, and the field of machine translation, in particular.

References

AMEUR M. S. H., MEZIANE F. and GUESSOUM A. (2020). "Arabic machine translation: A survey of the latest trends and challenges" in *Computer Science Review*. 38, pp. 1-29.
ARNOLD D. *et al.* (1994). *Machine translation: An introductory guide*. London: NCC Blackwell.
BAHNADAU D., CHO K. and BENGIO Y. (2016). "Neural machine translation by jointly learning to align and translation" in *ICLR*. arXiv:1409.0473v7 [cs.CL], pp.1-15.
EBADAT A. R. (2009). Using genetic algorithm for the decoder in SMT, thesis under the direction of SMAÏLI K. and LANGLOIS D. Saarland University.
HEARNE M. and WAY A. (2011). "Statistical machine translation: A guide for linguists and translators" in *Language and Linguistics Compass*, pp. 1-21.
KOEHN P. and KNOWLES R. (2017). "Six challenges to neural machine translation" in arXiv:1706.03872v1[cs.CL], pp. 1-12.
KOEHN P. (2017). "Neural machine translation" in arXiv:1709.07809v1 [cs.CL], pp. 1-117.
LEE S. *et al.* (2023). "A Survey on Evaluation Metrics for Machine Translation" in *Mathematics*. 11(1006), pp. 1-23.
OKPOR M. D. (2014). "Machine translation approaches: issues and challenges" in *International Journal of Computer Science Issues*. 11(5), pp. 159-165.
SAGER J. C. (1994). *Language engineering and translation: Consequences of automation*. Amsterdam/Philadelphia: John Benjamins.
SHUTTLEWORTH M. and COWIE M. (1997). *Dictionary of translation studies*. London: Routledge.
STAHLBERG F. (2020). "Neural machine translation: A review" in *Journal of Artificial Intelligence Research*. 69, pp.343-418.
WU Y. *et al.* (2016). "Google's neural machine translation system: Bridging the gap between human and machine translation' in arXiv:1609.08144v2 [cs.CL], pp. 1-23.
ZUGHOUL M. R. and ABU-ALSHAAR A. M. (2005). "English/Arabic/English machine translation: A historical perspective" in *Meta*. 50(3), pp. 1022-1041.

Links to Electronic Sources

Statistical machine translation, accessed 29 August 2023 [https://machinetranslate.org/statistical-machine-translation]
Vector, accessed 29 August 2023 [https://machinetranslate.org/vector]
Neural-machine-translation, accessed 29 August 2023 [https://machinetranslate.org/neural-machine-translation]
Google_Translate, accessed 3 September 2023 [https://en.wikipedia.org/wiki/Google_Translate]
Yandex_Translate, accessed 3 September 2023 [https://en.wikipedia.org/wiki/Yandex_Translate]
Reverso, accessed 3 September 2023 [https://en.wikipedia.org/wiki/Reverso_(language_tools)]