OPTIMIZATION OF EXTRACTIVE AUTOMATIC TEXT SUMMARIZATION USING DECOMPOSITION-BASED MULTI-OBJECTIVE DIFFERENTIAL EVOLUTION AND PARALLELIZATION

By

MUHAMMAD HAFIZUL HAZMI WAHAB

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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DEDICATION

I dedicated this thesis to my beloved

Father and Mother,

whose undying faith and silent love have soothed my soul and kindled the ever-burning pertinacity that I never thought I had. Whose kindness has caressed my very being into devoting myself to this fleeting, forlorn, melancholic journey of becoming someone they could be proud of. We might not be born wealthy and privileged, but we will not die with ignorance and without knowledge, for God's blessings are for those who seek, and I choose to seek.

Last but not least, I dedicated this thesis to my

younger self,

who sacrifices his youth to seek knowledge and overcome his self diffidence.

If I could look into the mirror of time, I would say,

"Never be so kind, you forget to be clever. Never be so clever, you forget to be kind.

You deserve as much as you gave to others."

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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September 2024

Chairman : Associate Professor Nor Asilah Wati binti Abdul Hamid, PhD
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The central challenge in Automatic Text Summarization (ATS) is efficiently generating machine-generated text summaries through optimization algorithms, a critical component for systems dealing with textual information processing. The current approach encounters a significant hurdle due to the long execution time, especially when employing complex optimization techniques alongside a computationally expensive ATS repair operator that repairs multiple candidate solutions.

While the current approach yields impressive Recall-Oriented Understudy for Gisting Evaluation (ROUGE) metrics for the generated summary, it struggles

with inefficiencies, mainly attributed to the substantial optimization time consumed by the ATS repair operator scheme. In order to address this, a novel solution called Decomposition-based Multi-objective Differential Evolution (MODE/D) is proposed. It is built upon the foundation of Differential Evolution for Multi-objective optimization (DEMO) and the weighted sum method (WS), coupled with an innovative ATS repair operator scheme. Through experimentation on Document Understanding Conferences (DUC) datasets, the novel approach of MODE/D is validated by evaluating the results using ROUGE metrics. The outcomes are twofold: a remarkable reduction in serial execution time and a noteworthy enhancement over existing techniques in the scholarly domain, as evidenced by improved ROUGE-1, ROUGE-2, and ROUGE-L scores.

The multi-core variant of MODE/D explored an alternative computational environment, which not only demonstrates stability but also achieves remarkable efficiency when static loop scheduling is employed. Notably, in a multi-core environment, parallel multi-core MODE/D attains a commendable speedup of 2 times faster than the serial version of MODE/D, with the highest efficiency peaking at an impressive 86.35% when employing 6 CPU cores. Additionally, when the input size is tripled, the parallel multi-core MODE/D achieves a 7.9 speedup with 98.98% efficiency under static scheduling. The commendable speedup achieved comes with a slight degradation in terms of

ROUGE-2 metrics. However, this efficiency milestone underscores the robustness and scalability of the proposed approach, showcasing its ability to harness the computational power of multiple cores while maintaining stability in summary quality metrics, yielding 31 words per second (WPS), a 233.13% increase compared to its serial counterpart for the topic of d061j in DUC2002.

Furthermore, two GPU variants of GMODE/D, namely variant I and variant II, are implemented, with both incorporating unified and non-unified memory architectures. Variant I performs sentence scoring at the outset of the accelerator region, while variant II conducts sentence scoring within the accelerator region. GMODE/D variant I with unified memory achieves a significant speedup of 18.17 compared to the serial variant when a 256 vector size is used with NVIDIA Tesla V100 as an accelerator device, resulting in a substantial increase in WPS, amounting to 215.517. Despite suffering a slight reduction in ROUGE scores, it exhibits the most stable CV values among the serial, multi-core, and many core variants.

These advancements collectively propel optimization-based ATS approaches closer to real-time applications where thousands of documents could be involved, demonstrating the versatility and efficiency of the proposed MODE/D algorithm across diverse computing architectures, including multi-core and many core environments.

Keywords: Automatic Text Summarization, Document Understanding Conferences, Multi-objective Differential Evolution, Multi-objective Artificial Bee Colony.

SDG: GOAL 9: Industry, Innovation, and Infrastructure.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PENGOPTIMUMAN PENJANAAN RINGKASAN TEKS EKSTRAKTIF AUTOMATIK MENGGUNAKAN ALGORITMA OPTIMASI EVOLUSI PEMBEZAAN BERBILANG OBJEKTIF BERDASARKAN PENGURAIAN DAN PENYELARIAN

Oleh

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Cabaran utama dalam bidang ilmu Peringkasan Teks Automatik (PTA) ialah proses menjana ringkasan teks keluaran mesin secara berdaya guna melalui teknik algoritma optimasi. PTA merupakan komponen yang amat mustahak bagi sistem pemprosesan informasi teks. Selain itu, teknik yang sedia ada sekarang mengalami halangan yang sangat besar, disebabkan pengkomputeran yang sangat tinggi keamatannya yang menyebabkan masa pelaksanaan yang sangat lama. Hal ini demikian kerana, teknik yang sedia ada sekarang menggunakan algoritma optimasi yang rumit dan skema

pembaiki PTA yang mahal dari segi keamatan pengkomputeranya membaiki lebih daripada satu solusi berpotensi secara serentak.

Kebelakangan ini, walaupun teknik-teknik sedia ada menghasilkan nilai metrik *Recall-Oriented Understudy for Gisting Evaluation (ROUGE)* yang amat memberangsangkan bagi ringkasan teks yang diterbitkan, teknik-teknik ini masih menghadapi kesukaran dalam perihal keberdaya gunaannya. Hal ini tercetus apabila teknik-teknik ini menghabiskan masa yang terlalu lama dalam proses mencari penyelesaian, terutamanya ketika proses pembaikan solusi yang disebabkan oleh skema pembaiki PTA yang mahal dari segi keamatan pengkomputerannya. Sebagai langkah penyelesaian, solusi novel diberi nama *"Decomposition-based Multi-objective Differential Evolution (MODE/D)"* diperkenalkan. Seterusnya, teknik solusi ini dibina dan direka bentuk berdasarkan asas algoritma *"Differential Evolution for Multi-objective Optimization (DEMO)"* dan juga teknik penguraian jumlah berpemberat *(the weighted sum method)* yang digandingkan dengan inovasi skema operator pembaiki PTA yang ditambah baik. Di samping itu, melalui uji kaji menggunakan set data yang diperolfeh daripada *Document Understanding Conferences (DUC)*, teknik peringkas novel ini, MODE/D, telah ditentusahkan menggunakan ringkasan teks yang dijana oleh teknik ini melalui metrik-metrik *ROUGE.* Hasil teknik inovatif ini adalah dua kali ganda: iaitu pengurangan masa pelaksanaan bersiri yang luar biasa, dan juga penambahbaikan yang menakjubkan dalam domain ilmiah ini, hal ini terbukti melalui nilai *ROUGE-1*, *ROUGE-2*, dan *ROUGE-L* yang ditambahbaik.

Seterusnya, dalam meneroka persekitaran sistem pengkomputeran, varian berbilang teras teknik MODE/D telah diperkenalkan. Varian berbilang teras ini juga telah menunjukkan kestabilan yang lebih kukuh dibandingkan dengan varian asal teknik ini. Selain itu, varian berbilang teras ini mengalami sedikit kemunduran kualiti ringkasan yang diimbangi dengan nilai pekali kolerasi *Pearson* (CV) yang lebih sedikit, sekaligus menunjukkan varian berbilang teras teknik MODE/D adalah lebih stabil dalam menjana ringkasan teks esktraktif. Di samping itu, varian berbilang teras ini juga telah mencapai nilai pecutan sebanyak dua kali ganda berbanding varian bersiri MODE/D dalam sistem persekitaran pengkomputeran berbilang teras, menggunakan penjadualan statik gelung untuk. Keadaan ini, mencapai kerberdaya gunaan yang sangat tinggi, yakni sebanyak 86.35% ketika enam teras *CPU* digunakan dalam uji kaji. Selain itu, apabila jumlah input didarab tiga kali, nilai pecutan diperoleh adalah sebanyak 7.9 kali berbanding varian bersiri MODE/D, juga menggunakan pengjadualan statik gelung untuk. Tuntasnya, kebolehan keberdayagunaan varian berbilang teras ini membuktikan kelasakan dengan menghasilkan lebih 31 perkataan per saat *(WPS)* dan skalabiliti teknik ini dalam memanfaatkan kuasa pengkomputeran dari berbilang teras *CPU* secara efisien dan juga kebolehan teknik ini menghasilkan ringkasan teks yang stabil kualitinya.

Begitu juga dengan varian banyak teras teknik ini yang menggunakan unit pemprosesan grafik *(GPU)*, yang menggunakan seni bina memori bersatu dan juga tidak bersatu. Terdapat dua varian selari GMODE/D, diberinama varian I dan varian II. Varian I MODE/D banyak teras teknik ini yang menggunakan seni bina memori bersatu *GPU* menghasilkan nilai pecutan yang sangat tinggi, iaitu sebanyak 18.17 kali ganda lagi laju dari varian bersiri teknik ini dan nilai pecutan ini dicapai dengan menggunakan saiz vektor sebesar 256 dan peranti pecutan NVIDIA Tesla V100. Selain itu, varian I GMODE/D banyak teras teknik ini menghasilkan sebanyak 215.17 perkataan per saat *(WPS)* yang sangat memberangsangkan. Walau bagaimanapun, varian banyak teras teknik ini juga mengalami kemunduran kualiti dari segi ringkasan teks yang dihasilkan, hal ini dibuktikan oleh nilai ROUGE yang diperoleh. Selain itu juga, walaupun mengalami sedikit kemunduran dari segi kualiti ringkasan, varian banyak teras teknik ini menzahirkan kestabilan yang paling utuh jika dibandingkan dengan varian berbilang teras dan juga varian bersiri. Hal ini dibuktikan dengan nilai pekali kolerasi *Pearson* (CV) yang sangat kecil jika dibandingkan dengan varian bersiri dan berbilang teras.

Secara tuntasnya, kemajuan-kemajuan ilmiah yang telah diperoleh secara kolektif ini telah membolehkan teknik ekstraktif PTA yang menggunakan algoritma optimasi untuk menjadi lebih bermanfaat dalam domain yang memerlukan teknik peringkas teks yang sedar prestasi dalam masa sebenar ketika menjana ringkasan teks dari beribu-ribu dokumen. Selain itu, kejayaan pelaksanaan varian-varian MODE/D yang berbeza persekitaran sistem pengkomputerannya telah mengukuhkan perihal kebolehgunaan teknik ini dalam pelbagai domain yang telah terbukti keserbagunaannya.

Kata Kunci: Automatic Text Summarization, Document Understanding Conferences, Multi-objective Differential Evolution, Multi-objective Artificial Bee Colony.

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Date: 12 December 2024

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LIST OF ABBREVIATIONS

ADE	Adaptive Differential Evolution
ALU	Arithmetic Logic Unit
AMD	Advanced Micro Devices
ATS	Automatic Text Summarization
BLUE	Bilingual Evaluation Understudy
ChatGPT	Chat Generative Pre-trained Transformer
CHC	Cross-generational elitist selection, Heterogeneous recombination, Cataclysmic mutation
CIDER	Consensus-based Image Description Evaluation
CNN	Convolutional Neural Network
CPU	Central Processing Unit
CRFs	Conditional Random Fields
CUDA	Compute Unified Device Architecture
CV	Coefficient of Variation (Ratio of the Standard Deviation to the Mean)
DE	Differential Evolution
DEMO	Differential Evolution for Multi-objective
DSO	Dolphin Swarm Optimization
DtoH	Device-to-Host
FbTS	Firefly-based Text Summarization
FCNN	Fully Connected Feed Forward Neural Network
FPGAs	Field Programmable Gate Arrays
GA	Genetic Algorithm
GPGPU	General-Purpose Graphics Processing Unit

GPT	Generative Pre-trained Transformer
GPU	Graphical Processing Unit
GSO	Glowworm Swarm Optimization
HMMs	Hidden Markov Models
HPC	High-Performance Computing
HtoD	Host-to-Device
I/O	Input/ Output
ILP	Integer Linear Programming
IoT	Internet of Thing
LCS	Longest Common Subsequence
LLM	Large Language Model
LSSA	Large-scale Sparse Algorithm
METEOR	Metric for Evaluation of Translation with Explicit ORdering
MMR	Maximal Marginal Relavance
MO	Multi-objective
MOABC	Multi-objective Artificial Bee Colony
MOABC/D	Decomposition-based Multi-objective Artificial Bee Colony
MODE/D	Decomposition-based Multi-objective Differential Evolution
MOO	Multi-objetive Optimization
MOSFLA	Multi-objective Shuffled Frog-leaping Algorithm
NDA	New Drug Application
NER	Name Entity Recognition
NGSA	Non-dominated Sorting Genetic Algorithm
NIST	National Institute of Standards and Technology

NLP	Natural Language Processing
NLTK	Natural Language Toolkit
NUMA	Non-Uniform Memory Access
NVLINK	NVIDIA Link (High-Speed Interconnect for GPU and CPU)
OpenACC	Open Accelerators
OpenCL	Open Computing Language
OpenMP	Open Multi-processing
PBI	Penalty-based Boundary Intersection
PCIe	Peripheral Component Interconnect Express
POSIX	Portable Operating System Interface
PSG	Product-Specific Guide
PSO	Particle Swarm Optimization
RF	Random Forest
ROUGE	Recall-Oriented Understudy for Gisting Evaluation
SDK	Software Development Kit
SIMD	Single Instruction Multiple Data
SPMD	Single Program Multiple Data
SSO	Shark Smell Optimization
SVMs	Support Vector Machines
WPS	Word Per Seconds
WS	Weighted-Sum

CHAPTER 1

INTRODUCTION

This chapter serves as a comprehensive introduction to the dissertation, providing insights into its motivation, addressing encountered problem statements, and outlining the research questions that have led to the formulation of subsequent objectives. It includes a clear delineation of the research objectives, elucidating the specific goals and aims of the study. Additionally, this chapter encapsulates the collective essence of the dissertation's contributions to the field, offering a roadmap for the subsequent chapters.

1.1 Motivation

Amid the rapid advancements of the Fourth Industrial Revolution and the growing reach of the Internet of Things (IoT), the amount of digital information is increasing at an exponential rate. As our interconnected devices generate vast volumes of data, navigating this information deluge becomes a pressing challenge. In this context, the need for efficient tools to distill and comprehend the massive textual information sprawled across the internet has become paramount.

Automatic text summarization (ATS) is a pivotal tool in the arsenal of information processing in this era of data abundance. As the digital landscape burgeons with diverse content, from articles and research papers to news updates and social media posts, the sheer volume can overwhelm traditional methods of comprehension. Indeed, as astutely observed by Jerry Mander four decades ago when discussing the elimination of television:

"The problem was too much information. The population was being inundated with conflicting versions of increasingly complex events. People were giving up on understanding anything. The glut of information was dulling awareness, not aiding it. Overload. It encouraged passivity, not involvement." (Mander, 1978)

Parallel to this historical insight, the ongoing conundrum of information overload persists as an inescapable consequence of technological advancements. However, ATS emerges as a beacon, offering a systematic and intelligent approach to distill the essence of extensive textual information into concise and digestible summaries. This tool not only aids in overcoming information overload but also aligns seamlessly with the tenets of the Fourth Industrial Revolution, where intelligent automation and data-driven decision-making are at the forefront. By leveraging natural language processing (NLP) and scientific-based algorithms such as optimization, machine learning, deep learning, and fuzzy logic, ATS becomes a catalyst for efficiency, allowing individuals and organizations to extract meaningful insights from copious textual data with unprecedented speed and accuracy.

The significance of ATS extends far beyond the realms of the internet, finding integral importance in various domains such as health, law, and news. In the realm of health, ATS streamlines the analysis of medical literature, providing succinct summaries that facilitate quicker comprehension for healthcare professionals. In addition, ATS is also needed in the real-time telehealth domain, where even quicker summarization is crucial for healthcare professionals to make split-second decisions. In the legal domain, ATS expedites the review of legal documents, aiding legal professionals in extracting essential information efficiently. Moreover, in the fast-paced realm of news, ATS accelerates sentiment analysis by condensing lengthy articles into concise summaries, enabling a swift understanding of public opinion.

The needs of ATS are further emphasized in real-time applications such as media monitoring, especially in the cybersecurity realm, where live textual analysis requires summarization before processing. Additionally, in question-and-answer bot frameworks, Large Language Models (LLMs) can process input more efficiently once more salient information is provided. Moreover, real-time financial research benefits from ATS, facilitating split-second decision-making in unpredictable markets based on real-time financial news aggregated by real-time ATS. In these varied applications, ATS stands as a versatile and indispensable tool, enhancing efficiency and enabling timely and informed decision-making in a rapidly evolving digital landscape.

As mentioned before, the ATS leverages a variety of scientific techniques, including Machine Learning, Deep Learning, Optimization Algorithms, Fuzzy Logic, and Semantic-Based techniques. Machine learning approaches involve training models on datasets annotated with labels indicating whether a piece of text is a "summary" or "non-summary." However, these methods heavily depend on having access to extensive and accurately labeled data, which can be a limitation. Deep learning techniques, as demonstrated in works by researchers like (Yao et al., 2018), (Nallapati et al., 2017), and (Warule et al., 2019), offer the potential to mimic human reading styles and comprehension.

In addition, the rise of Large Language Models (LLM) has recently illuminated the landscape of ATS, where LLM has found widespread adoption across various domains, including ATS. The works demonstrated by (Tang et al., 2023) and (H. Zhang, Liu, et al., 2023) challenge the prevailing sentiment surrounding deep learning-based ATS, showcasing promising summary results. In addition to summarization generation, the work by (Gao et al., 2023) has also explored the usage of ChatGPT to perform a human-like summary evaluation. Moreover, newer approaches in LLM, like (H. Zhang, Liu, et al.,

2023) and (Sun et al., 2023), have used ChatGPT and GPT4, respectively, through an iterative prompt method that shows promising results in producing summaries. Next, it is noteworthy to highlight that the summaries generated by the deep learning-based ATS approach leveraging Large Language Models (LLM) are significantly influenced by the design of the prompts. This influence has been discussed and investigated by (J. Wang et al., 2023) and (Ma et al., 2023).

Next, the optimization-based ATS approaches come with a notable computational cost, as highlighted by (El-Kassas et al., 2021). This computational expense demands substantial resources and power, posing challenges to the execution speed and cost-effectiveness of optimization-based ATS approaches. Efforts to mitigate these challenges have led to the parallelization of optimization algorithms, as demonstrated in studies by (Sanchez-Gomez et al., 2019b, 2020). While parallelization improves efficiency, achieving real-time application of ATS remains a persistent challenge, as observed in the studies. Notably, albeit yielding impressive ROUGE metrics results, the optimization-based ATS approaches suffer from performance issues deeply rooted in the employment of a computationally expensive ATS repair operator[1] alongside complex optimization algorithms. Undeniably, the performance issue renders these optimization approaches not applicable in the real-time application of ATS.

In essence, the symbiotic relationship between the Fourth Industrial Revolution, the Internet of Things, and the ATS domain underscores a paradigm shift in how information is made sense of and processed. Navigating this era of digital transformation, the ability to distill the pertinent from the vast sea of textual information becomes not only a necessity but a strategic imperative for informed decision-making and innovation.

Hence, the motivation behind this dissertation lies in discerning the underlying performance issues within existing literature and proposing a solution within the domain of optimization-based ATS approaches. This dissertation seeks to address and enhance the performance-inhibiting issues inherent in optimization-based ATS approaches, contributing to the ongoing evolution of effective extractive multi-document automatic text summarization.

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[1] An automatic text summarization repair operator modifies the candidate solution by adding or removing sentences based on their sentence scores, whilst ensuring the final summary meets the required length constraints.

1.2 Problem Statement

Lately, there has been a surge in the introduction of optimization-based ATS techniques. Notably, optimization algorithms like Multi-objective Artificial Bee Colony (MOABC), as well as Decomposition-based Multi-objective Artificial Bee Colony (MOABC/D), Composite Differential Evolution (CDE), Non-dominated Genetic Sorting Algorithm II (NGSA-II), and Adaptive Differential Evolution (ADE) have been harnessed to solve the optimization problem of ATS. Alongside these optimization-focused ATS strategies, there exists a spectrum of alternative approaches rooted in machine learning, such as (John & Wilscy, 2013; Shetty & Kallimani, 2017), deep learning such as (Bharathi Mohan et al., 2023; Goyal et al., 2022; Kieuvongngam et al., 2020; Shi et al., 2023; Sun et al., 2023), and fuzzy logic such as (Agarwal & Chatterjee, 2022; Goularte et al., 2019; Patel et al., 2019; Qassem et al., 2019; Srivastava et al., 2022; Verma et al., 2022; Warule et al., 2019) to tackle ATS problems. The merits and drawbacks of these scientific avenues have been subject to thorough deliberation in the work presented by (El-Kassas et al., 2021). Recent advancements in optimization-centric ATS have specifically leveraged MOABC and MOABC/D, yielding noteworthy results in terms of ROUGE metrics, especially within the realm of extractive multi-document ATS. However, it is worth noting that this approach has been associated with a significant performance concern due to its reliance on computationally intensive swarm intelligence optimization algorithms coupled with a resource-demanding ATS repair operator scheme.

Furthermore, the need for an improved ATS repair operator becomes evident when observing that an ATS repair operator is deemed both computationally expensive and inefficient in cases where a significant portion of optimization time is allocated to the repair operation rather than the pursuit of refining a superior solution. This issue is exacerbated by the prevalent approach in current high-performance optimization-based ATS strategies, wherein the ATS repair operator is executed at the end of each optimization cycle. This concern is further magnified when the repair operation must be carried out across multiple potential favorable candidate solutions. In situations involving extractive multi-document ATS challenges, the requirement is for a solitary optimal solution, or more precisely, a single excellently crafted summary. The challenges in question are depicted in the following Figure 1.1.

Consequently, repairing numerous potential solutions and singling out the most exceptional one for the final summary assessment becomes counterproductive to achieving optimal performance. Adding to the complexity, the existing ATS repair operator mandates the intermediate creation of a document mean vector and frequency table for each sentence within a solution. These components are then utilized to compute a relative score for each sentence within the solution. This score is integral in determining which sentences should be included or excluded. Given this complex conundrum, it is clear that an enhanced ATS repair operator that prioritizes performance optimization is vital. A particularly desirable feature of this enhanced repair operator would be a more straightforward sentence-scoring method streamlining the process.

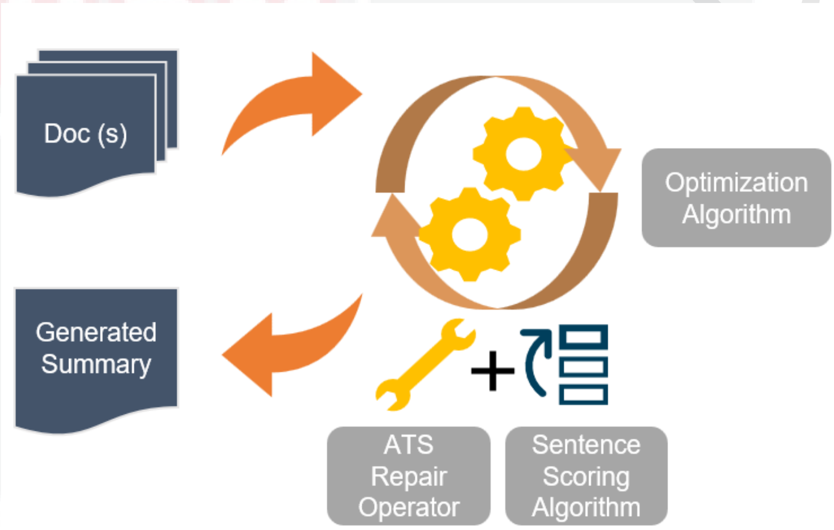

Figure 1.1: Computationally expensive ATS repair operator scheme repairing multiple solutions at every optimization cycle.

An enhanced ATS repair operator needs to be developed in tandem with a more effective foundational optimization algorithm to address the performance challenges inherent in optimization-based ATS approaches. The logical choice for this endeavor is the Differential Evolution (DE) algorithm, initially introduced by (Storn & Price, 1997). Since its inception, the DE algorithm has undergone various adaptations to accommodate evolving needs and advancements. In addition, it has been proven to be performance forgiving compared to the swarm intelligence algorithms. (H. Li et al., 2010). Its widespread adoption in engineering, biology, and even NLP underscores its effectiveness. This success can be attributed to DE's impressive performance, capacity for true convergence, and minimal requirement for control parameters compared to newer optimization algorithms.

Concurrently, the domain of multi-objective optimization (MOO) has also made significant progress, leading to the introduction of various techniques to address this challenge. Among these methods, the Weighted Sum (WS) approach, the Tchebycheff approach, and the Penalty-based Boundary Intersection (PBI) approach (Fan et al., 2020; Santiago et al., 2014) stand out as common decomposition strategies designed to aggregate Pareto optimal solutions while considering the shape of the Pareto front. The WS approach emerges as the simplest yet highly adaptable of these techniques. Notably forgiving in terms of performance, it remains particularly suitable for scenarios where the Pareto front's shape is convex, as evidenced in the case of the extractive multi-document ATS problem by (Sanchez-Gomez et al., 2019a). The WS approach excels due to its compatibility with parallel processing paradigms, displaying minimal data dependencies among parallel tasks. This property positions it favorably for execution within such programming frameworks, facilitating efficient parallelization efforts in the future.

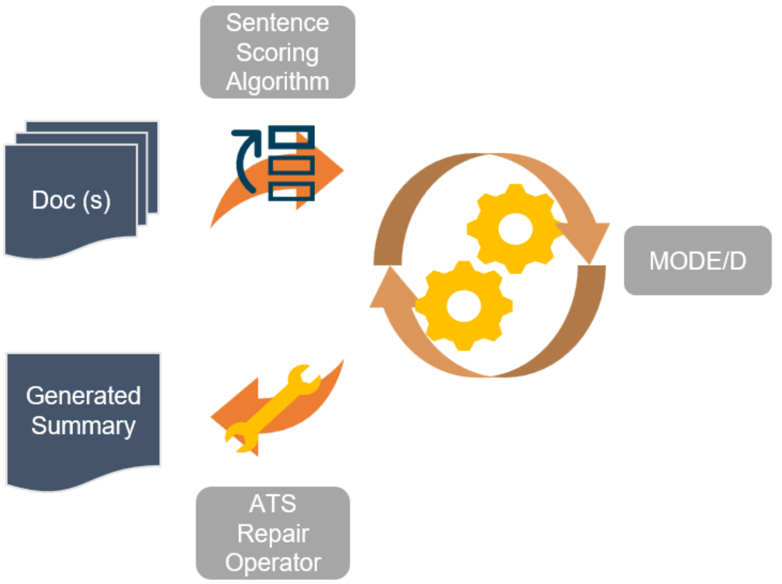

Figure 1.2: MODE/D's enhanced ATS repair operator scheme decouples the sentence scoring and repair operation tasks.

Integrating the DE algorithm as the core and complementing it with the WS approach makes it possible to distill the complex multi-objective problem of extractive multi-document ATS into a simplified single-objective optimization problem. This unified approach paves the way for an enhanced ATS repair operator to focus repair operations solely on the most promising solution. Furthermore, the optimization process can be fortified by introducing a more straightforward sentence scoring paradigm, pre-cached at the outset of the optimization process. Integrating DE and the WS approach lays the groundwork for an enhanced ATS repair operator and streamlines the optimization process, effectively tackling the performance challenges in optimization-based ATS approaches solving for extractive multi-document

ATS. Figure 1.2 provides a visual explanation of how the foundation components of MODE/D are constructed, further clarifying this proposal.

In summary, the central challenge in Automatic Text Summarization (ATS) revolves around efficiently generating machine-generated text summaries through optimization algorithms. An ATS plays a critical role in systems dealing with textual information processing. However, the current optimization-based ATS approach encounters a significant hurdle due to the long execution time, especially when employing complex optimization techniques like swarm intelligence optimization alongside a computationally expensive ATS repair operator.

Moreover, repairing multiple candidate solutions at the end of each optimization cycle is attributed to the substantial optimization time consumed by the expensive ATS repair operator scheme. Despite the impressive Recall Oriented Understudy for Gisting Evaluation (ROUGE) metrics yielded by the current approach, it grapples with inefficiencies. This latency poses a substantial obstacle in scenarios where real-time information extraction and summarization are critical, such as in media monitoring for cybersecurity, live textual analysis, or applications requiring instantaneous decision-making.

In response to the long execution time and computationally expensive ATS repair operator scheme in the literature body of optimization-based ATS approach, it is imperative to introduce both a performant optimization algorithm and an enhanced ATS repair operator. This operator should repair only the most promising solution concurrently to comprehensively address the performance issues inherent in the optimization-based ATS approach at the root.

This dissertation presents a novel optimization-based ATS approach named Decomposition-based Multi-objective Differential Evolution (MODE/D). Building upon the Differential Evolution for Multi-objective (DEMO) algorithm as the foundation and incorporating the WS approach, this approach introduces an innovative ATS repair operator scheme to address the performance challenges commonly encountered in optimization-based ATS. Explicitly selected to address the optimization problem in extractive multi-document ATS scenarios, the MODE/D algorithm utilizes the WS approach to optimize content coverage and minimize redundancy across multiple documents.

1.3 Research Questions

In light of the identified challenges in the current optimization-based ATS approach, the following research questions aim to explore the heart of these issues. By addressing these questions, the research endeavors to propose innovative solutions that enhance the efficiency and applicability of ATS, particularly in real-time scenarios. The following research questions provide a structured framework for this dissertation:

1) (RQ1) How can the development of the MODE/D algorithm and an enhanced ATS repair operator scheme effectively reduce execution time in extractive multi-document automatic text summarization?

2) (RQ2) How can the development of a parallel multi-core MODE/D algorithm and parallel multi-core enhanced ATS repair operator scheme effectively reduce execution time in extractive multi-document automatic text summarization?

3) (RQ3) How can the development of a GPU-accelerated MODE/D algorithm and GPU-accelerated enhanced ATS repair operator further reduce execution time in extractive multi-document automatic text summarization?

1.4 Research Objectives

Building upon the identified challenges and guided by the delineated research questions, this study establishes clear research objectives to address and overcome the existing limitations in optimization-based ATS systematically. The primary objectives of this research are crafted to serve as targeted milestones, each contributing to the overarching goal of enhancing the efficiency and applicability of ATS, particularly in real-time scenarios. The following objectives will guide the investigation:

1) (RO1) To develop the MODE/D algorithm and an enhanced ATS repair operator to effectively reduce execution time in extractive multi-document automatic text summarization.

2) (RO2) To develop a parallel multi-core MODE/D algorithm and parallel multi-core enhanced ATS repair operator to address and reduce execution time in extractive multi-document automatic text summarization.

3) (RO3) To develop a GPU-accelerated MODE/D algorithm and GPU-accelerated enhanced ATS repair operator to reduce execution time in extractive multi-document automatic text summarization.

1.5 List of Contributions

This research makes significant contributions to the field of ATS by addressing critical challenges and proposing innovative solutions. The following list of contributions is presented in a structured, chapter-ordered manner, outlining the unique insights and advancements that this dissertation offers to the existing body of knowledge:

Chapter 4, namely "Decomposition-based Multi-objective Differential Evolution for Extractive Multi-Document ATS," is the first contribution of this dissertation is a novel optimization-based ATS approach, namely Decomposition-based Multi-objective Differential Evolution (MODE/D). MODE/D is built upon the DEMO foundation, and incorporating the WS approach, it introduces an innovative ATS repair operator scheme to address the performance challenges commonly encountered in optimization-based ATS. The following are the critical sub-objectives associated with Objective 1 (RO1) listed in Section 1.4.

- Develop an implementation strategy for integrating the MODE/D algorithm and the Weighted Sum (WS) method into the existing framework for extractive multi-document ATS.

- Develop an enhanced ATS repair operator scheme to be seamlessly integrated into the MODE/D approach.
- Evaluate the MODE/D approach, focusing on its impact on the optimization problem of extractive multi-document ATS in terms of ROUGE metrics and performance metrics.

Chapter 5, namely "Parallelizing Decomposition-based Multi-objective Differential Evolution for Extractive Multi-document ATS on Multi-core Environment," is the second contribution of this dissertation, presents an introduction to a parallel variant of this novel algorithm tailored for execution in multi-core. The increasing importance of parallel computing is recognized, particularly in handling vast volumes of textual data. The multi-core parallel variant aims to harness the computational power offered by modern parallel architectures, specifically in multi-core computing environments. This extension enhances the MODE/D's scalability, enabling efficient execution in parallel processing environments and contributing to its practical applicability in real-world, large-scale ATS scenarios where it involves large input for an ATS system. The parallel variant represents a forward-looking exploration into optimizing the novel MODE/D algorithm for contemporary computing architectures, paving the way for advancements in the field of parallel optimization-based ATS. The following are the critical sub-objectives associated with Objective 2 (RO2), as listed in Section 1.4.

- Develop a parallel multi-core for the asynchronous application of MODE/D in multi-document ATS optimization.
- Develop a parallel multi-core for the enhanced ATS repair operator.
- Evaluate the efficiency of the multi-core execution approach across different types of loop scheduling, comparing it to serial execution.
- Analyze the impact of multi-core execution on key performance metrics, such as ROUGE metrics and performance metrics.

Chapter 6, namely "GPU-accelerated Decomposition-based Multi-objective Differential Evolution for Extractive Multi-document ATS," is the third contribution of this dissertation, presents an introduction to a GPU variant of this novel algorithm tailored for execution on a GPU device. This GPU-accelerated parallel variant represents an innovative exploration into optimizing the novel MODE/D algorithm for contemporary GPU architectures, paving the way for advancements in the field of parallel optimization-based ATS. The utilization of GPU acceleration not only aligns with the increasing trend toward high-performance computing but also holds the potential to expedite and enhance the processing of vast textual datasets, making it a crucial step forward in the quest for efficient and scalable ATS solutions. The following are the critical sub-objectives associated with Objective 3 (RO3), as listed in Section 1.4.

- Develop a GPU-accelerated MODE/D algorithm for multi-document ATS optimization.
- Assess and optimize the performance gains achieved through non-managed and managed memory GPU-CPU execution strategy.
- Assess and optimize the vector size suitable for the optimization problem of extractive multi-document ATS.
- Evaluate the computational efficiency and scalability of the GPU-accelerated MODE/D optimization-based ATS approach.

1.6 Research Scope

This dissertation focuses on advancing and innovating optimization-based approaches in the field of Automatic Text Summarization (ATS). Specifically, the contributions presented in this research are directed toward addressing challenges and introducing advancements within the context of extractive ATS scenarios, with a particular focus on multi-document ATS tailored for multiple documents as input using the Document Understanding Conferences (DUC) 2002 datasets.

This research targets the computationally expensive ATS repair operator and the long execution time challenges faced by existing approaches. Within this scope, the novel Decomposition-based Multi-objective Differential Evolution (MODE/D) algorithm, alongside its enhanced ATS repair operator scheme, seeks to optimize the summarization process and reduce execution time.

Furthermore, the dissertation explores the adaptation of the MODE/D algorithm to parallel computing environments, with a specific emphasis on GPU acceleration and multi-core parallel computing environments. This extension broadens the applicability of the algorithm to real-world ATS scenarios with large-scale document input, aligning with the contemporary trend of harnessing parallel architectures for improved performance.

In summary, the contributions of this dissertation are situated within the domains of optimization-based ATS approaches, extractive ATS, and multi-document ATS tailored for multiple documents as input. By focusing on these specific areas, the research aims to make targeted and impactful advancements, contributing to the ongoing evolution of extractive multi-document optimization-based ATS approaches.

1.7 Dissertation Structure

The structure of this dissertation adheres to the format provided by the current School of Graduate Studies (SGS) guidelines at Universiti Putra Malaysia

(UPM). The structure and organization of each chapter, as outlined in the dissertation, align with the specified standards set forth by the SGS, ensuring a consistent and compliant presentation of the research. This dissertation is structured to comprehensively address challenges and make significant contributions to the field of Automatic Text Summarization (ATS). Each chapter is meticulously crafted to build a cohesive narrative and present the research findings in a logical progression.

Chapter 1: Introduction

- Motivation: Unveil the rationale behind the research and identify the gaps in the current ATS approaches.
- Research Objective: Clearly define the goals and objectives of the research.
- Research Questions: Formulating precise questions to guide the investigation.
- Problem Statement: Identifying the central challenges in optimization-based ATS.
- Contribution Outline: Provide an overview of the unique contributions made in the dissertation.
- Dissertation Structure: Outlining the organization of chapters to follow.

Chapter 2: Literature Review

- Surveying related works from various sources to establish the context of existing ATS approaches.
- Leading to the introduction of the novel MODE/D algorithm and its foundational concepts.

Chapter 3: Methodology

- The standard methodology shared across all three main contributions is presented.
- Detailing aspects such as the dataset selection, optimization problem formulation, and other fundamental methodological elements.

Chapter 4: Decomposition-based Multi-objective Differential Evolution for Extractive Multi-Document ATS

- Design and development insights of MODE/D.
- Introduction to the enhanced ATS repair operator scheme.
- Providing an in-depth exploration of the newly proposed Decomposition-based Multi-objective Differential Evolution (MODE/D) algorithm.

- Detailing the algorithm's components, functionality, and its application to optimization-based ATS.

Chapter 5: Parallelizing Decomposition-based Multi-objective Differential Evolution for Extractive Multi-document ATS on Multi-core Environment

- Introducing the parallel multi-core variant tailored for execution in a multi-core environment.
- Introduction to the multi-core enhanced ATS repair operator scheme.
- Exploring the adaptation of MODE/D to harness the computational power offered by modern multi-core architectures.
- Exploring the effects of different types of scheduling on the Parallel Multi-core MODE/D algorithm.

Chapter 6: GPU-accelerated Decomposition-based Multi-objective Differential Evolution for Extractive Multi-document ATS

- The GMODE/D algorithm is introduced for execution in many core computing environments, explicitly focusing on the GPU acceleration (CPU-GPU) execution strategy.
- Introduction to the parallel GPU-accelerated enhanced ATS repair operator scheme.

- Exploration of unified and non-unified memory architecture.
- Detailing the optimization and adaptation processes for contemporary GPU architectures.
- Exploration of suitable vector size for GPU-accelerated MODE/D solving the optimization problem of extractive multi-document MODE/D.

Chapter 7: Conclusion and Future Works

- Summarizing the essential findings and contributions of the dissertation in the form of theoretical and practical contributions.
- Reflecting on the implications of the research and proposing avenues for future exploration and enhancement within the field of ATS.

This structured approach aims to guide the reader through a cohesive and comprehensive exploration of the research, from the foundational concepts to the innovative contributions and their practical applications.

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