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COMPOSITION AND EVALUATION OF MUSIC USING ARTIFICIAL
INTELLIGENCE: A GENETIC ALGORITHM APPROACH

BY

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Declaration

I hereby declare that I am the sole author of this thesis and all materials used from other sources or in collaboration with other researchers have been properly and fully acknowledged.

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Abstract

Advancement in technology has contributed enormously to music composition, distribution and consumption. Algorithmic music is the use of technologies and techniques to aid music composition. Currently, there are various algorithms including rule-based, memetic, deep convolutional generative adversarial networks (GAN), particle swarm optimization (PSO) and stochastic composition algorithm for composing music. However, music obtained from these algorithms may not be appealing although the algorithm used may produce the optimal music based on the criteria defined by the composer. Furthermore, the optimal music produced shows that the aesthetic quality of the music is limited. This study, therefore, seeks to compose monophonic music using genetic algorithm and assess how it is appealing to humans. Nine (9) melodies were composed. The compositions were three versions each for a GA terminated at ten thousand, twenty thousand and sixty thousand generations. The changes in total fitness scores over the various generations were plotted and analysed. It was concluded that the algorithm performed best when terminated at ten thousand generations by producing the optimal music around 750th generation. However, a survey conducted to evaluate the aesthetic performance of the algorithm through human evaluation demonstrated that the music obtained from the termination at 60000th generation was the most pleasant composition. This therefore suggests that although a GA algorithm may perform better in terms of composition time, it does not guarantee an aesthetic music.

Dedication

This work is dedicated to my husband, Dr. Isaac Wiafe for his wonderful encouragement, endless support and contribution to my education and also to my children Kofi Osei Wiafe, Kwabena Asante Wiafe and Kweku Obe Wiafe.

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Related Publications

- i. **Wiafe A.**, Nutrokor C., Owusu E., Kastriku F.A., Wiafe I., (submitted). *Design and Evaluation of Algorithmic Music Using Genetic Algorithms* in the 2020 Science and Development Platform, Accra, Ghana
- ii. **Wiafe A.**, Owusu E., Armah Z. A., Wiafe I., (accepted) *A Systematic Review of Artificial Intelligence Methods in Automatic Music Composition* in 3rd International Telecommunications Society Conference, Cape Town, SA
- iii. **Wiafe A** and Fränti P. (2020) *Security and Ethical Concerns of Affective Algorithmic Music Composition in Smart Spaces* in Modern Theories and Practices for Cyber Ethics and Security Compliance. eds. Yaokumah, W., Rajarajan, M., Abdulai, J., Wiafe, I., & Kastriku, F. A. Hershey, PA: IGI Global. doi: 10.4018/978-1-7998-3149-

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Chapter 1

INTRODUCTION

1.1 Research Background

The success of machine learning (ML) as applied to music composition enables researchers, artists and novice musicians to use computers and software tools to compose music.

Development of computer or algorithmic music is related to the different technologies and techniques that aid in music composition. Many individuals and artists compose music using their knowledge, however, some of these pieces of music lack aesthetic and creativity because a formal approach used. Music composition requires in-depth knowledge of numerous processes and thus the introduction of machine learning and artificial intelligence for composition presents a number of benefits including reducing financial cost, time and stress (Lopez-Rincon et al., 2018).

Artificial Intelligence (AI) aids in the composition process by analysing data from various musical pieces to produce new music. This approach is referred to as automatic music composition. In most cases minimal human intervention is required in generating the music (Alpern, 1995). The adaptation of formal instructions and processes to create music dates back to the ancient Greek era where Pythagoras (the Greek philosopher) laid the foundation or the domain of study (Simoni, 2003). He discovered that numbers and mathematical equations can be used for music composition (Fauvel et al., 2006; Papadopoulos, 2002; Pitkänen, 2014) since the study of music is based on creating sound patterns which can be applied in mathematics. This has been emphasised in recent times (Beynon 2012).

Researchers and practitioners of algorithmic music composition adopt different approaches of composing music (Roads & Strawn, 1996). Mathematical modelling is perhaps one of the earliest formulations of automatic music composition. Methods including stochastic processes (Jones, 1981) and Markov Chains (Ramanto et al., 2017) have been demonstrated to be effective in algorithmic music composition. Other researchers and practitioners have adopted different approaches including grammars. Grammars have been identified to be effective in the analysis and composition of algorithmic music. In particular, relevant studies identify six types of grammars used for music composition (Roads & Wieneke, 1979). Also, methods such as knowledge-based systems (Delgado et al., 2009), evolutionary methods (Matić, 2010), learning systems (Rodrigues et al., 2016) and hybrids of these methods (Fox & Crawford, 2016) have been used to compose music.

Amidst the development and advancement in algorithmic music composition, the ability to compose music that is pleasing to listen to remains. This study, therefore, seeks to use a machine learning algorithm to compose monophonic music and evaluate its aesthetics. Specifically, genetic algorithms are used to compose different music files at different generations and the aesthetic quality of the resulting music at the various generations is assessed by human listeners to evaluate it. *Aesthetic quality* describes the expression of personal “taste” in music (Aldrich, 1963; Scruton, 1982) relating to how beautiful, great, dynamic, noisy or terrible a music is composed.

1.2 Research Problem and Relevance

The adoption of machine learning techniques for music composition seeks to ease composition process. Currently, there are various techniques for composing music. However, overtly some experience challenges because well-defined fundamental theories for compositions are not integrated in the field of music. This therefore suggests that music obtained from these algorithms may not be appealing although the algorithm used may produce the optimal music based on the criteria defined by the composer. Yet, studies that seek to assess the relationship between the optimal music produced versus the aesthetic quality of the music is lacking.

1.3 Aims and Objectives

This research therefore seeks to compose a simple music and assess how it appeals to humans through evaluation. The motivation to produce a simple composition is based on the fact that, most existing ML compositions are complex and thus make it difficult for humans to assess its basic aesthetics quality. The study adopts a genetic algorithm (GA) to compose the music. GAs have been largely adopted by a number of researchers for composing music (Anderling et al., 2014) and it has also been demonstrated to produce “good” music of high aesthetic quality.

To achieve this aim, the following objectives are identified:

- i. To review existing machine learning methods for music composition.
- ii. To compose a simple music using a genetic algorithm.
- iii. To evaluate the performance of the algorithm using fitness scores.
- iv. To evaluate the aesthetic performance of the algorithm through human evaluation.

Although the above-listed objectives seek to address the main aim of the study, it is also expected to contribute to the knowledge gap in ML algorithms for music composition as well as music composition in general. It is emphasised that the aim of this study is not to produce an appealing music, but to compose a monophonic music using a simple population of musical tones, and also to evaluate the relationship between the optimal music and human quality assessment. The next section discusses the expected research contributions to the study.

1.4 Expected Contributions

The result of this research is expected to contribute to machine learning and artificial intelligent research with specific emphasis on music composition algorithms. Particularly, it is hoped to contribute to theory and practice regarding the aesthetics quality of music composed using machine learning methods (genetic algorithms).

1.4.1 Theoretical Contribution

This research shall provide theoretical insights on the relationship between aesthetic quality of music generated using genetic algorithms. It seeks to explore and explain the music quality of an optimal music generated using a genetic algorithm that is pleasing to the human listener. As argued earlier, research that seeks to assess the aesthetic quality of simple ML generated music is limited. Yet, this information provides relevant insight that may guide the development of complex ML music models that will meet the aesthetic quality of listeners. It is therefore expected that the findings of this study shall extend existing literature on algorithmic music composition.

1.4.2 Practical Contribution

In terms of practice, the findings are expected to facilitate the design of music composition systems. In effect, it will provide both novice and experienced composers basic but relevant information that will guide the use of ML methods for music composition. In addition, it is expected that, this study will provide developers of automatic music composer information regarding GA fitness functions that will guide the composition of better-quality music that are pleasing to the human ear.

1.5 Outline of Thesis

This thesis is in seven chapters. **Chapter One** presents the introduction and background of the research by providing a brief highlight of the problem. The chapter also states the research aim and objectives and explains briefly the expected contribution of the research. Highlights of the structure of the thesis are also presented in this chapter.

Chapter Two discusses the related literature. It explains the basic concepts of music and discusses the various categories in the field. The chapter further discusses the various methods used in the composition of music and the advancement of algorithmic compositions in the composition of affective music.

Chapter Three presents a summary of algorithmic music composition. It explains a systematic review conducted and reported findings of existing studies in algorithmic music composition. It discusses existing reports that perform literature reviews by conducting a systematic review of the literature. Furthermore, to ensure that the review performed is auditable and verifiable, the approach and search strategy used for conducting the systematic

mapping are explained. The findings and results from the survey are presented to guide the direction of the study.

Chapter Four provides a guide on how the research was conducted. It presents design science research paradigm as appropriate for this study and thus demonstrated the systematic and scientific approach used in the study.

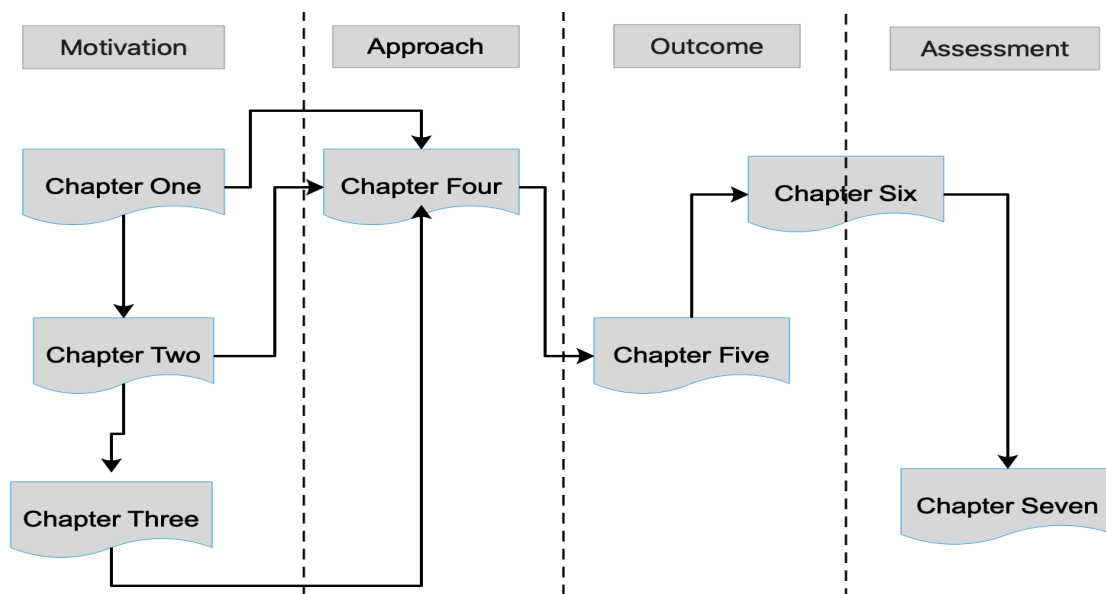


Figure 1-1 Thesis outline

Chapter Five presents a discussion on the development and evaluation of algorithmic music. It discusses how the genetic algorithm was implemented, the experimental setup, and the resultant composition after 10,000 generation, 20,000 generation and 60,000 generation. The chapter also presents an evaluation of the composed music. It further presents results of a survey conducted as part of the validation process of the composed music.

Chapter Six presents implementation of the study including the theoretical implication, practical implication, and related security implications of ML music models.

Chapter Seven concludes the study. It provides the limitations associated with the study and future research directions. It also evaluates the research objectives to assess how well the study addressed its objectives.

Figure 1-1 shows how the various chapters are related to guide the reader. The chapters are categorised into four main types (i.e. motivation, approach, outcome and assessment). Chapters 1, 2 and 3 present discussions on the motivation for the study while chapter 4 is the research approach. Chapters 5 and 6, present the outcome of the study with parts of chapter 6 and all of chapter 7 discussing the assessment of outcome.

Chapter 2

BACKGROUND LITERATURE

2.1 Overview

According to Merriam & Merriam (1964), human history has witnessed the creation and pleasure of music by various cultures across the globe. Music entails unique sounds that humans attribute to creativity and aesthetic in the composition process. It is the organisation of sound with the potential to convey a feeling either in a power-driven or natural sense (Hermitary & Meng-hu 2010). “Pure” music is made of instrumentals without any accompaniment (Kania 2017).

This chapter seeks to partially address the second objective of this study. It provides the basic concepts of music. It starts with a presentation on the basic terminologies of music, followed by existing methods that are used for composing music. Methods such as grammars, learning systems, evolutionary systems and the handwriting approach to music composition are discussed. The chapter demonstrates how advancement in algorithmic compositions advances the composition of affective music.

2.2 Basics of Music

Music composition involves creativity in order to generate new and unique melodies. Compositions can be done by writing the music with the hand (Charles, 1958), using an instrument (Chew, 2011; Magnusson & Mendieta, 2007), software (Lumsden & Ludlow, 2007; Magnusson & Mendieta, 2007) or by training the ear to listen and compose (Woody

& Lehmann, 2010). The use of various terminologies facilitates the understanding, writing and reading of music. Table 2-1 is a list of some terminologies in music and their meanings.

Table 2-1 List of music terms and their meanings

<i>Term</i>	<i>Meaning</i>
<i>Note</i>	A small bit of sound or is a symbol denoting a musical sound.
<i>Pitch</i>	The highness or lowness of a note
<i>Semitone</i>	The smallest practically usable space between two tones
<i>Octave</i>	The interval between one musical pitch and another with half or double its frequency
<i>Rhythm</i>	The timing of how long or short a musical note will last
<i>Volume</i>	The loudness or intensity of a tone
<i>Melody</i>	Represented by pitches arranged in a horizontal sequence, one sounding after another
<i>Tonality</i>	The notes in which specific hierarchical pitch relationships are based on a key "centre" or tonic
<i>Interval</i>	The distance between the two notes, either when they sound simultaneously or one after the other
<i>Tempo</i>	The speed of a given musical piece. It is measured in beat per minute
<i>Time signature</i>	Notation used to measure how music is counted
<i>Key signature</i>	A set of symbols sharps [#] and flats [b] natural (♮) on a musical staff to indicate which note will be played.
<i>Chord</i>	A harmonic set of pitches that consist of notes

<i>Term</i>	<i>Meaning</i>
<i>Chord</i>	How the series of chords are played in sequence, also known as
<i>Progression</i>	harmonic progression
<i>Diatonic scale</i>	A scale that with five whole steps or tone and two half steps in each octave
<i>Voice leading</i>	The linear progression of individual melodic lines and the interaction between that creates harmonies
<i>Smoothness</i>	The connection between notes in music
<i>Step</i>	The difference in pitch between 2 consecutive notes in a musical scale
<i>Rest</i>	A musical notation sign that indicates the absence of a sound

2.3 Music Composition Methods

There are different methods for generating music and below is a brief description of the various methods.

2.3.1 Handwriting, Listening and Instruments

The concept of paper and pencil was considered as the best tools for the music composition in the 1940s. This is because it was considered to be handy (Day & Jarrett, 2008). Composers with knowledge in the solfege (do, re, mi, fa, so, la, ti) used them to represent a composition. The sequential flow of the notes was known and thus made it easier for others to play or translate to music notation.

The effect of music listening is to aid people in composing music. Hedden (1981) researches how music educators develop one's ability to hear and compose music by using various

strategies. A listener, listening without any distortion, and a repeat hearing have positive influence on the individual such that the individual's attention is absorbed in the music. Furthermore, with music classified as a universal language (Campbell, 1997) when good listening skills are developed with critical thinking phrases, it can be understood and used in the composition of meaningful music.

Piano, keyboard, flute, harp, saxophone, xylophone, violin and double bass are some examples of instruments that are used in the composition of music. The piano is a polyphonic instrument that can play two melodies at the same time, unlike flute. Both the keyboard and piano are easy to learn in the composition of music.

2.3.2 Software and Computer-Generated Music

Nowadays, the use of computers and software programs play a vital role in music composition. Novice, researchers and artist are able to compose music that fit their ideas, reduce their financial cost and provide them with a stress-free environment for the composition process. Software such as MuseScore, Cubase, Anvil studio, Finale, Famitracker, Anvil studio, Pro Tools are all examples of composing tools used for creating music.

Additionally, some instruments work together with software packages to aid music generation. Music sequencer software and hardware are connected to computers to facilitate composition, recording, editing or playing back of the music. MIDI (discussed later in this chapter) or other plug-ins are used to control notes and generate music. It is however limited because sequencers have less music notation capabilities and thus can play only simple melodies when compared to other plug-ins. Plug-ins such as Capella allows keyboard or

MIDI instruments to be plugged into its hardware to facilitate music creation by interpreting what is played and produces a written music notation.

2.4 Generating Music with Algorithms (Algorithmic Music)

There are two approaches used in generating algorithmic music; music composed by the computer (when the algorithm can make choices of its own during the creation process) and music composed with the aid of computer. Although algorithmic composition was recognised in the mid 1950s, many composers use different techniques in composing music (McAlpine et al., 1999).

AI technologies are useful in music composition since intelligent agents can “think” and solve problems like humans. Algorithmic music composition follows a set of rules to compose music. It is the process of using a structured methods to create music with minimal human intervention (Alpern 1995). In some cases it uses a trial and error approach (Simoni, 2003) and this may lead to some “useless” melody. Hence, some researchers have advocated for the use of humans to listen and revise melodies to help determine its quality (Jacob, 1995, 1996). Human may provide a better result as compared to the automatic composition process which adheres to rules and constraints in the algorithms and by its propositions is not able to determine the quality of music. However, although this assertion is intuitive, it has not been empirically demonstrated.

2.5 Algorithms for Generating Music

Currently, researchers and practitioners of algorithmic music composition adopt different AI approaches to facilitate music generation. These AI approaches are classified based on their

development and features. Papadopoulos & Wiggins (1999) grouped these algorithms into six namely, mathematical models, grammars, knowledge-based systems, evolutionary methods, systems which learn and hybrid systems. Below is a brief discussion on these models.

2.5.1 Mathematical Models

Developing mathematical models and implementing it effectively and efficiently enhance algorithmic composed music. Stochastic process for music composition (Jones, 1981) and Markov Chains (Ala & Wadi, 2012; Ames, 1989; Cambouropoulos, 1994; Ramanto et al., 2017; Volchenkov et al., 2012) are similar. Markov chains are used for composition by generating different states of sequences and each sequence state is evaluated using probability theories. Random note selection are used to compose high-quality music (Moorer 1972). Markov chains are mostly used for melody generation but exhibit some challenges. One of such challenges identified is how it assesses probabilities of the state diagrams that are generated randomly. This is because they have to be derived from the existing composed music. Thus, they most seek to generate outputs similar to the inputs. They also produce unconnected pitch values (Järveläinen, 2000).

2.5.2 Grammars

Grammars are methods which display special features in the analysis and composition process. They exert some degree of hierarchical structure in music composition with rules that connect notes to form phrases, segments and pieces of music. Linguistic models which lead to the discovery of grammars that can be used for music composition was developed by Chomsky (1957). Roads & Wieneke (1979) argued that there are six types of grammars. This

includes the four basic types introduced earlier by Chomsky (1957). The first type is free grammar. *Free grammar* has no constraints on the rules used in the composition process as compared to *context-sensitive* (Swyter, 2009).

Context-free grammar aids in the generation of multi-level hierarchical trees and *finite -state* requires at least one non terminal token on either side to enable rewriting of rules since they are not able to compose music generated by the context-free grammars. *Transformation* grammar covers three sections with the first creating the abstract sentences, the next converts it into sentences and map the sentence to a phoneme. The sixth type is the *regulated grammar* which uses control languages to decide when to combine production rules with a context-free grammar.

2.5.3 Knowledge-Based Systems and Learning Systems

The knowledge-based system is a form of Artificial Intelligence (AI) which uses human expert knowledge to aid in decision making. Algorithmic music incorporates knowledge-based systems in composition by modelling computers to compose music. The process is facilitated by using the knowledge-based to select notes based on precise reasoning.

Also, some applications are designed to learn and compose music. These systems use current information available but not previous knowledge for composition. They are grouped into artificial neural network (ANN) and ML based on how they perform their task and store information. ANN uses a set of input patterns to train the network in order to generate similar patterns thus compositions are achieved by representing music notation in the form of temporal patterns as inputs trained to generate outputs in a network. They are also capable of using classification algorithms to classify features for music composition.

2.5.4 Evolutionary Methods

An evolutionary algorithm is an algorithm that follows the laws of evolution. It is an AI technique and can be used for music composition. Evolutionary algorithms (EAs) are driven by optimization process such as the Darwinian evolution. Genetic algorithm (discussed in the next chapter) is an example of an evolutionary algorithm. Genetic algorithm, Evolution Strategies (Rechenberg, 1989) and Evolutionary Programming (Jones, 1998) are three basic application of evolutionary algorithm. Although they demonstrate similarities such as the use of fixed-length strings, mutation and selection operators they behave differently (Fraser, 1957; Goldberg & Holland, 1988; Holland, 1975; Sastry et al., 2005).

2.5.5 Hybrid System

Hybrid systems consist of a mishmash of AI techniques used in the composition process. Gutknecht (1992) suggested that the “postmodern mind” identifies various AI potencies combines and adopts them. HARMONET a hybrid system (Hild et al., 1992) combines back propagation methods and symbolic algorithms in a hierarchical system to compose music. In some cases a combination of stochastic processes and genetic algorithms are used (Fox & Crawford, 2016). Although, they have been demonstrated to be effective in composing music (Chuan & Chew, 2007).

Some researchers (Papadopoulos & Wiggins, 1999) have argued that hybrid systems demonstrate complications when used with a fully integrated mode. This is because the implementation of the algorithm is time-consuming when checking for verification and validation.

2.6 Application of Algorithmic Music

The ability to generate music using algorithms and modern advancement in parallel computing have provided both researchers and practitioners the opportunity to advance the use of music in various domains. Below is a discussion of three main areas of application.

2.6.1 Video Games

Background music in video games plays an important role such that it creates a lifelike environment with natural sound and an add-on for better entertainment. Creation of music in video games enhances user's interaction experience. Algorithmic music can be used to generate music to influence the events of the game, the characters, as well as provide a clue about the position or distance of an enemy, or an event about to happen (Prechtl, 2016; Prechtl et al., 2014). AMEETM by Hoeberechts et al., (2007) is a music composition engine used for generating adaptive music for video games. Other video games that uses automatic composed music includes Avatar (Rice et al., 2013), the Thief (Kennerly et al., 2009) and Splinter cell (Thorsen, 2018).

2.6.2 Movies

Similar to video games, music generated for movies provide appropriate emotional support for the various states and functions. Livingstone et al., (2007) explained how the altering of music can produce emotional variation based on structural and performance rules. Algorithmic compositions are used in movies to help create and shape emotional response such that the movie captures the emotions of the audience. They are used as background music to provide audience feelings of being scared, anxious or hopeful. They also provide

rhythms to scenes and interpret the next activity about occur. Metascore is an example application designed to provide and improve movie music (Callum et al., 2008).

2.6.3 Therapeutic Properties

Music has gained recognition for its therapeutic purposes (Rafieyan & Ries, 2007). It is safe and does not involve the introduction of medical instrument. It is also less expensive and can be delivered to reduce postoperative pain and anxiety needs (Hole et al., 2015). Kemper & Danhauer (2005) explained how selected music can reduce stress, surgical, acute, procedural and chronic pain among patients and also provide comfort and relaxation. Algorithmically composed music therapy focuses on all aspects of humans: from the brain, through the body to the mind. It provides emotional healing for people. An example of computer-aided music therapy is Carnatic music used for curling ailment (Vasudha et al., 2011).

2.6.4 Affective Algorithmic Music Composition

Advancement in Algorithmic music composition has made it possible to compose music with improved affective response. Over the years, different algorithmic music composition models and applications have been developed based on artificial intelligent (AI) techniques such as neural networks, deep learning, stochastic and heuristic composition models (Lopez-Rincon et al., 2018). Lopez-Rincon et al., (2018) further acknowledged that recent advancements have improved automation of algorithmic music composition. Therefore, use of computers for automatic composition presents an opportunity in which computer-aided composition and emotional assessment are combined to produce affective algorithmic composition (AAC).

AACs are emotionally intelligent automatic music generation systems that explore current emotions or mood of listeners to compose affective music (Kirke et al., 2013, Williams et al., 2017). These compositions aim at altering a person's mood to a predetermined one. Specifically, they seek to target an individual's affective descriptor (emotional response) in order to alter his or her mood (Williams et al., 2015).

Williams et al., (2015) explained that AAC presents several opportunities and benefits to almost all aspects of human wellbeing. For example, AAC is used to compose music that reduces the emotional distress of patients based on their mood (Kemper & Danhauer, 2005). Again, they have the ability to produce larger music samples within a short time: a feature that provides a larger sample of music that can be selected by users for reducing stress levels.

Similar to arguments made by Boyes (2003), AAC is challenged in terms of security. These are threats from malicious outsiders; malicious insiders; non-malicious insiders; and nature. These threats may come in different forms including, impersonation and identity spoofing, eavesdropping, user profiled tampering, malicious codes and denial-of-service.

The security impact of impersonation in this context may lead to two major issues: such as data theft and unauthorized composition or unauthentic (i.e. non-affective music) music for legitimate users. When AAC is enabled in smart space, the impersonator may have access to sensitive data about a user and use it for malicious purposes. Particularly, the impersonator can compose music. In such instances, the authenticity of the composed music becomes questionable. Considering the possible impact of impersonation, it is recommended that biometric authentications are used in these systems.

Eavesdropping is another common network attack that needs to be considered in AAC systems. It is an unethical act in which an individual illegitimately intercept a private conversation, communication, digital transmission or activities of others without their consent. It poses privacy issues in AAC because it may lead to the disclosure of listeners profiles which can later be used for impersonating. There is no ambiguity about the emotional contagion ability of music (Egermann & McAdams, 2013) and hence measure that seek to prevent eavesdropping cannot be overemphasised.

Ethical considerations are vital in all systems that seek to alter cognition, emotions or mood. AAC systems have functionalities that include compositional processes and affective performance structures. They use generative or transformative algorithms to induced or perceived to induce affective states of users (Williams et al., 2015). They adopted emotional models (i.e. categorical or dimensional models) to profile its users. Since users interact with systems that have intentions, any unethical practice may result in an unwanted effect.

2.7 Chapter Summary

Understanding the concepts of music and the use of computers to compose music is relevant since they facilitate the composition process. Although there are various techniques, a comprehensive analysis of the techniques is important. Accordingly, discussions in this chapter have demonstrated that research in algorithmic music composition is advanced. However, literature that summarises existing studies in the domain is scare. Hence, in the next chapter, a summary and discussion of existing studies that seek to compose music using algorithms is presented.

Chapter 3

EXISTING STUDIES IN ALGORITHMIC COMPOSITIONS

3.1 Overview

As mentioned in the previous chapter, advancement in algorithmic composition of music has made it possible for it to be used in various domains and there is no ambiguity that its application will continue to be diverse. Yet, studies that seek to provide summaries in the domain is lacking. To ensure a comprehensive review, this chapter addresses the first objective of the research (partially) by reporting findings of a systematic review of existing studies in algorithmic music composition. It deviates from existing reports that perform classic literature reviews by conducting a systematic review of literature. To ensure that the review is auditable and verifiable, the approach and search strategy used for conducting systematic mapping are explained. The findings and results from the survey are presented to guide the direction of the study.

3.2 Existing Literature

Advancement in algorithmic music compositions have made it possible to produce lyrics and melodies from real-world data such as academic papers (Scirea, Barros, Shaker, & Togelius 2015), self-generating composition (Papadopoulos, Roy, & Pachet 2016) and also enhance voice and word representation in music composition (Makris et al., 2015; Shin et al., 2017). Yet, the complexities and the multi-disciplinary nature of the domain makes it a challenge for researchers and practitioners in the domain to realise its full potential.

Radhakrishnan et al., (2007) explained that algorithm music is tied with the field of music composition since it involves a finite set of precise instructions that performs computation or solves a music problem. Nonetheless, it is significant to distinguish algorithm as important in music composition since it enables one to know the impact it has on the various music styles and genres. The pressing interest in computer-generated music is motivated by the fact that contemporary artists, novice and researchers can use computers to compose music reduced financial cost, stress and composition time (Chamberlain et al.,2018).

Although there is success regarding algorithmic composition, literature in the domain is scarce and this poses a challenge to researchers regarding the successes, challenges and future directions. To address this knowledge gap, a well-established method (Kitchenham, 2007; Kitchenham & Charters, 2007; Petersen et al., 2015) for conducting systematic reviews studies was adopted. The method involves a systematic approach to answering research questions that seek to provide relevant outcomes within a specific research domain (Da Mota Silveira Neto et al., 2011; James et al., 2016; Petersen et al., 2015).

Some existing studies have reviewed works on algorithmic music composition. Roads (1985) reviewed how computers use AI techniques to analyse music focusing on the composition, performance, music theory and digital sound processing. Although the study provided a meaningful understanding of how systems can learn and compose music using the various AI techniques, it failed to further explain the various types of techniques that are applied. Papadopoulos & Wiggins (1999) provided a summary of the early history of the field. The review discussed the various AI techniques used in algorithmic composition and concluded that systems that apply only one method for composition are not efficient. Although Papadopoulos & Wiggins, (1999) review outlined the various techniques, the study

was arguably not systematic, since the methods used to select was undefined open to biasness. The study also failed to provide discussions concerning patterns and trends of the various AI techniques used.

Fernandez & Vico (2013) provided summaries on AI techniques in algorithmic composition. Their study emphasised the techniques, languages and tools used to automatically perform a creative compositional task with minimal or no human intervention. Again, their study cannot be a systematic review as it failed to discuss the methods used in the selection of the literature. Furthermore, the study failed to discuss concerns about the patterns and trends of various techniques and languages.

Similarly, other studies (Lopez-Rincon et al., 2018) have provided summaries on techniques in automatic music composition and identified that the main challenge in algorithmic composition is performance measurement. Although the review identified the trends, it cannot claim to be systematic when compared with the systematic review guidelines as defined by Kitchenham & Charters (2007) and Petersen et al. (2015). They failed to outline the method adopted for the paper selection (i.e. inclusion and exclusion criteria, search terms and phrases), the databases which were queried, and the data extraction method used. Also, even though they reported on known existing AI techniques, trends and performance measure, they fail to discuss the approach. Accordingly, a systematic review was conducted to validate existing claims by empirically evaluating existing studies to draw conclusions to either support or refute such claims. The next section provides the step used for conducting the systematic study.

3.3 Review Approach

Figure 3-1 provides an overview of the process followed in the systematic study. The process was divided into three phases, i.e. planning, conducting, and documentation. Each phase has inputs and output artefacts that were followed to minimize potential bias. The artefacts were assessed and by external experts for independent views and their comments and recommendations were adopted. This led to a review protocol for the study.

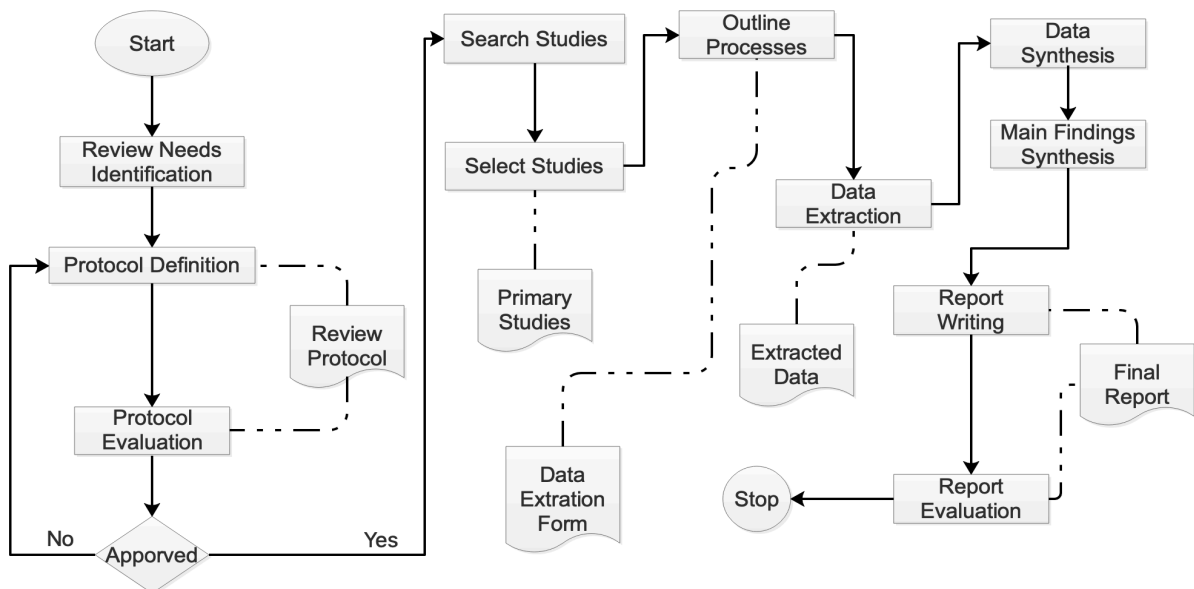


Figure 3-1 Steps in the Review Process

3.3.1 Planning, Conducting, Study Selection and Documentation

To perform a systematic mapping study on algorithmic composition, the research questions were identified with a well-defined review protocol evaluated and accepted to further describe the various steps the study needs to follow. The Conducting phase involved a search that combines the various techniques applied in identifying a comprehensive set of candidate studies on algorithmic music composition. An outline consisting of a set of parameters for

analyzing the primary studies was also defined. The final phase involved reasoning to obtain findings to evaluate the quality of the study. Some activities performed include a systematic explanation of the data extracted in the previous phase to achieve results that relate to the context, analysing the evaluating techniques and writing a detail report describing the systematic mapping study conducted.

3.4 Review Questions

The Goal-Question-Metric perspectives were adopted to guide the review process (see Table 3-1). The purpose, issue, objective, view point were formulated before identifying and outlining the research questions as suggested by Basili (1992). This approach ensures a precise and concise review questions tailored to fit the knowledge gap (Brereton et al., 2007). Based on the goal, the review questions in Table 3-2 were crafted.

Table 3-1 Goal-Question-Metric adopted from (Basili et al., 1994)

<i>Purpose</i>	Analyze the Review Questions
<i>Issue</i>	Publication trends, AI techniques, type of music files used and validation strategies
<i>Object</i>	of existing algorithmic music composition
<i>Viewpoint</i>	from a researcher's point of view

A search strategy was adopted to detect as many relevant studies as possible. Therefore the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) approach (Stovold et al., 2014) was used.

Table 3-2 Review Questions and their Objective

	<i>Question</i>	<i>Objective</i>
<i>RQ1</i>	What are the publication trends of studies in algorithmic music composition between 2010 and 2019?	To classify primary studies to assess interest, relevant venues, and contribution types; depending on the number of primary studies, trends can be assessed over the years
<i>RQ2</i>	What AI techniques are dominating in algorithmic composition?	to analyse and classify all the existing approaches for algorithmic music composition concerning the specific concerns they want to address.
<i>RQ3</i>	What are the evaluating techniques for validating the composition algorithms?	to analyse and classify all the existing evaluating approaches for algorithmic music composition to the strategies used for assessing their validity
<i>RQ4</i>	What type of music files are mostly used for automatic compositions?	to analyse and classify all the existing music files used for the algorithmic composition

An automatic search was performed. This included the execution of a search string on a set of electronic databases (see Table 3-3 for list of databases used). This approach is mostly used due to its potential to identify relevant studies. The keywords Algorithmic music, Composition, Machine Learning, Artificial Intelligence and Music Composition were used to form different phrases and searched in the databases.

Figure 3-2 presents the number of studies realised at each stage of the search process. The after-effect of the automatic search indicated that all irrelevant sets that are not stated in the inclusion criteria are removed. This include workshops, tables of contents, maps, lists of program committee members, keynotes, surveys, tutorial or invited talks, and messages from chairs and co-chairs and book chapters are all not included (see Figure 3-2). Only studies conducted between 2010 and 2019 were considered. The search resulted in 4413 potentially relevant studies. Furthermore, a manual search is also performed on the relevant publications. The search performed considers title, keywords and abstract of each study.

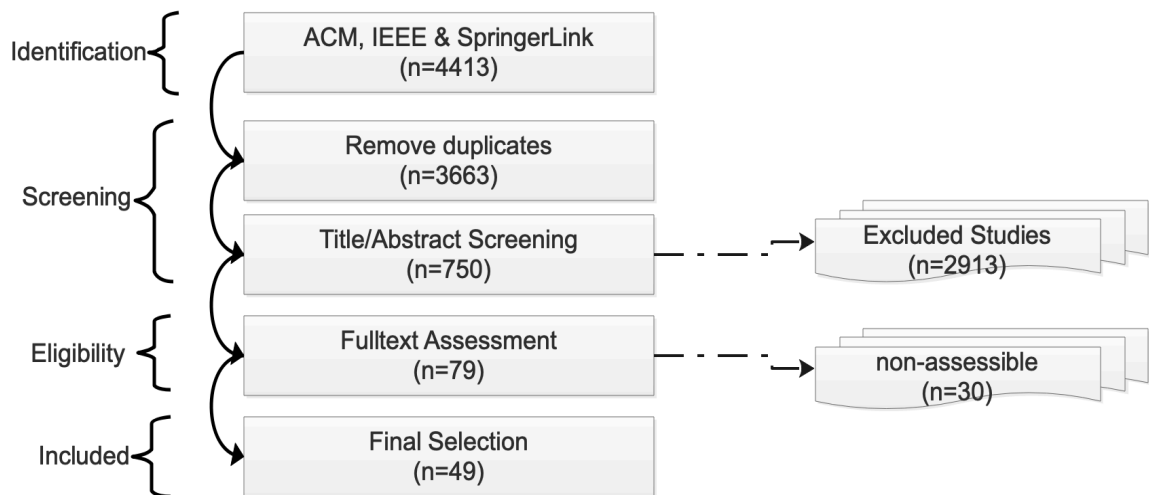


Figure 3-2 Number of Studies Identified for the Review

The obtain optimal search strings Zhang et al., (2011) quasi-gold standard (QGS) was used. It argues that the search process is valid and acceptable when the results obtained the meet the search criteria.

Table 3-3 Databases, Websites and Keywords

<i>Library</i>	<i>Website</i>	<i>Keywords</i>
ACM Digital Library	https://dl.acm.org	Algorithmic music Composition, Machine Learning, Artificial Intelligent, Music Composition
<i>IEEE Explore</i>	https://ieeexplore.ieee.org	Algorithmic music Composition, Machine Learning, Artificial Intelligent, Music Composition
<i>SpringerLink</i>	https://link.springer.com	Algorithmic music Composition, Machine Learning, Artificial Intelligent, Music Composition

3.4.1 Selection Strategy

As illustrated in Figure 3-2, after the search activity, all identified studies were filtered using the exclusion criteria specified in the review protocol and stated below. The following were considered as exclusion criteria:

- i. Studies not subject to peer review
- ii. Studies not in English
- iii. Studies focusing on methods or techniques not specific to algorithmic music composition system (e.g. studies focusing on either the composition components of the systems)
- iv. Secondary or tertiary studies (e.g., systematic literature reviews and surveys)
- v. Studies that were not retrievable from the selected databases

- vi. Studies in the form of tutorial papers, short papers, poster papers and editorials

3.4.2 Data Extraction

In analysing each primary study, an outline for classifying research studies on algorithmic music composition was defined (Jonnalagadda et al., 2015). Also, parameters for classifying AI methods or techniques used in algorithmic music composition were defined. A data extraction form that comprised a list of attributes was designed to collect information from each primary study. This included the name of authors, authors country, year of publication, title, and publication details of the study, methods or technique used for composing the music and the method of evaluating the music. The data was organized and summarized from the extracts to understand, analyse, and classify current research on algorithmic music composition. Both quantitative and qualitative synthesis methods were applied in analysing the 49 primary studies.

3.5 Review Findings and Results

To assess the publication trends concerning algorithmic music composition, a set of variables focusing on the publication and bibliographic data of each primary study is identified. Each primary study including its title, authors, authors' countries, publication year, publication venue (i.e., journal, conference) were analysed.

Error! Reference source not found. presents the distribution of the selected publications on algorithmic music composition from 2010 to 2019. It can be observed that there is research in the domain that has not been growing in a sturdy pattern. Although the number of studies per year have increased, the increase is not progressive. However, from 2014 there was a

continuous growth trend over the years, climaxing in 2015 and decreasing again in 2016. In 2017 the highest number of publications were achieved. Publication score decreased to 9% in 2018 but there was an emergent increase again in 2019. Furthermore, it can be concluded that the sharp increase in the number of selected studies in the year 2015 and 2107; would be trace to innovation of algorithmic music composition techniques gaining interest and attention (Liu & Ting, 2016).The study covers papers published before October 2019 and for a partial year, it accounted for 17% of the primary studies surveyed. This result further confirms the growing attention and need for research on algorithmic music composition.

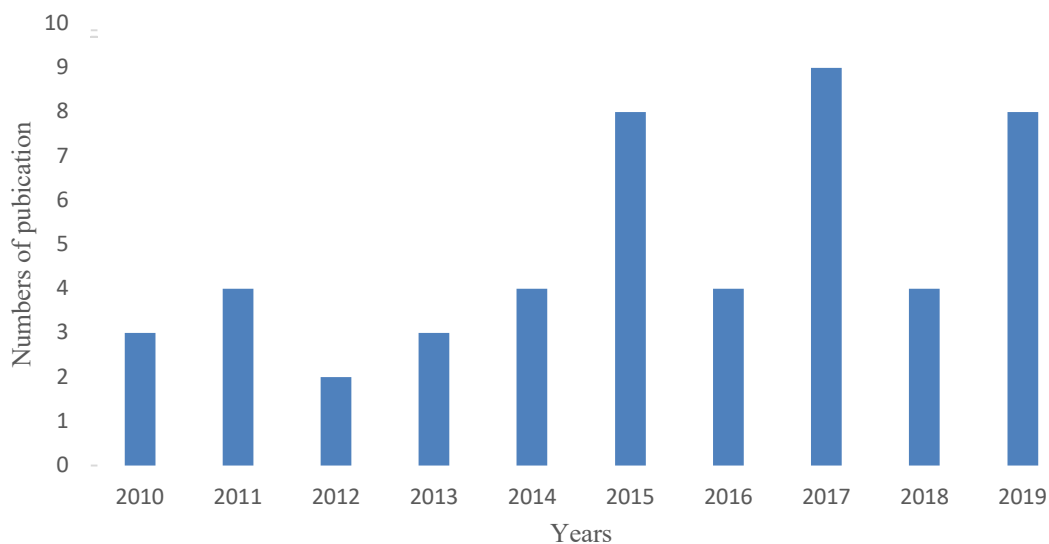


Figure 3-3 Distribution of primary studies by year

3.5.1 Publication Trends

Each primary study used was either published as a journal paper or conference paper. Figure 3-4 shows the distribution of primary studies over the study period and the publication type.

The most common publication were conferences. It accounted for 43 (88%) while journals were 6 (12%). The number of conference publications on algorithmic music suggests that the domain is still at its infancy and thus researchers are actively discussing progress and also consolidating ideas.

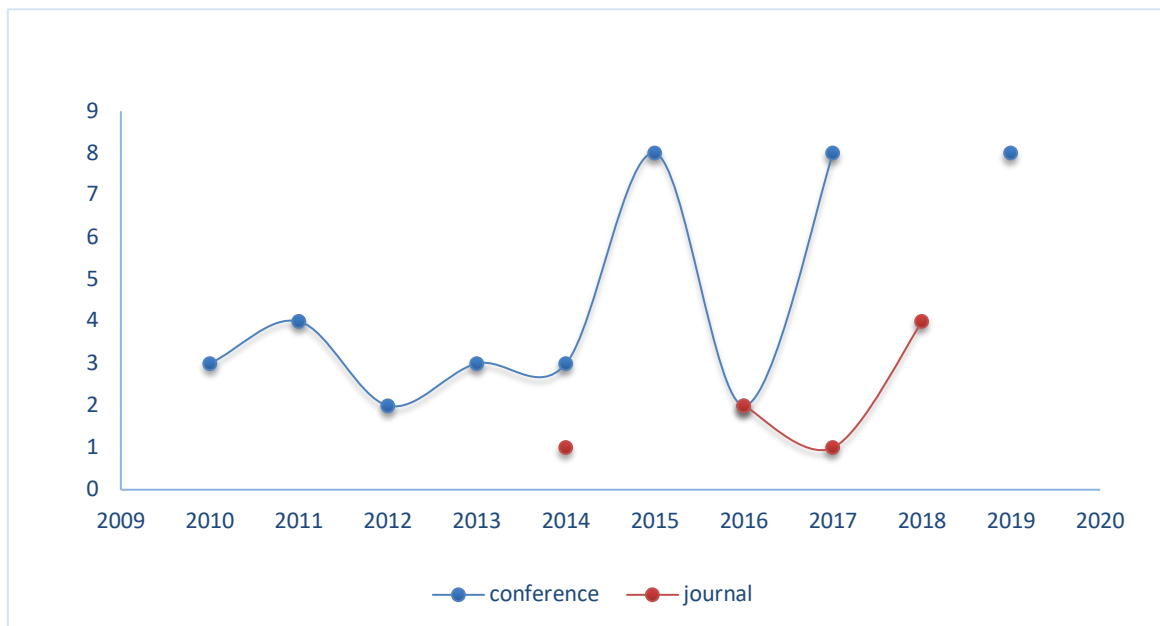


Figure 3-4 Distribution of publication venue

Research on algorithmic music composition is pursued across the Globe. However, the study revealed, identified Europe, Asia, North America, South America, and Oceania. Europe has (58%) of the publication while South America and Oceania have 4% each. It was also observed that most of the researcher's work on algorithmic music composition were from Europe and there was no publication from Africa. See Figure 3-5 is a chart for the geographical distribution of studies surveyed.

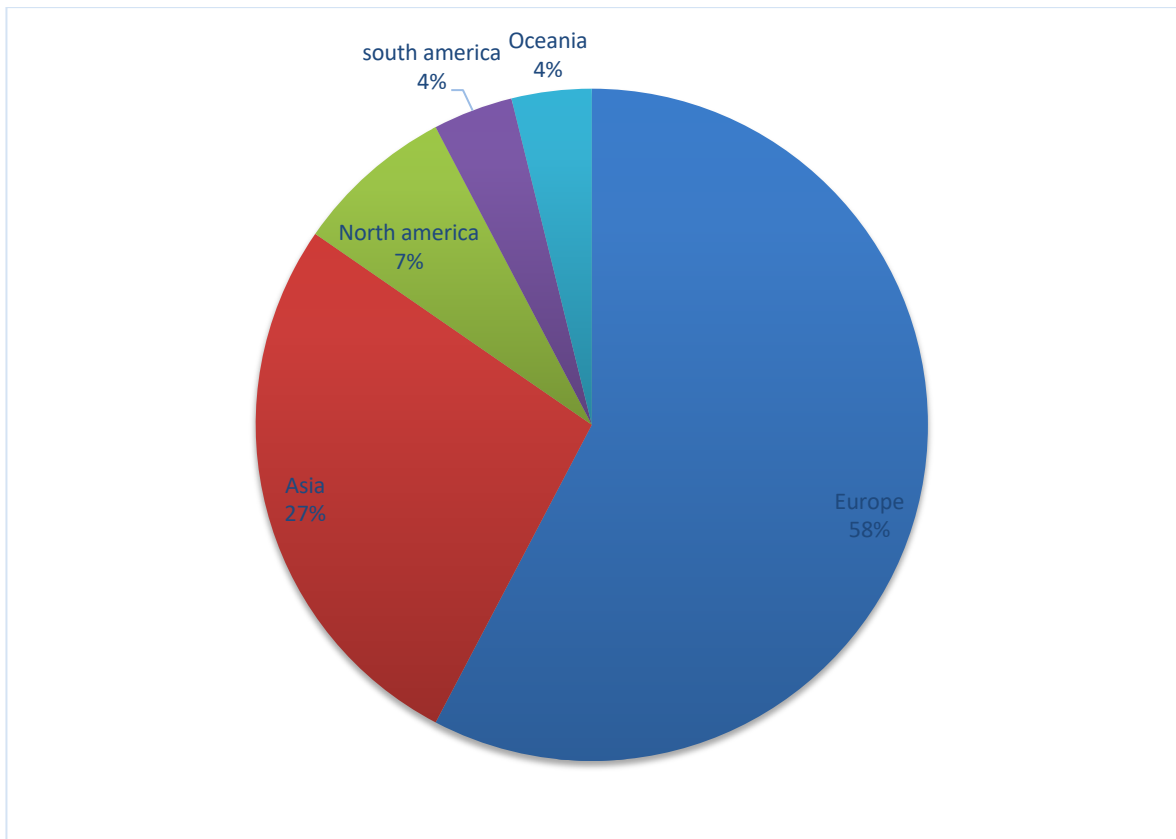


Figure 3-5 Geographical distribution of primary studies

AI Methods for Algorithmic Composition

The study indicated that AI techniques for generating algorithmic music are progressively becoming popular. With a series of techniques identified, evolutionary algorithms were mostly used, and it contributed eighteen (37%) of the primary studies. Artificial neural networks and deep learning models followed with eleven (23%) while mathematical models covered eight (16%). The heuristic methods were seven (14%) of the primary studies whereas grammar models were the least as it contributed five (10%) of the primary studies. Table 3-4 shows the various techniques used and the corresponding study that used the technique. It was observed that genetic algorithm was the most used evolutionary algorithm.

It recorded a total of eighteen (18) out of ten (10) (Genetic Algorithms is discussed later in this chapter).

Table 3-4 AI methods for composing music

<i>Algorithm Used</i>	<i>Method Description</i>	<i>Study</i>	<i>%</i>
<i>Mathematical models</i>	The process of developing mathematical models and implementing it effect.	[31],[13],[46],[33], [49],[23],[29],[32]	16
<i>Grammar</i>	Grammars are powerful methods which display unique features in the analysis and composition of algorithmic music. There exists a degree of hierarchical structure in the composition of music with rules that connect notes to form phrases, segments, and pieces of music.	[12],[44],[45],[20], [41]	10
<i>Evolutionary methods</i>	An evolutionary algorithm is described as algorithms that follow the laws of evolution. Evolutionary algorithms (EAs) are driven by optimization process such as the Darwinian evolution.	[1],[2] ,[3],[4],[5], [16],[11],[7],[35], [36], [8],[37],[9], [38],[24], [39],[26],[10]	37
<i>Knowledge-based systems</i>	The knowledge-based system is a form of Artificial Intelligence (AI) which	[43],[14],[19],[40], [42],[28],[48]	14

<i>Algorithm Used</i>	<i>Method Description</i>	<i>Study</i>	<i>%</i>
	intends to use human expert knowledge to aid in decision making.		
<i>Learning systems</i>	Applications including systems which learn can be used to compose music. Systems which learn use current information available but not previous knowledge to compose music. These are grouped into an artificial neural network (ANN) and ML based on how they perform their task and store information.	[47],[15],[18],[34],[22],[30],[25],[27],[17], [6], [21]	11

3.5.2 Evaluating Techniques in Algorithmic Composition

Evaluating techniques are used to validate the formal mathematical proof used to ascertain the appropriateness of the model. In all a total of 9 different techniques were found to have been used for evaluating the use of algorithms for composing music. From **Error! Reference source not found.** eighteen representing 37% of the studies used qualitative observation (listening test) for assessing the quality of the composed music. This is followed by Fitness function which is a method for selecting individuals to mate in a GA (discussed later in this chapter). Ten studies used fitness functions alone while 5 studies combined fitness function and listening for evaluating the resultant music. Seven of the studies failed to report the method used for evaluating the composed music.

Table 3-5 Methods for Evaluating Algorithmic music

<i>Type of evaluation</i>	<i>Method Description</i>	<i>Study</i>	<i>%</i>
<i>Fitness value</i>	The value of the fitness function for that an individual (the fitness function is how close a given solution is achieving its aim)	[1], [2],[3],[4],[5], [6],[7],[8],[9],[10] [11]	26
<i>By observation (listening)</i>	Observation is an assessment method which provides information about the quality, strengths, weakness and interest of a thing.	[12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31]	35
<i>Up sampling and down sampling</i>	Up sampling is the process of increasing sample by inserting zero-valued whites down sample is the process of reducing the sampling rate by introducing integers.	[32]	2
<i>Markov's process (Probability)</i>	It is a mathematical framework for modelling decision in situations where the outcomes are partly random and partially regulated by a decision maker.	[33], [34]	5
<i>Application of both fitness</i>	This is a combination of the fitness function and human judgement	[35], [36], [37], [38], [39]	12

<i>Type of evaluation</i>	<i>Method Description</i>	<i>Study</i>	<i>%</i>
<i>function and listening</i>	(listening) in order to assess the quality of a melody.		
<i>Test run (prototype)</i>	A test run on a prototype is to evaluate the design, product or creativity generated.	[40]	2
<i>Precision and recall measures</i>	Using precision and recall measure in evaluation is to measure the success of prediction when there is an imbalance situation.	[41]	2
<i>Benchmark functions</i>	A function which is used to test the performance of any optimization problem.	[42]	2
<i>Not stated</i>	-	[43], [44],[45],[46],[47], [48]	14

Other methods such as rest measuring melodic and harmonic errors, application of frequency spectrum, up sampling and down sampling, harmonic evaluation function, precision and recall measures, continuous optimization functions, subjective evaluation and multi-attribute decision-making techniques were all identified. It can be observed that the most used technique for the evaluation of the performance of the various algorithm is qualitative observation (i.e. listening test). In this approach, listeners assess the quality of a composed

music by listening to and classifying it as appealing or not. Although this method is appropriate some researchers argue that the use of fitness function and human evaluators is more effective.

3.5.3 Music File Used for Composition

Considering the complexity exhibited in the representation of music scores by computers, music files are created to make composition less challenging. They create flexibilities for research and artist during composition.

From Figure 3-6, thirty (30) representing 61% of the primary studies used did not specify the type of music file used. This is worrying considering that the domain is relatively new and thus researchers in the field need adequate information from existing studies to support their work. The most used music file was Musical Instrument Digital Interface (MIDI). In one instance the pdf file displaying MIDI notations (or instructions) was used. MIDI file is a standard protocol that governs the interaction of digital instruments using computers. They are more compact than digital audio files and allows for easier editing. It is therefore envisaged that these properties enable it to outperform other audio files in automatic compositions.

From the review, it is evident that genetic algorithms and MIDI files are used predominantly for algorithmic compositions. Accordingly, the next section in this chapter discusses some relevant details on them.

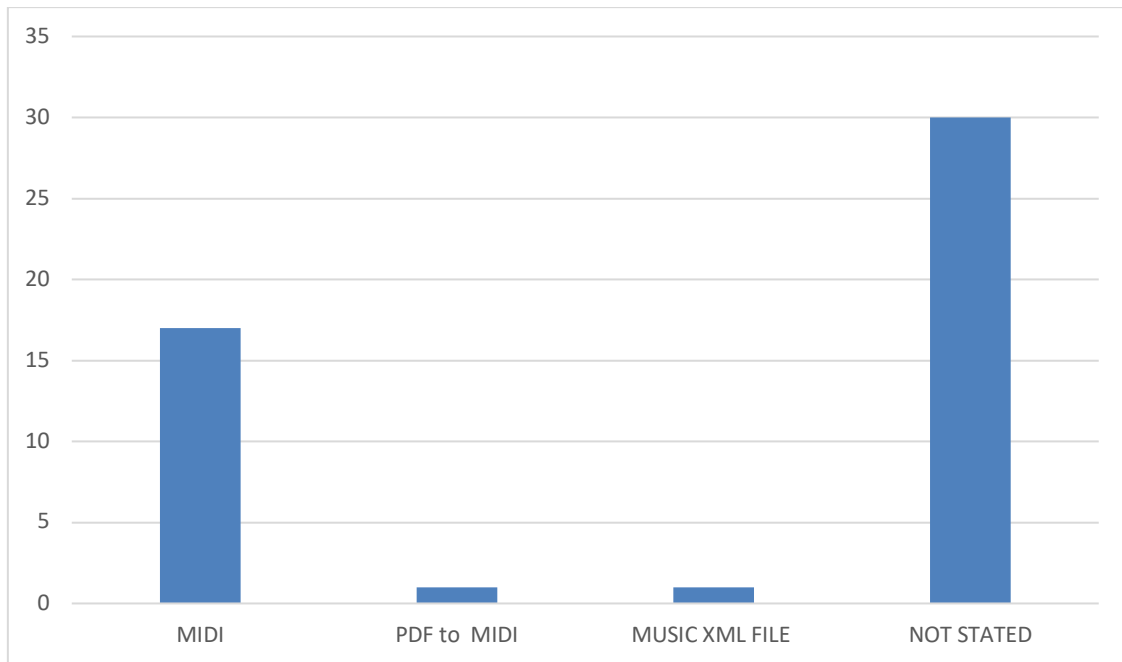


Figure 3-6 Types of file Used for Composition

3.6 Musical Instrument Digital Interface (MIDI)

Before the development of *Musical Instrumental Digital Interface* (MIDI) digital musical instrument from the various manufacturers was unable to communicate with each other. However, the evolution of MIDI and standardization permitted interoperability and exchange of information with other musical instruments. Hardware including computers, sequencers and sound module from different manufacturers were able to communicate with each other. MIDI is a protocol which allows electronic instruments and other digital musical devices from different manufacturers to communicate with each other. It is worth mentioning that MIDI is not a music file, but rather a set of instructions that enables a device to play music. The quality of music produced by a MIDI file is relative to the output device. The electronic keyboard is one of the most popular devices used in generating MIDI messages.

In generate a MIDI file, MIDI INPUT port receives data that is transmitted from another MIDI device while the MIDI OUTPUT port transmits MIDI data to another MIDI device. Also, a MIDI THRU sends out a copy of an incoming MIDI data. The messages are channelled unto a computer or any MIDI instrument. Figure 3-7 is a diagrammatic representation of how various devices may be connected to a computer to generate a MIDI file (.mid).

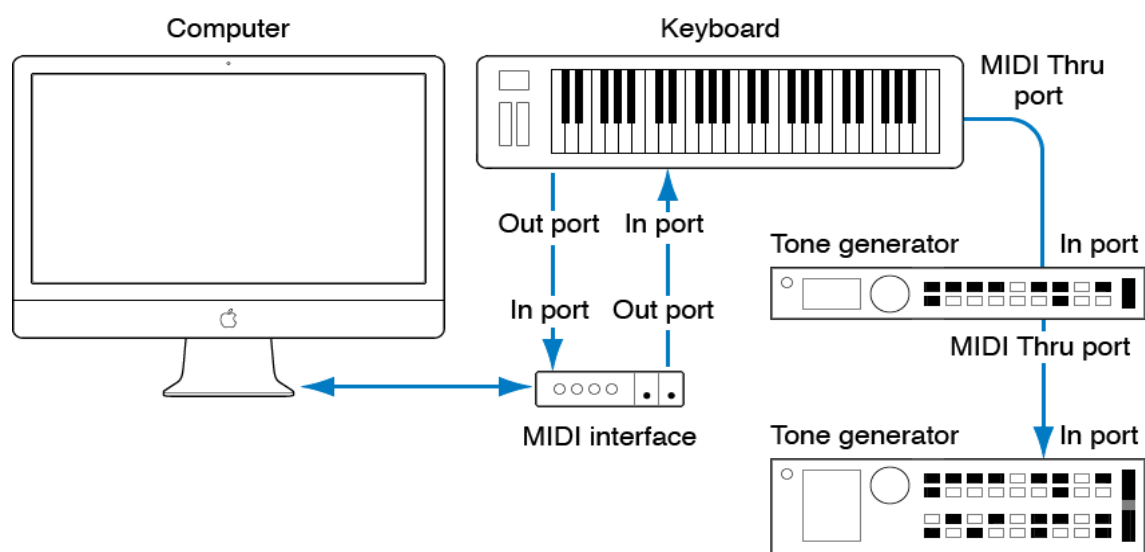


Figure 3-7 Connected keyboard, PC and one generator for MIDI

By pressing or selecting a key on the keyboard, the **note on** message and the **note-off** messages are generated. Notes have two linked parameters; the note number and the velocity number. The note number indicates the pressed key (with the middle C note having a note number of 60). Note- on messages are channel voice messages, therefore, uses one of the 16 channels. A **Channel voice message** uses the performance event transmitted from one instrument to the other using any of the sixteen (16) MIDI channels. A selected key illustrates the note information in bytes showing the MIDI channel, MIDI pitch “note” and the velocity. Pressed notes have values between 0-127, channel (1-16) and the velocity (0-127) describing

how hard the key is pressed. The velocity denotes the loudness of the sounding note which increases in volume with higher velocity values. Furthermore, the release of a key from the keyboard shows a **note-off** message is created which contains information about the “note” and also indicating the end to that specific MIDI note been played.

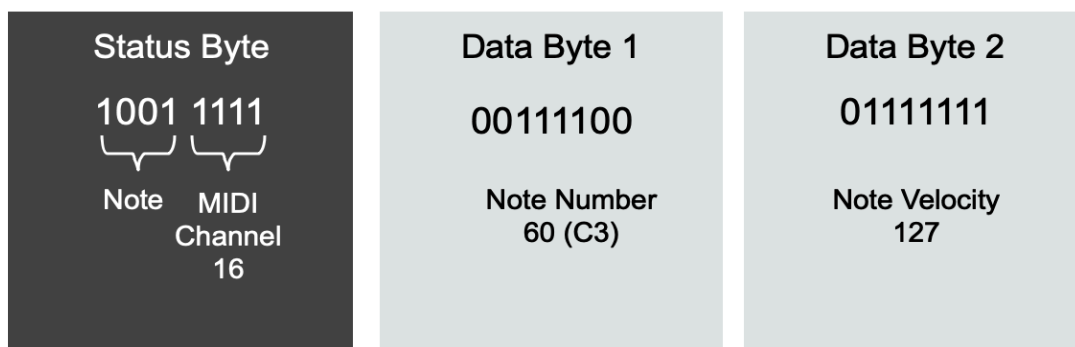


Figure 3-8 A Byte structure of a MIDI file

The note-off message stops the notes-on message from playing the note. However, the note-off messages contain information such as the note -off MIDI channel, the MIDI pitch “note” and the note-off velocity. The note-off velocity indicates the speed or rate at which the key is released. A low value expresses the slow release of the key and vice versa. Once the note-on velocity is zero, it is the same showing a note-off message and therefore a current sound note will have a velocity of zero. Figure 3-8 shows the byte structure of a MIDI file.

3.6.1 MIDI File Format

MIDI files are not sound or audio files (MP3 files) but a set of instructions or messages events. A MIDI performance can be recorded, stored in a data format and replay later. The file contains details about the data describing the various musical events including the note on, note off, channel pressure, key pressure, program change, pitch bend and control change.

Furthermore, since MIDI recordings do not record sound, but performance data, MIDI instrument (synthesizer or keyboard) interpret the data to produce sound. A MIDI recording which includes the performance related to a keyboard could sound like a keyboard instrument and that of a flute will sound like a flute because MIDI only records the messages and information about the notes and not the specific sound. When a MIDI instrument is played the entire key pressed, button pressed, the knob turned, and slider changes are converted into MIDI data. MIDI file presents an advantage of allowing users to edit notes such as changing pitch, duration or other parameters without necessary recording again. Also, it allows the playing of different instruments.

3.6.2 Aftertouch, Pitch bend and Channels

Aftertouch is the pressure sensitivity applied to a key. Similar to a note's pitch and velocity, it ranges from 0-127. It determines the pressed key and assigns a value. There are two types of aftertouch in MIDI i.e. the polyphonic aftertouch (which allows each key to respond individually to aftertouch) and monophonic aftertouch (all the keys played on the keyboard can respond equally to the aftertouch). It is noted that not all electronic keyboards have that functionality of producing aftertouch messages as well as not all MIDI instruments also provide that support.

The pitch bend is a message control by the pitch bend wheel, and it is attached to the MIDI keyboard. It modifies the pitch of the notes being played either up or down. Pitch bend values range from 0-16,383 steps. The control range is between -8192 (lowered) and 8198 representing fully raised pitch with 0 being an unaltered pitch of an instrument.

MIDI channels are useful in sending messages or notes to other MIDI instruments and it has 16 channels. Each MIDI instrument can correspond to a MIDI channel when selected so that data can be shared. Additionally, different instruments can be set to communicate with the MIDI channels since they operate independently to produce a multitrack song.

3.7 Genetic Algorithms

Genetic algorithms (GAs) are search heuristic that uses the concept of evolutionary biology or mimics the natural evolution process. It uses probability search procedures designed to work on large spaces that can be represented as strings (Goldberg & Holland, 1988). GAs are used in solving optimization problems. It finds the optimal solution from all feasible solutions. GA uses a population of individuals where each individual represents a potential solution and each population is a subset of the total search space. Hence, they are population-based models and they use iterative processes that employ selection, mutation and recombination operators to produce new and better individuals (it considers individuals who can survive and reproduce as well as move to the next generation i.e. survival of the fittest).

A set of individuals known as the population is represented as a chromosome. The individuals are characterized by a set of parameters (variables) known as Genes. Genes form strings to form the chromosome (they are represented as a binary vector and each item in the vector is a gene). Each individual is represented in binary form and is assign a fitness score. A fitness function is used to calculate the fitness score and determine how well the problem can be optimized by an individual or chromosome (Mitchell, 1995). For each new population created, an individual fitness score is calculated, and the reproduction continues until the required criterion is met.

3.7.1 Selection, Cross Over, Mutation and Termination Process

Two individual variables are selected as parents from $V \in \{v_1, v_2, v_3 \dots v_n\}$. The fitness score of each variable v_n is calculated to select the most suitable parents for mating. The Crossover rule combines two parents to reproduce children for the next generation. See Figure 3-9 for details of the selection and cross over process.

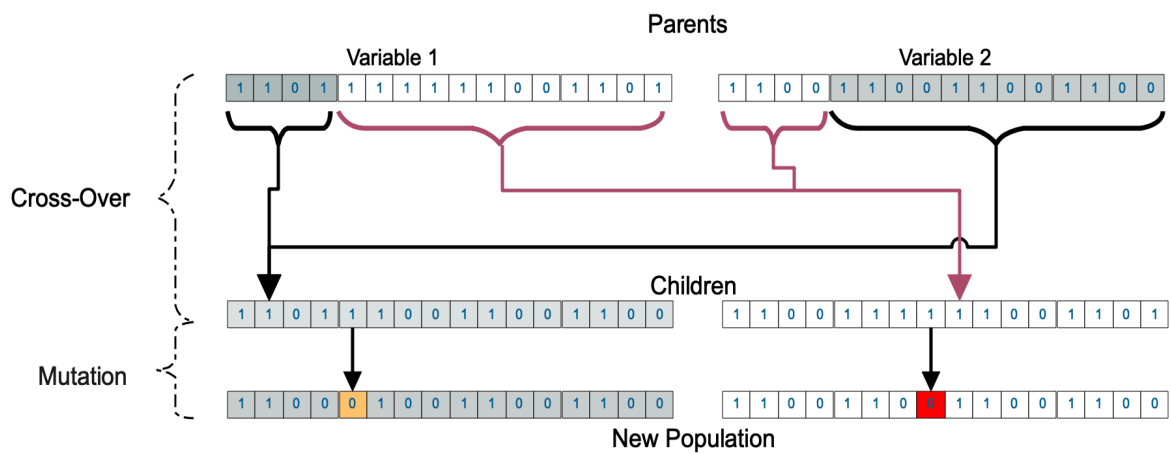


Figure 3-9 Cross-over and mutation

Mutation applies random changes to individual parents to form children and this occurs after the crossover is performed. It is intended to prevent the falling of all solutions in the population into a local optimum. It randomly changes the children produced as a result of the crossover. In binary encoding, probabilities are used to switch chosen bits from 1 to 0 or from 0 to 1 as illustrated in Figure 3-9. The generation process terminates when there is no improvement in the population for the iteration process to continue or when the required number of generations is achieved or when the objective function value has reaches it pre-defined value.

```

function GeneticAlgorithm ()
{
    Initialize population ()
    Define fitness
    Calculate fitness function;
    While (fitness value != termination criteria)
    {
        Selection; Crossover; Mutation; Calculate fitness function;
    }
}

```

Figure 3-10 Sample Pseudo code for GA

3.7.2 Areas of Application

GAs are used in solving complex optimization problems. Ghaheri et al., (2015) explained that they are effective in the healthcare problems as they provide optimal solutions to complex medical analysis within a reasonable time. They are also applied in radiotherapy (Hole et al., 2013) for improving image quality and segmentation .They provide a good perception of the image during such activities as well as the detection of breast cancer (Karnan & Thangavel, 2007). Genetic algorithm is also useful in the selection of relevant molecular descriptors (Zandkarimi et al., 2014). In more recent times, they have been used in robot trajectory (i.e. planning the route that a robot might take from moving from one destination to the other). Wu et al., (2018) argued that they are effective for improving tracking accuracy of the singularity- robust algorithm. They support planning of robot motions and pre-processing of path methods for non-differentiable paths and also for avoidance of obstacles (Kunz & Stilman, 2013).

They have been demonstrated to be effective in aircraft design (Dong et al., 2019; Marta, 2003) and economics (Brooks, 2000; Dawid & Kopel, 1998; Nicoară, 2015; Riechmann, 1998). In music composition GAs are used to determine optimal melodies (as established earlier in this chapter).

3.7.3 Advantages of Genetic Algorithms

Genetic algorithms exhibit various advantages including the provision of a possible solution to various search-space problems. Since each point in the problem represents a feasible solution, the use of robustness property enables it to generate a solution within a relative short time. Furthermore, it exhibits good comparability proficiencies and is useful in situations where the search space is large and with a large number of parameters. They do not require derivative information which may not be available for many real-world problems but rather it optimizes both continuous and discrete functions as well as multi-objective problems.

3.7.4 Limitations of Genetic Algorithms

Similar to any other techniques, genetic algorithms suffer some limitations. During selections, GAs need to be designed carefully, since incorrect choice of operators affect the outcome of the application. In such situations, some optimal solutions are not covered. GAs are not suitable for simple problems which have readily available information (Bajpai & Kumar, 2010). Some researchers have argued that the computation of fitness scores can be computationally expensive for some problems (Leblanc et al., 2002) .

3.8 Chapter Summary

This chapter provided a review of literature on the application of algorithms for music composition. It discussed the current state of research by highlighting on the dominant algorithms, techniques and methods of evaluating algorithmic music. It was concluded that the most dominant algorithms are evolutionary algorithms. Performance evaluation continues to be one of the major challenges of algorithmic music composition: the ability to effectively evaluate the efficiency of the algorithm as well as the music. It was observed that most studies used human evaluation (listening test) as the preferred method. Thus, it can be inferred that less attention is given to model performance testing (fitness function evaluation).

Majority of existing algorithmic compositions are achieved using genetic algorithm. Also, the most used music file was MIDI. Accordingly, further discussions on MIDI and genetic algorithms were presented. It was argued that the flexibility of MIDI (its ability to instruct systems to play melodies on different instruments), makes it a suitable file format for algorithmic composition of music. Genetic algorithm was also suitable because it is effective in solving complex problems that has a large number of variables. From the above, this study seeks to generate a monophonic music using genetic algorithm in a MIDI file format. In the next section, we discuss the research approach adopted for the study.

Chapter 4

METHODOLOGY

4.1 Overview

This chapter explains the research method used for the study. It presents the design science methodology as the appropriate approach for the study. It starts with a discussion on the basic beliefs and paradigms for conducting scientific studies. This is followed by a discussion on the design science method and how it supports this study. In line with suggestions made by (Hevner et al., 2004; Kuechler & Vaishnavi, 2008) the problem relevance, suggestions, development and evaluation of the artefact was discussed.

4.2 Paradigms and Beliefs in Algorithmic Music Composition

Discussions on the use of appropriate scientific methods in computer science and engineering continue to be a challenge, particularly, the use of appropriate methods in algorithmic music compositions. This can be attributed to the complexity and multi-disciplinary nature of the field. Algorithmic music composition combines disciplines such as mathematics, computer science, music, engineering and psychology. Some researchers argue that algorithmic music composition groupings are mostly mathematical or computer science approaches (Nierhaus, 2009) thus it is appropriate to use methods from such disciplines. That notwithstanding, the appropriateness of a study depends on the beliefs and paradigms that guide the researcher.

Beliefs are rational and they provide the philosophical assumptions for conducting research. According to Vaishnavi & Kuechler (2004), epistemological, ontological, methodological and

axiological are the fundamental beliefs observed in computer science research. Ontological beliefs are concerned with identifying research problems and examining the degree of improbability surrounding the occurrences. Epistemological belief probes the nature of knowledge by considering its firmness and how it is theorized, whilst axiological belief discusses what constitutes values or what is considered to be good or bad, like or dislike (Hart, 1971). Methodological belief, on the other hand, deals with a set of guidelines and it expedites the understanding of viewpoints for better understanding.

The foundation of this study is based on the premise that complexities in music production (i.e. the arrangements of notes at variable pitches to form a melody) can be minimised using mathematical algorithms. Given any set of particular notes, there is an optimal melody produced in which human judges the quality. Thus, the study is founded on a combination of ontological and methodological belief and adopts the design science method.

4.3 The Design Science Method

Some researchers have advocated for the use of design science method in computer science (Hevner et al., 2004), since it is considered to be a rigorous process used for designing artefacts for solving problems, evaluating the solution and communicating the outcome (Çağdaş & Stubkjær, 2011). Vaishnavi et al., (2012) explained that design science is a set of analytical methods that promote development of research in various sectors. It focuses on solving specific problems (Van Aken, 2005) in order to achieve “good” solutions. It provides results such as methods, models, constructs and instantiations (March & Smith, 1995). It can be considered as a science, a research strategy and a method (Johannesson et al., 2013).

Hevner et al., (2004) proposed guidelines for conducting research when using the design science approach. These are:

- i. ***Design as an Artefact:*** a suitable artefact should be produced in the form of a construct, technique, instantiation of or a representation
- ii. ***Problem relevance:*** to develop a technology-based solution that is applies to the problem
- iii. ***Design evaluation:*** the utility and quality of the design artefact must be meticulously and well evaluated
- iv. ***Research contributions:*** clear and demonstrable contributions must be made in the field where the design artefact is applied
- v. ***Research rigour:*** appropriate methods for the design and evaluation of the artefact
- vi. ***Design as a search process:*** the search for a successful artefact depends on the use of available methods to achieve a desirable result while satisfying the rules of the problem domain
- vii. ***Communication of research:*** design science research presentation must be effective in terms of its technology-orientation and management-orientation

4.4 Limitation of design science method

Although design science presents a number of benefits, it is also characterised with some limitations. Design research seeks to develop knowledge that is used to solve problem (Van Aken, 2005), yet it lacks formalized details of the process (Offermann et al., 2009). Sein et al., (2011) explained that it concentrates on building artefact than its evaluation. In some cases, it concentrates on building artefacts and values technological rigour at the expense of

organizational relevance. Some have argued that the method is not able to establish sufficient and convincing rigour in its approach (Purao, 2002).

Although there are some limitations, the method was appropriate because it provides a thinking frame for this study. Next is a discussion about the various steps that were followed for conducting the research.

4.5 Research Approach for the Study

In order to follow an applicable method in this research, guidelines proposed by Vaishnavi & Kuechler (2004) is implemented. Accordingly, the following five phases were used in the research.

4.5.1 Awareness of the problem

Several issues may prompt problem awareness and it is important to find appropriate solutions. Recently, the concept of developing new solutions for known problems has resulted in rise of new technologies. Swift changes provide new ways of thinking and designing better solutions to solve known problems (Persson et al., 2000).

As stated earlier, the research seeks to develop an artefact (AI model) for composing music. This addresses some current existing problems in composition of aesthetic music. Accordingly, the study is within the improvement quadrant. See Figure 4-1.

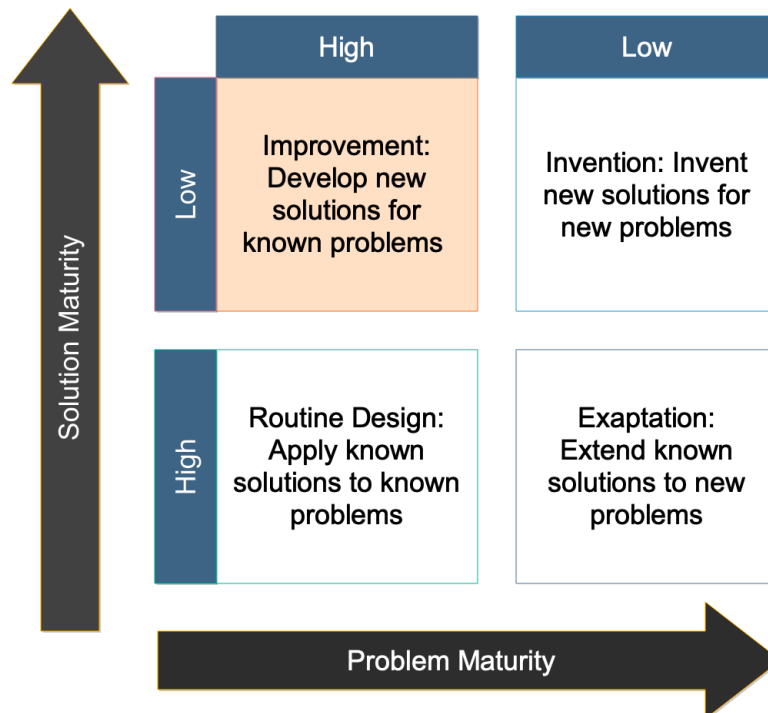


Figure 4-1 Relevance of the study

4.5.2 Suggestions

The use of rigorous methods in composition and design of artefacts is important in design science (Hevner et al., 2004; Kuechler & Vaishnavi, 2008). During the suggestion phase, GA and existing music composition theories were considered. The application of knowledge and theories on music composition provides an in-depth understanding of using GA techniques for music composition. Moreover, relevant literature relating to existing methods in algorithmic music composition was considered. Thus, a systematic review on algorithmic music composition was conducted to facilitate the identification of existing methods that can be used in the research. The suggestion phase also assisted the identification of appropriate methodology for the research.

4.5.3 Development

At the development phase searching for the optimal solution to solve the problem is the best approach (Hevner et al., 2004). To search and identify an applicable technique that can be used for the composition of music, a GA model for music composition is identified and programmed. The decision to use GA was informed by the study conducted in Chapter 3 that identified it as the most used algorithm for developing algorithmic music. The development phase is reported in chapter five and addresses objective ii.

4.5.4 Evaluation

The evaluation of a design artefact in design science is vital and also an essential activity that confirms that the artefact produce addresses a relevant problem (Peppers et al., 2012; Venable et al., 2012). It provides guidance for a better development or improvement of the artefact. Experimentation, observation, testing, analytical, descriptive can be used to evaluate artefacts (Hevner et al., 2004; Kuechler & Vaishnavi, 2008).

In this study, the design artefact was evaluated using experimentation and observation. The fitness score of compositions and the human evaluators were used to assess the quality of music produced. Fitness function guides attainment of optimal solutions in GAs. It demonstrates an enhanced role by accepting the best melody and decreasing the lack of harmony in a musical note (dissonance) in the resultant music.

4.5.5 Conclusion

Conforming to suggestions that results of design research must be communicated to the appropriate audience (Hevner et al., 2004; Kuechler & Vaishnavi, 2008). This study has been

communicated to a number of scholarly communities. Sections of these have been accepted for publication.

4.6 Chapter Summary

The need to ensure that scientific studies are auditable and can be refuted cannot be overemphasised. It is a basic requirement of all studies and accordingly this section provided foundation and steps used for conducting the study. It adopted the design science approach and argued that it is the most appropriate method for conducting the study. Justification for the awareness of the study and the evaluation method adopted were all discussed.

The next chapter presents the findings from the study. It highlights the steps used in composing and evaluating the resultant music.

Chapter 5

COMPOSITION MODELLING AND FITNESS ANALYSIS

5.1 Overview

As mentioned earlier, this study seeks to generate a monophonic music using genetic algorithms. Accordingly, the chapter presents the various steps used for composing the music. Six monophonic melodies were composed using GAs terminating at generations 10, 000, 20,000 and 60, 000. The chapter starts with a discussion on how the population was selected, scored and crossed. The method for mutation is also discussed.

Additionally, the chapter discusses how fitness scores were used to assess the performance of the various composition models. It is emphasised that the use of fitness scores seeks to evaluate the performance of the model rather than the quality of music produced.

5.2 Genetic Algorithm Implementation

The algorithm used two types of operators i.e. crossover and mutation to generate music. As explained earlier, the need to mutate after crossing ensures the use of best individuals for future crossing. This ensures that a good “choice” is attained to create a new and a better music. Figure 5-1 shows the steps used for composing melodies in this study.

5.2.1 Composition Modelling

Conforming to “objective iii” of the study, a set-up was made to compose a simple 4/4 bars compositions. Nine compositions were made. These compositions are 3 versions of melodies terminated at 10000th, 20000th and 60000th generations. Refer to Figure 5-2 to Figure 5-19 for

the various sheets songs and their corresponding fitness score charts. The different music versions are attached to the electronic version of this thesis in a MIDI file format. The GA took input parameters of pitches, tones, iterations, number of generations, and the range of tones allowed.

Considering music composition as an optimal search problem with a population of melodies, then a population of melodies is defined as $M_n: n \in \{1,2,3 \dots 100\}$ i.e. limiting the population size to 100. The population size of 100 was used to reduce computation time and complexities. In genetic algorithms, large populations affect computation time because it increases the search space.

For each M_n , $F_s = f_i(M_n)$ where F_s is defined as the fitness value (score) of melody,

M_n for generation G_i in the genetic evolution where $i \in \{1,2,3 \dots \psi\}$ and

$$f_i(M_n) = \gamma_n + \mu_n + \zeta_n + \varphi_n + \vartheta_n$$

Where

$\gamma_n = \text{chord progression score}$

$\mu_n = \text{diatonic fit score}$

$\zeta_n = \text{voice leading score}$

$\varphi_n = \text{smoothness score}$

$\vartheta_n = \text{chord score}$

$$\text{Total fitness } F(G_i) = \sum_{n=i}^k f_i(M_n)$$

Refer to Table 2-1 for the meanings of the various terminologies. During the calculation of the fitness value of a melody, its chord progression, diatonic fit, voice leading, and smoothness are assessed. Defined values are assigned to each of these variables based on its appropriateness.

Mutation types is defined as $\omega_\tau : \tau \in \{1,2,3,4,5,6,7\}$ where

$\omega_1 = \text{half step} - \text{up}$, $\omega_2 = \text{half step} - \text{down}$, $\omega_3 = \text{whole step} - \text{up}$, $\omega_4 = \text{whole step} - \text{down}$,

$\omega_5 = \text{octave} - \text{up}$, $\omega_6 = \text{octave} - \text{down}$ and $\omega_7 = \text{flip rest}$

The genetic operators initiate a random population of melodies M_n and for each M_n , it calculates the fitness score F_s . The number of generations is compared to the defined maximum number of generations. In this study, three (3) maximum generations are defined (i.e. $G_{max} = 10000, 20000$ or 60000). If the number of generations $G_i = G_{max}$ then the process is terminated else two melody parents are selected to cross. Best melodies are selected based on the value of $f_i(M_n)$.

Next, each melody is split into two for crossing. The splitting is based on the splitting rule define below:

There are three (3) types of melody splitting S_1, S_2 and S_3 , for parent melodies M_n and M_{n+i}

Where i is an arbitrary number such that $n + i \leq 100, i \neq n$

Then

S_1 is a 50, 50 split (50% of M_n and 50% of M_{n+i})

S_2 is a 25,75 split (25% of M_n and 75% of M_{n+i})

S_3 is a 75,25 split (75% of M_n and 25% of M_{n+i})

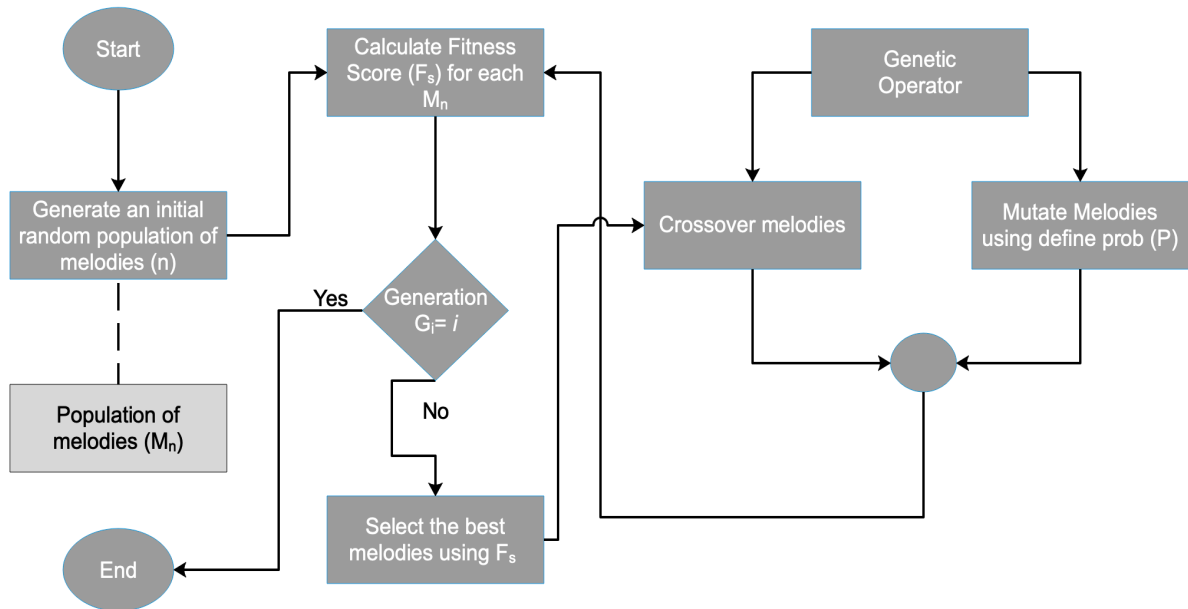


Figure 5-1 GA music composition process used for the study

The roulette wheel is used to select the splitting method. The all melodies in the population, M_n and M_{n+i} are crossed randomly and mutated (based on the mutation probability) to produce a new offspring to form a new population (new M_n). New offspring is produced until total population of offspring is 100. The fitness scores of all M_n in the new population is calculated and the selection process is repeated until the desired generation is achieved. Refer to Figure 5-1 for the steps in the composition process.

5.3 Resultant Melodies

There were nine melodies generated in all based on the termination rule used. As mentioned earlier, the algorithm was terminated at three different generations (i.e. $G_{max} = 10000, 20000$

or 60000). For the purpose of evaluating the efficiency of the algorithm and the authentic quality of the music, three compositions were created for each termination value. The fitness scores of the various melodies composed are discussed in the next section.

5.3.1 Compositions at 10K Generations

At a composition of ($G_{max} = 10000$) generations, the first version achieved an optimal composition with a fitness score of 10348 at a generation of 750. The second version also achieved a fitness score at 10347 at a generation of 7300 and lastly, the third version had a fitness score of 10341 at a generation of 5300. It is observed that at a composition of 10k generations, the first version obtained optimality earlier having achieved the optimal fitness score of 10348 with a generation of 750. Refer to Figure 5-2, Figure 5-4, and Figure 5-6 for the various sheets music of the three compositions terminated at 10K generations. The sheet music is in Bass- Clef.



Figure 5-2 Resultant composition after 10 K generations (v1)

The fitness score graph (see Figure 5-3) shows the value of fitness scores versus the generations (*note: the generations axis for all the graphs is in a \log_{10} scale*). It can be observed that fitness values increased steadily until generation 150 and drops. At generations

between 200 and 250, the fitness score also increased from 2651 to 5224, exhibiting two local maximum points before it converged at about 750 generations with a score of about 10300.

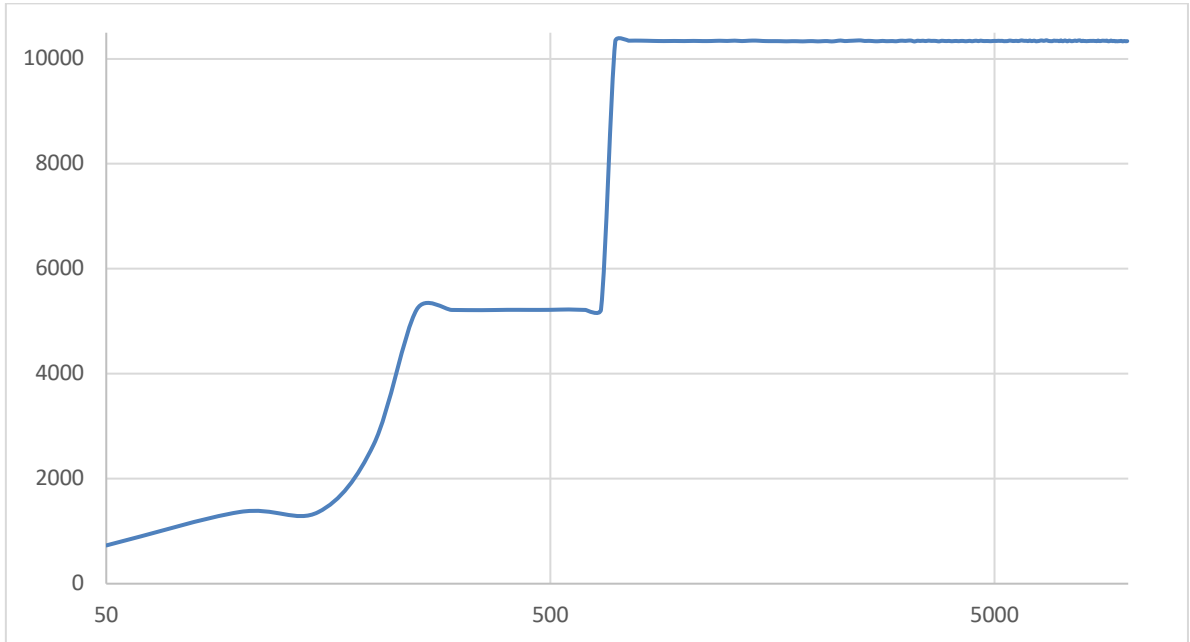


Figure 5-3 Total fitness scores for 10k generations (v1)

Observe also that a generation of 650, the fitness score swiftly increased before converging. This performance is different from that of the second composition (v2). Figure 5-5 shows a steady increase until 100 generations with a fitness score of 2617 but experienced a decrease in the fitness score from generation 150 to 950.



Figure 5-4 Resultant composition after 10K generations (v2)

At a generation of 1000, the fitness score increased to 5220 and again became steady until it declined to 2653. However, with a generation of 2800, and a fitness score of 5216, the fitness score increased dramatically to 10345 at a generation of 4450.

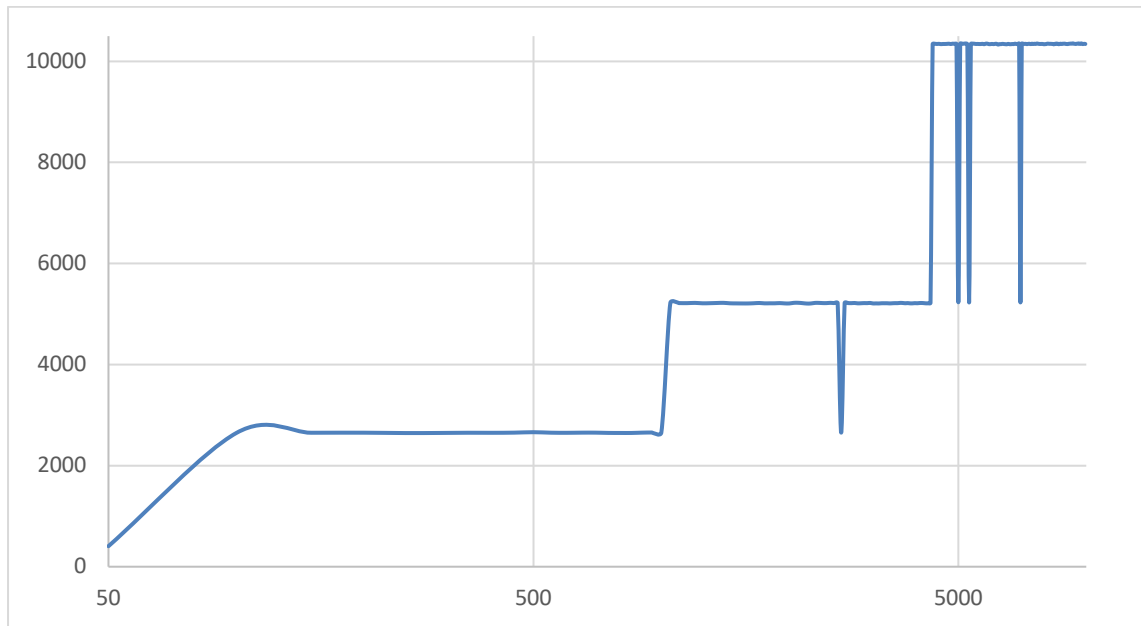


Figure 5-5 Total fitness scores for 10K generations (v2)

Between the generation of 5100 and 5400 the fitness score slowly decreased again from 5223 to 5229. Furthermore, at a generation of 5500 the fitness score increased steadily but decreased again at a generation of 7100 with a fitness score of 10350 before converging generation 7300.



Figure 5-6 Resultant composition after 10K generations (v3)

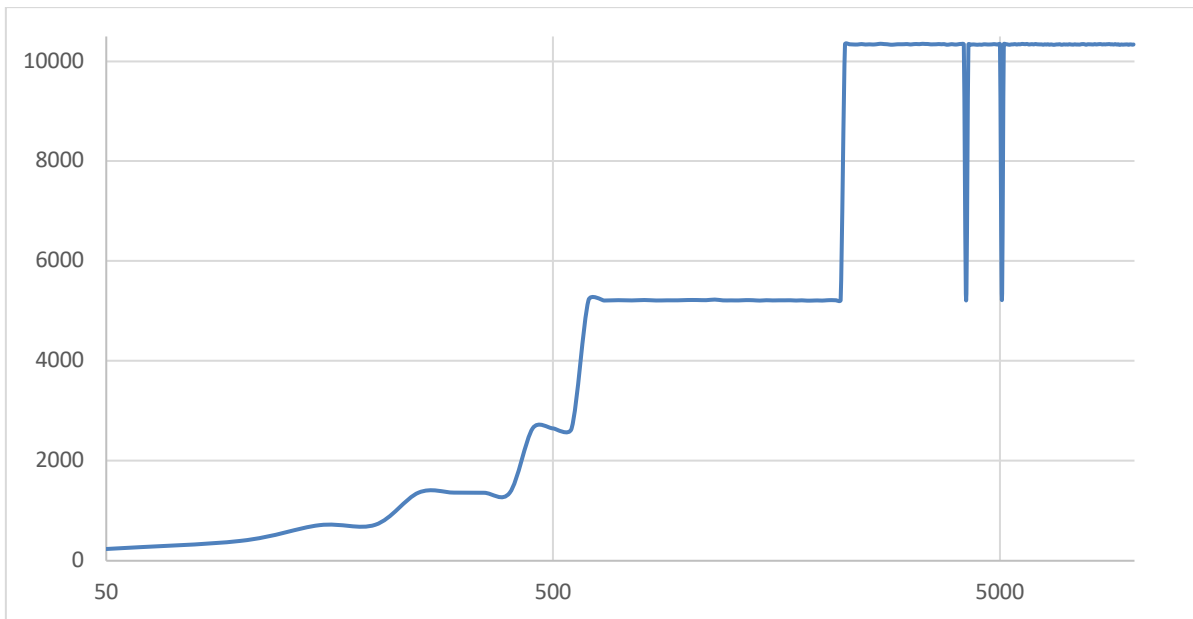


Figure 5-7 Total fitness Scores for 10K generations (v3)

As compare to Figure 5-3 and **Error! Reference source not found.**, Figure 5-7 shows a gradual increment in the generation from until 350. At a generation of about 400 compositions the GA attained a fitness score 1364, before increasing steadily to a fitness value of 2652 at a generation of 450. It decreased again at a generation of 500 and increased sharply to a score of 5218 at a generation of 600. From generation of 650 to 2150 the fitness score is steady with less change in the score however, between generations of 2200 and 2300 it increased to 10341. At a generation between 4250 and 5050, there is a decrease in the fitness score to 5213 and 5220 respectively. The composition algorithm converged at generation of 5300 with a fitness score of 10341. Evidently, the GA performed differently in all the 3 trails for the first 10k generations with less similarity.

5.3.2 Compositions after 20K generations

At the 20K generations (i.e. $G_{max} = 20000$), the first version achieved it highest fitness score at a generation of 1730 whereas the second version achieved at a generation of 4000. The third

version was at a generation of 1700. Refer to Figure 5-9, Figure 5-11 and Figure 5-13 for the evolution behaviour of the genetic algorithm.



Figure 5-8 Resultant composition after 20K generations (v1)

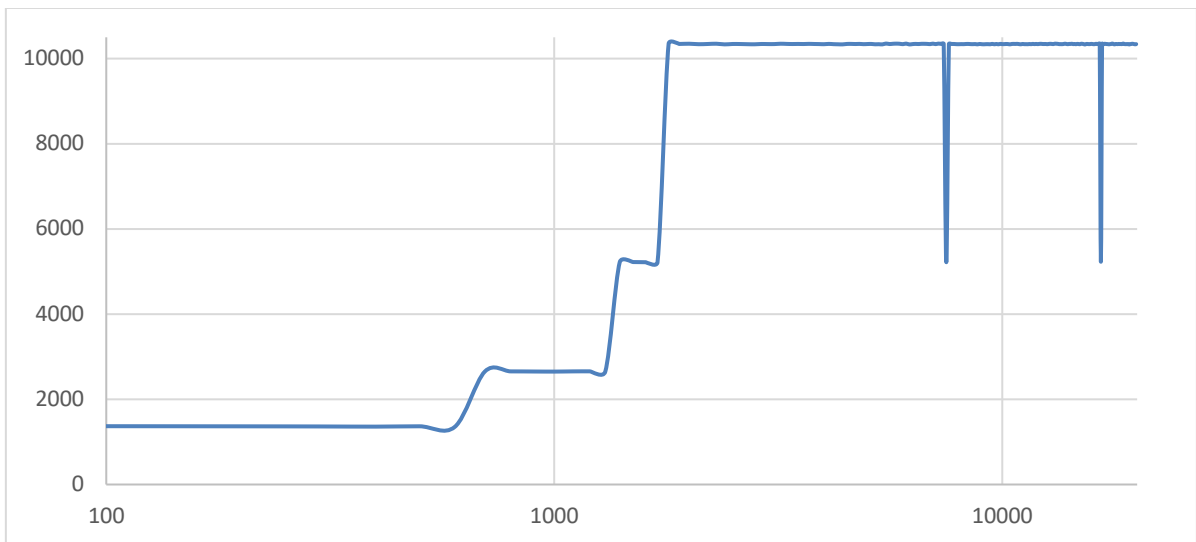


Figure 5-9 Total fitness Scores for 20K generations (v1)

It is observed that in the 20000 generation trails, the earliest optimal value was obtained at 1700 generations as compared to the compositions for 10000 generations. The graph (see Figure 5-9) shows a gradual increase in the generation the first 500 generations. At generation 600, it dropped before increasing again at a generation of 700 with a fitness score 2653. The GA decreased at generation 1300 with a fitness value of 2653 and steeply increased to 5220 at generation 1500. At a generation of 1700 there is a sharp increase in the fitness score from 5220 to 10349 at a generation of 1800 (it converged around this generation).



Figure 5-10 Resultant composition after 20K generations (v2)

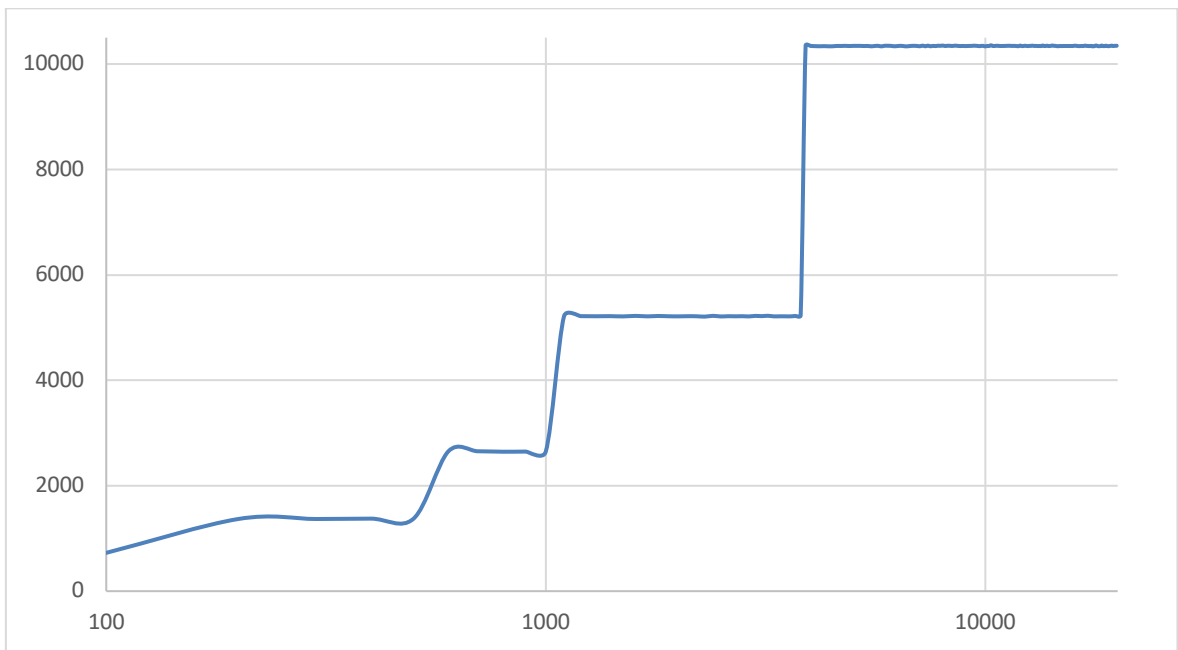


Figure 5-11 Total fitness Scores for 20K generations (v2)

Figure 5-11 illustrates the GA performance for the second version of the 20k composition. It can be observed that there was a gradual increase in the generation from 100 to 200 demonstrating a steady fitness score between 727 and 1370. The fitness score became steady until a population of about 400 where it fell slightly but dramatically increased at a generation between 500 and 600. At a generation of about 4000 the fitness score attained its highest value.



Figure 5-12 Resultant composition after 20K generations (v3)

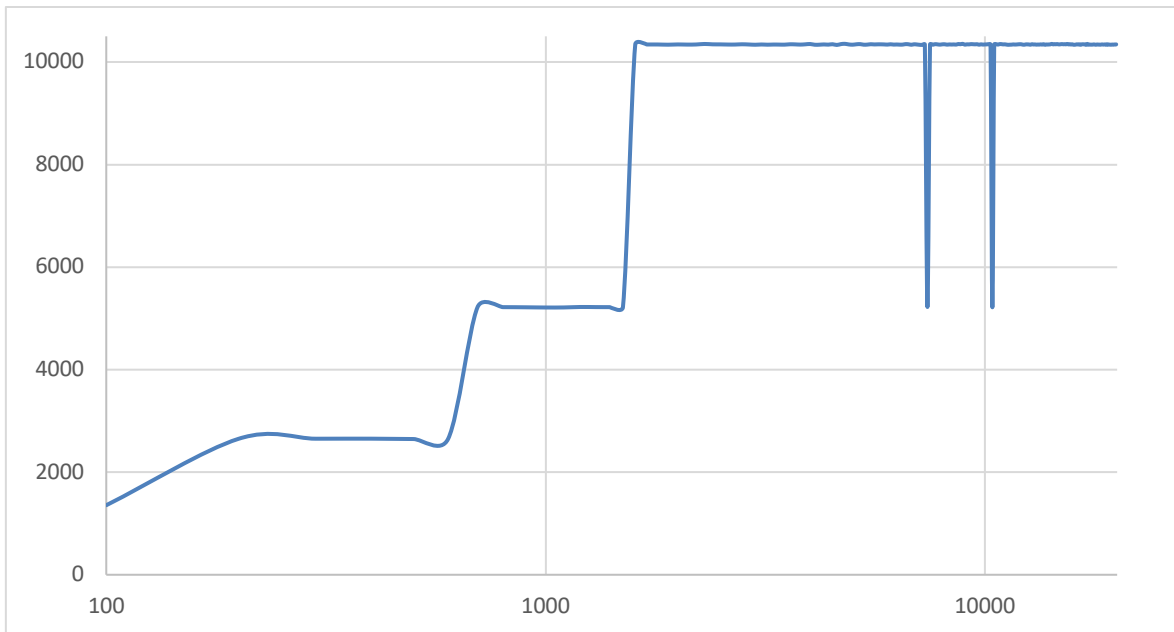


Figure 5-13 Total fitness Scores for 20K generations (v3)

Figure 5-13 shows the behaviour of the GA over 20k generations. It can be observed that GA behaved differently from previous ones. At generation of 500 a fitness score of 2647 was achieved and fell before rising between the generation of 1400 and 1600. The optimal fitness value was obtained at generation of 1700. Thus, the third trail performed better than all previous versions in the 20k trails.

5.3.3 Compositions after 60K generations

For the 60k composition trails (i.e. $G_{max} = 60000$), the first version achieved it highest fitness after 11,000 generations. However, the second was around 1800 and the third at 2400. Similarly, to observations made in the earlier trails (i.e. compositions for generations up to 10k and 20k), the GA performed different in all instances.



Figure 5-14 Resultant composition after 60K generations (v1)

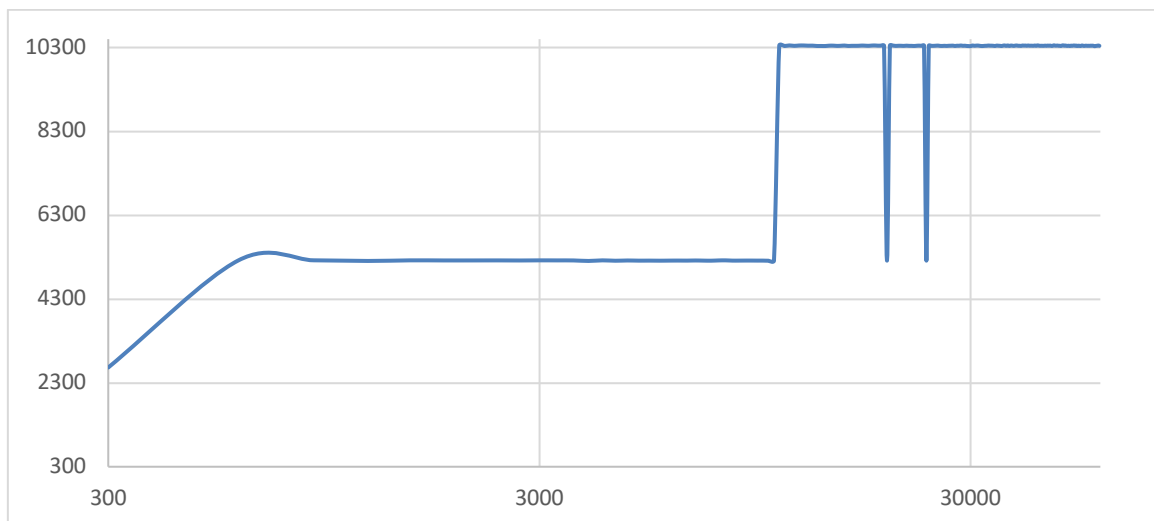


Figure 5-15 Total fitness Scores for 60K generations (v1)

The best performance for the 60k generations was the second version where it converged around 1800 generations. Figure 5-15 shows a steady increase in fitness values before 600

generations and a sharp increase at generation 10500 before attaining optimality around generation 110000.



Figure 5-16 Resultant composition after 60K generations (v2)

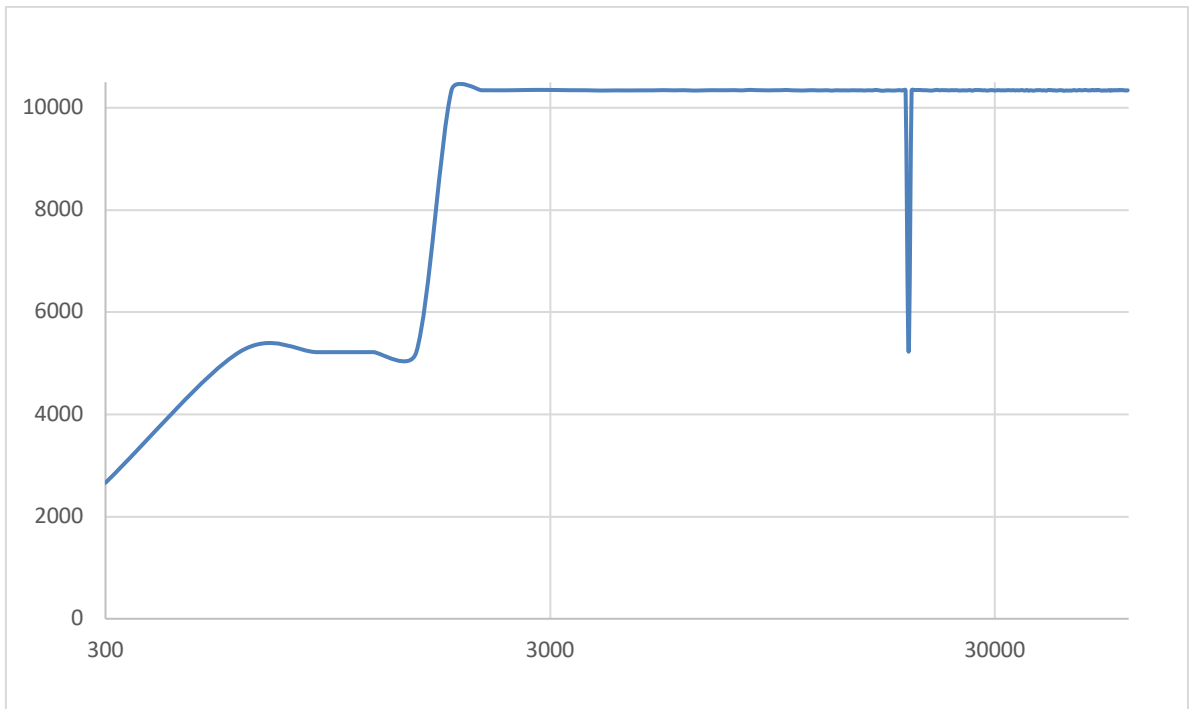


Figure 5-17 Total fitness Scores for 60K generations (v2)

In the second trail the graph (Figure 5-17) shows a steady increase in fitness at the beginning until generation 600 with a score of 5219. At generations ranging from 900 to 1200 the fitness score remained steady from 5217 to 5218, before increasing to attain the optimal fitness value.



Figure 5-18 Resultant composition after 60K generations (v3)

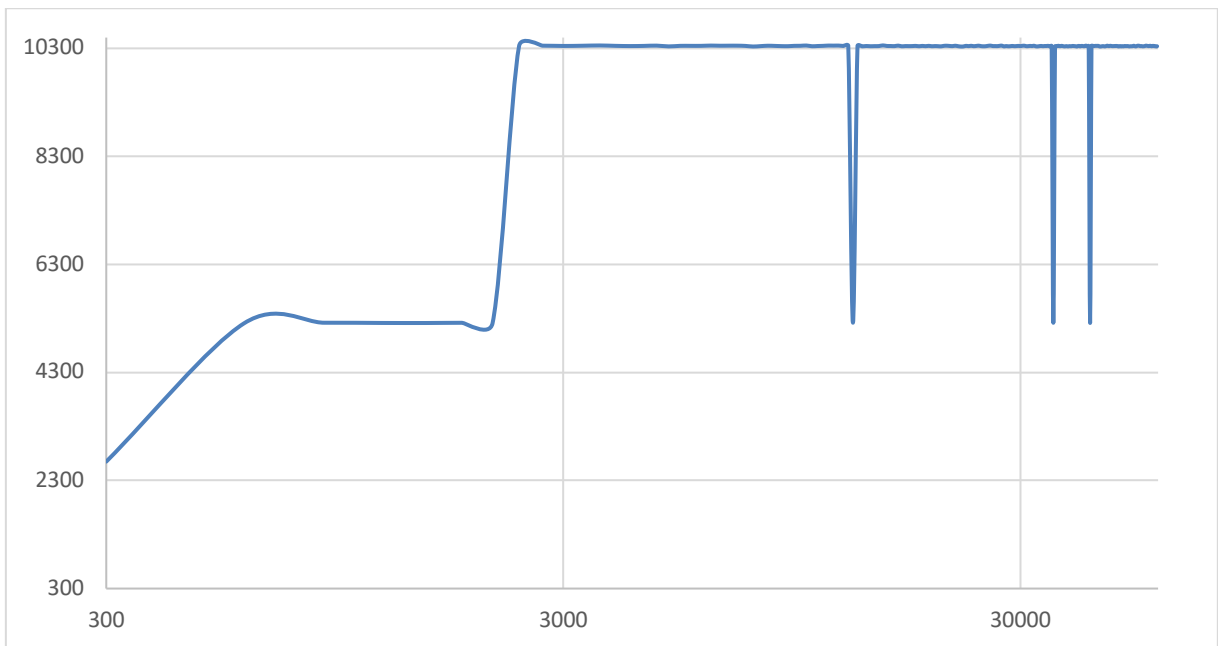


Figure 5-19 Total fitness Scores for 60K generations (v3)

In the third version (Figure 5-19) the GA behaved similar to the second. Its fitness increased to 5208 by the 600th generation (compare to 5219 for the second version) however it remained steady for a longer period as compared to that of second version. It converged at a later generation (i.e. 2400) when compared to the second generation. Thus, although v2 and v3 for the 60k generation trail started behaving similarly, the performance of the GA differed.

5.4 Chapter Summary

This chapter presented the steps used in the composition process. The sheet song of the resultant composition is displayed, and the total fitness scores are discussed. The relationship between total fitness and the generations are explained to assess the performance of the model in all the nine compositions. The findings indicated that the first version of the 10k composition (i.e. $G_{max} = 10000$) converged faster than the other compositions.

Chapter 6

EVALUATION AND DISCUSSIONS

6.1 Overview

The chapter discusses the importance of the results achieved during the study. It further provides a new in-depth understanding of the composition of melodies using GA. A discussion on the evaluation performed using human judgement validated the experiment set-up since the quality of the music produced was pleasing to the ear.

6.2 Human Evaluation

It is imperative to conduct human evaluation in compositions because the existing methods for evaluating music quality are limited in evaluating the aesthetic quality of music (Loughran & O'Neill, 2016). As compared to methods such as frequency spectrum, Harmonic evaluation, precisions and recalls, optimization functions, melodic and harmonic error, and fitness functions that seek to evaluate the performance of the algorithm used for the composition process, human listening test seeks to assess the aesthetic quality of the music. The aesthetic quality of music may be assessed through its pleasantness (Friedmann, 2015) and pleasantness is experienced when there is satisfaction of objectives.

Currently, studies have not established the relationship between model performance and music quality. This is to say that although a model or an algorithm for composing music may be effective and efficient (i.e. can compose optimal music with the shortest possible time), the resultant composition may not be the most appealing music for a listener.

It has been argued that, human evaluation is the method mostly used for assessing music quality (Matić, 2010). Although, it does not provide a measure for assessing model performance, it provides indications of the model's ability to produce aesthetic music.

Accordingly, a human evaluation test was performed to assess the performance of the algorithm in terms of its ability to produce aesthetically good music. A survey was conducted. A convenience sample was used to select subjects. The participants were to listen to all different composed music (all versions composed) and complete a questionnaire. They were tasked to rate each of the nine compositions on a scale of 1 to 9 (based on their likeness for the music).

6.2.1 Data Gathering

Out of the twelve subjects, two were females and ten males. Whose ages range from eighteen and above. During the subject selection process, 15 prospective participants were selected. The selection process was purely arbitrary based on convenience. Each participant was called (on the phone) and the procedure for the assessment was explained to them. Three of the participants rejected to participate in the study, thus 12 were used. All the subjects were graduate students: five from the University of Ghana, five from Vellore Institute of Technology, India and two from Ghana Technology University College. The resultant music after each generation (i.e. compositions *10k v1*, *10k v2*, *10k v3*, *20k v1*, *20k v2*, *20k v3*, *60k v1*, *60k v2*, *60k v3*) and a link to a Google Forms question in English were sent to each participant through WhatsApp in a MIDI file format. Each subject downloaded all the nine compositions and they were given a period of 30 minutes to listen and complete the questionnaire (each composition was less than a minute long). The data obtained from the experiment was collated and analysed.

Table 6-1 Description of Participants (n=12)

Category

<i>Gender</i>		Total
	Male	10
	Female	2
<i>Age</i>		
	18-25	2
	26 -30	5
	31-35	3
	Above 35	2
<i>Music Player Used</i>		
	Windows Media Player	2
	QuickTime	1
	VLC	4
	Other	5
<i>Device Used</i>		
	Desktop	2
	Laptop	4
	Tablet	1
	Smartphone	5

6.2.2 Evaluation Results

To ensure that responses from subjects were unbiased, they were not told that the music were composed using a machine learning technique. Specifically, they were asked to listen to 9 different melodies label (v1 to v9) to ranking their preference for each. The number of generations, fitness scores for each composition, etc. was not communicated.

The rankings of subjects were summed to calculate the most appealing music. The findings indicated that the most preferred music was the third trail of composition after 60k generation. It had a raking score of 81. Refer to Table 6-2 for details of response. It can be observed that apart from one participant that scored it “1”, all other participants scored a 5 or more. However, the respondent who scored “1” for composition 60k (v3), score the same value for all compositions. This indicates that he or she does not find any of the composition appealing (similar observation can be found in one instance that the subject scored “7” for all compositions. The next preferred composition was that of 60k (v1). It scored a value of 69. The least preferred composition was observed to be 10k (v1). It scored a value of 43.

In all, it was observed that compositions that were terminated at 60,000 generations were considered to be more appealing by the subjects. The average score recorded for all compositions of 60, 000 was 71. This is followed by melodies obtained at 20,000 generations with an average value of 57. Melodies obtained at 10,000 generations were the least preferred since it scored an average of 46 for the 3 versions. Again, the least 3 preferred melodies were the 3 version of the 10,000th generation composition.

Table 6-2 Responses of subjects (n=12)

Question Items	Subjects Response												Σ	Σ
Rank the music [VI] (<i>10k v1</i>)	8	4	7	2	7	2	1	1	3	3	1	4	43	46
Rank the music [V2] (<i>10k v2</i>)	7	3	7	3	8	3	1	6	2	2	1	5	48	
Rank the music [V3] (<i>10k v3</i>)	8	3	7	1	8	1	1	9	1	1	1	6	47	
Rank the music [V4] (<i>20k v1</i>)	7	6	7	2	8	2	1	2	4	6	1	7	53	57
Rank the music [V5] (<i>20k v2</i>)	7	5	7	4	8	4	1	4	5	5	1	5	56	
Rank the music [V6] (<i>20k v3</i>)	8	5	7	3	8	3	1	8	6	4	1	7	61	
Rank the music [V7] (<i>60k v1</i>)	9	7	7	4	7	4	1	3	9	9	9	69	71	
Rank the music [V8] (<i>60k v2</i>)	8	5	7	4	8	3	1	5	8	8	1	5		63
Rank the music [V9] (<i>60k v3</i>)	9	8	7	5	8	6	1	7	7	7	9	7		81

6.3 Implications of Study

6.3.1 Fitness Functions and Human Evaluation

The aim of this is to compose a monophonic music using a GA. The algorithm's performance is evaluated by using a fitness function while the aesthetic quality is evaluated using human judgement. From the two assessments, it can be concluded that there is no evidence that there is a relationship between model performance and the aesthetics quality of the music produced. Considering the trails (9) conducted, the first version of the composition obtained at 10k generation (i.e. *10k v1*) converged earlier than all the other models. It attained a total fitness score of 10348 at the 750th generation. This indicates that it took a lesser time to

obtain optimality. Yet, it produced the least preferred music. Melodies composed at the longer generations were considered to be more appealing to respondent.

For instance, the average number of generations for compositions that were terminated at 60,000 generations are 5066. This score is the highest average among the termination criteria (10k, 20k, 60k). Terminations at 10k produced an average generation of 2684, while that of 20k produced an average generation of 2500 to reach optimal compositions. Refer to Table 6-3 for details on the relationship between model performance and human preference.

Table 6-3 Model Performance vs Human Evaluation (n=12)

	Version	Generation for Optimal Fitness		Human Evaluation	
		Generation	Average	Preference Score	Average Preference
<i>10,000</i>	1	750	2684	43	46
	2	7300		48	
	3	5300		47	
<i>20,000</i>	1	1800	2500	53	57
	2	4000		56	
	3	1700		61	
<i>60,000</i>	1	11000	5066	69	71
	2	1800		63	
	3	2400		81	

6.4 Variations in Convergence Timing

The findings from this study present relevant theoretical implications that need further investigations. This is because similar studies conducted by Zad et al., (2006) using twenty (20) of Bach's preludes attained optimality at 500 generation for the first trial and 200 generation for the second trial. Compared to findings of this study, human evaluation of their composed melodies demonstrated there is no difference between the two compositions since 50% of the evaluators found both melodies amusing. Ohlsson, (2016) also performed a similar study and concluded that an optimal music is attainable at 500 generations.

Considering the findings above, the performance of the model does not determine the aesthetic quality of the melodies produced. Also, it can be observed that as compared to the other studies (Ohlsson, 2016; Zad et al., 2006), the present study did not attain optimality at generations around 500.

Perhaps, this is a challenge in GAs, because the use of probabilities in the selection, crossover and mutation process makes it difficult to predict the time required for a model to converge. The initial selection of parents and the mutations plays a key role on how quickly the algorithm will converge to the optimal value.

6.5 Chapter Summery

This chapter has discussed how the study evaluated all the nine composed music as compared to the chapter 5 that discussed the evaluation of the model. This chapter assessed the aesthetic quality of the music produced. Convenience sampling technique was used to select fifteen subjects to rank how the music is pleasant. It was observed that the most pleasing music were the versions obtained for $G_{max} = 60000$.

Comparing the findings of human assessment to the model performance (i.e. the number of generations required to obtain the optimal composition), it was concluded that models that converged at later times produced more pleasant music.

Chapter 7

STUDY LIMITATION AND CONCLUSION

7.1 Overview

This chapter concludes the thesis. It presents summaries of the activities performed in the study and details its findings and contributions. Furthermore, it presents a discussion on the limitation of the study, particularly, limitations regarding the design and evaluation and evaluation processes or methods. Finally, it suggests future research studies.

7.2 Evaluation of Research Objectives

As explained earlier, a design research is expected to be relevant (Hevner et al., 2004; Kuechler & Vaishnavi, 2008) and thus the need to demonstrate the relevance of this study is paramount. As such in this section, the various objectives of the study are assessed.

Objective one was to review existing machine learning methods for music composition. This was addressed in chapters two and three. Chapter two started by presenting the background and foundation of music and its composition. In chapter three, a systematic review was used to assess the current state of literature in the domain. As compared to traditional literature reviews, systematic reviews are less bias since they follow a specified protocol throughout the review process (Kitchenham & Charters 2007; Petersen et al. 2015).

Objective two was to compose a simple monophonic music using a genetic algorithm. The decision to use genetic algorithm was inspired by the review process that established that

genetic algorithms are the most used methods in algorithmic music composition. Accordingly, chapter five reported the development of a genetic algorithm. Nine (9) melodies were composed. The compositions were three versions each for a GA terminated at ten thousand, twenty thousand and sixty thousand generations.

Objective three was to evaluate the performance of the algorithm using fitness scores. This was reported in chapter five. The changes in total fitness scores over the various generations were plotted and analysed. The chapter further explained the behaviour and performance of the algorithm. It was concluded that the algorithm performed best in the first trail which terminated at ten thousand generations. It achieves the optimal composition around 750th generation.

Objective four was to evaluate the aesthetic performance of the algorithm through human evaluation. Accordingly, a survey was conducted to assess how the quality of the various composed melodies can be pleasing to humans. Subjects were tasked to rate the 9 melodies and it was observed that the music obtained from the termination at 60000th generation was the most pleasant composition.

7.3 Limitations and Future Work

From evaluation of the research objectives, this study has made contributions to the domain, yet it has limitations and drawbacks. Based on these limitations future research studies are recommended. Below is a discussion on its limitations and future research suggestions.

7.3.1 Monophonic Composition

Since the study aimed to understand the basic functionalities and features of algorithm music composition and its aesthetic quality, a monophonic music was used. However, the simple

nature of monophonic melodies makes it a challenge for human assessment. In particular, the resultant composition was in the bass-clef and this makes it a challenge for assessment. Although monophonic compositions are easy to process and analyse by computing systems (Meredith et al., 2002), because it can be represented as sequences (Hanna et al., 2007), polyphonic melodies are more pleasant to humans and thus reduce the evaluation stress.

Accordingly, future research must be conducted using polyphonic compositions to assess aesthetic quality of GA composed melodies.

7.3.2 MIDI Files

Although, the study confirmed in chapter 3 that the most appropriate file for algorithmic composition is MIDI, it presented some challenges during the evaluation stages. This is because MIDI files are not sound files, rather, they instruct a device to produce. Considering that the melodies were sent to participants for evaluation in MIDI format, the aesthetic quality of the music will differ based on the instrument selected for playing the file. The same file may be pleasing when played on a device using piano as compared to a guitar. Although it would have been interesting to instruct the participants to use a specific instrument, it was envisaged that this may bring added stress to them and may also affect their responses.

It is therefore suggested that future studies should evaluate the resultant music using a quasi-experiment by controlling some of the parameters such as the type of instrument used and the duration of listening. Instrument used may also be varied to assess with instrument produce the most aesthetic music for a specific composition.

7.3.3 Sequence of Listening by Subjects

Considering that the music files were sent to participants without instructions on the sequence of listening, it is expected that participants will listen to the versions of music in the chronological order that was sent to them. This may cause biasness in the evaluation of the melodies. Some researchers have also argued that although human rating is useful in assessing pleasant compositions, the process of rating music individually is tedious; this may affect the evaluation judge at the later stages of the assessment process.

Again, the use of laboratory experiment will be useful in addressing these limitations. This is because participants could be asked to listen to the composition severally before evaluating them.

7.3.4 Expert Evaluation

Although, music is enjoyed by all and its aesthetic quality is subject to the listener, the use of experts for assessment may provide technical information that may be relevant. Their ability to confirm the performance of the algorithm by measuring the pitch, timing, tone, etc. shall provide the relevant information for the various compositions. Thus, it is recommended that future research must include music experts during the evaluation of the music.

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Appendix One: List of Primary Studies Used for Review

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