AN IMPROVED GREY WOLF OPTIMISER SINE COSINE ALGORITHM FOR MINIMISATION OF INJECTION MOULDING SHRINKAGE

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DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

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ABSTRACT

The injection moulding process in plastic manufacturing parts is widely used and the products can be seen anywhere as daily use items. This process includes a big scale of production. This sometimes leads to defects that affect the quality of the products. As a result, the production is inefficient, time-consuming, and costly. However, one of the solutions that have been discovered is the fact that hybridisation improves product quality, especially in minimising shrinkage defect at a thick plate part by providing the best parameter setting. For an excellent performance of the injection moulding process, it is crucial to have an optimum set of parameters and this study considered melt temperature (°C), mould temperature (°C), cooling time(s), and packing pressure (MPa) as a set of parameters. In this study, an improved hybridisation technique of Grey Wolf Optimiser Sine Cosine Algorithm (GWOSCA) was developed to estimate optimal parameter settings so that the value of shrinkage at the thick plate could be minimised. The improved GWOSCA was made to enhance the searching strategy of GWOSCA by increasing the movement of direction and speed while sharing information among the alpha, beta, and delta to find the optimum value. The simulation and improved results from GWOSCSA were compared and validated by using experimental work of percentage error, regression model, and analysis of variance (ANOVA). It showed that the improved GWOSCA could minimise the shrinkage at the thick plate by 0.48% at x-axis and 0.35% at y-axis in contrast with the simulation result, which was only 0.58% at x-axis and 0.60% at y-axis in this study. Eventually, the improved GWOSCA optimisation technique significantly showed that it could minimise the values of shrinkage in the injection moulding process for manufacturing fields

ABSTRAK

Proses suntikan acuan dalam penghasilan bahagian plastik telah digunakan secara meluas dan hasilnya boleh dilihat di mana-mana sahaja. Produk dari proses ini dijadikan sebagai produk kegunaan harian. Proses ini melibatkan skala penghasilan yang besar dan kadangkala menyebabkan kecacatan pada kualiti produk yang dihasilkan. Kecacatan ini menjurus kepada ketidakcekapan, pembaziran masa dan kos tinggi terhadap proses pengeluaran. Walau bagaimanapun, salah satu masalah yang dikenal pasti ialah penggabungan teknik yang mampu meningkatkan kualiti produk terutamanya bagi meminimumkan kecacatan pada pengecutan di bahagian plat yang tebal dengan memperoleh tetapan parameter yang terbaik. Untuk memperoleh prestasi yang terbaik dalam proses ini, mengoptimumkan set parameter adalah amat penting. Kajian ini telah mempertimbangkan suhu pencairan (°C), suhu acuan (°C), masa penyejukan (s) dan tekanan pembungkusan (MPa) sebagai satu set parameter. Dalam kajian ini, satu penambahbaikan teknik gabungan *Grey Wolf Optimiser Sine Cosine Algorithm* (*GWOSCA*) dibangunkan untuk meramal set parameter optimum supaya nilai pengecutan pada plat tebal boleh dikurangkan. Penambahbaikan pada *GWOSCA* ini dilakukan untuk menambah baik strategi carian dalam *GWOSCA* dengan meningkatkan kadar perkongsian maklumat antara alpha, beta dan delta dalam mencari nilai optimum. Hasil simulasi dan penambahbaikan *GWOSCA* telah dibandingkan dan disahkan melalui kerja eksperimen ralat peratusan, model regresi dan analisis varians (ANOVA). Hasil kajian menunjukkan bahawa penambahbaikan *GWOSCA* boleh meminimumkan pengecutan di bahagian plat yang tebal dengan 0.48% pada paksi x dan 0.35% pada paksi y. Hasil ini berbeza dan lebih baik berbanding dengan hasil simulasi yang hanya 0.58% pada paksi x dan 0.60% pada paksi y. Akhir sekali, penambahbaikan pengoptimuman GWOSCA menunjukkan kepentingan yang ketara di mana ia dapat meminimumkan nilai pengecutan dalam proses pengacuan suntikan untuk bidang pembuatan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
ABC	-	Ant Bee Colony
ABS	-	Acrylonitrile Butadiene Styrene
ALO	-	Ant Lion Optimiser
BA	-	Bat Algorithm
BBO	-	Biogeography-based optimisation
BPANN	-	Back Propagation Artificial Neural Network
BSA	-	Backtracking Search Algorithm
CCD	-	Central Composite Design
CNSGA	-	Controlled Elitist Non Dominated Sorting Genetic Algorithm
CSA	-	Cuckoo Search algorithm
DA	-	Dragonfly algorithm
DE	-	Differential Evolution
EHO	-	elephant herding optimizing
FPIC	-	Fuzzy Proportional-Integral Controller
GA	-	Genetic Algorithm
GAMS	-	General Algebraic Modeling System
GSA	-	Gravitational Search Algorithm
GWO	-	Grey Wolf Optimiser
GWOSCA	-	Grey Wolf Optimiser Sine Cosine Algorithm
HM	-	Hopefield model
IMO	-	Ions motion optimisation
LI	-	Lambda Iteration
LJ	-	Luus-Jaakola
MCSA	-	Modified Cuckoo Search algorithm
NMS	-	Nelder-Mead simplex
PC	-	Polycarbonate
PID	-	Plus Integral Plus Derivative
PP	-	Polypropylene
PSO	-	Particle Swarm Optimisation

PSOGSA	-	Particle Swarm Optimisation Gravitational Search Algorithm
QP	-	Quadratic Programming
QRIMO	-	Quasi reflected ion motion optimisation
RSM	-	Response Surface Methodology
SCA	-	Sine Cosine Algorithm
TM	-	Taguchi Method

LIST OF SYMBOLS

t	-	current iteration
$\vec{A}$and $\vec{C}$	-	coefficient vector of prey
$\vec{X}$	-	position of grey wolves
$\vec{X}_p$	-	position of the prey
$\vec{a}$	-	element that will linearly decrease from 2 to 0 over looping
r_1 and r_2	-	random vector between [0,1]
A	-	mould temperature (ºC)
B	-	packing pressure (MPa)
C	-	cooling time (s)
D	-	melt temperature (ºC)
N	-	Number of iteration
$\vec{x}_i^t$	-	current position at the tth iteration in ith dimension
$rand_1, rand_2, rand_3$	-	random numbers [0,1]
l_i	-	targeted optimal solution
$0.5 \leq rand_4 < 0.5$	-	condition for exploration and exploitation

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

This chapter is an overview of the research conducted in the field of manufacturing. The topics discussed are the background of the study, problem statement, objectives, scopes, and contribution of the study.

1.1 Introduction

Plastic production in the injection moulding process has been widely used for more than 100 years (Hakimian and Sulong, 2012). The reason of the widely used of this process is because of its high production for various types of shapes and it is also a cost saving production (Lin and Chou 2002; Spina, 2004; Cho *et al.*, 2009). Plus, by producing a thin, small and light product leads to a large production of the injection moulding process and contributes to the industry of plastic manufacturing. Apparently, this process has been used and applied to many neccesities such as computers, daily products, medical devices (Oktem, 2012), vehicle accessories, and kids' toys. In fact, plastic has become a well-known material in numerous industries, for example, agriculture, foods, aerospace and automotive.

Generally, the injection moulding process is a very complex and unstable cycle process (Chiang and Chang, 2007). From the past studies, it is stated that when the injection moulding process producing a product, the quality of the product is measured by the defects. There are many defects can be found such as warpage, shrinkage, sink marks, short shots, residual stress, strength, void, flash, silver streaks, weld line and flow marks (Fischer, 2003; Harper, 2006; Osswald and Hernandez-Ortiz, 2006). Any defects happen are tend to be expected and can be reduced. By controlling the product quality, this process is gaining its own attention because of the promising standard by producing a good quality product.

Shrinkage is a downgrading form in form of size of dimensions of the products (Kazmer, 2016). The factor that makes the shrinkage happened are structure of the mould, plastic part shape, materials of the plastic and condition of the process (Chen and Ding, 2012). This happened when the thermal of the plastic was changed when in the moulding process. When the shrinkage at the part becomes excessive, it can lead to a warpage. It has been reported that, the quality of the products is low because of an improper clamping force, patchy setting, temperature of melting and seal clearance mould. In order to achieve maximum quality, the shrinkage need to be eliminated or reduced by process control at the initial of the process by parameter setting (Hilmi *et al.*,2012; Kitayama and Natsume, 2014) and a great setup of a set of parameter setting need to be made (Shoemaker, 2006; Kazmer, 2016).

Process parameter setting is actually give a huge effect in the injection moulding process specifically in product quality (Chien *et al.*, 2004; Ismail and Suriandy, 2004; Lin *et al.*,2008; Oktem et al.,2007; Sadbadi and Ghasemi, 2007; Chen *et al.*,2008; Chen *et al.*,2009). Besides, it can affect lots of problems at the production stage such high in production cost, long lagging time and defects. The injection moulding process is an endless production process cycles which the parameters are fixed. Because of that, the parameters are needed to be adjusted close to the goal of the moulding process by using optimisation techniques.

Before this, a trial and error method in obtaining a set of optimal parameter setting was being made by the experts and engineer experience in this field. Still, the value of a set of parameter itself is insufficient for a proper value for process parameters (Oktem *et al.*, 2005). Moreover, this process is technically repeated and need to do it regularly which consume to a high cost and time-consuming (Oktem *et al.*, 2005; Dang *et al.*, 2014). The high cost and time consuming process makes this method cannot contribute much in enhancing a complex product. It turned out that, the researchers came out with solution by finding a low cost method and more time effective by implying computational techniques either by simulation or artificial intelligence techniques. Hence, to minimise the shrinkage, the optimisation method need to be done so that, many manufacturer in this industry will get the benefit and be more competent in this field.

1.2 Problem Background

Based on past studies, many researchers were focusing on optimising shrinkage at thin shell plastic parts compared to thick plate parts (Ozcelik and Erzurmulu, 2005; Ozcelik and Erzurmulu, 2006; Kurtaran *et al.*, 2005; Shen *et al.*, 2007; Deng and Lam, 2010; Yin and Hua, 2011; Chen and Kurniawan, 2014). The thick plate part differs from the thin plate part especially on its thickness and weight mass. A thick plate part is contrary from thin plate part including thickness and weight of the part. Besides, a common thickness for injection moulding part is between 0.75 mm to 3 mm for filled materials and it depends on the design and functionality of each part (Najihah *et al.*, 2016). Because of that, this study wants to focus on minimising the shrinkage at the thick plate part.

By addressing critical issues like shrinkage, the defect is needed to be examined so that the plastic injection moulding process can enhance the shrinkage at the moulded parts. The crucial parameter setting that greatly affects the shrinkage must be investigated because it plays a big role in ensuring the standard of a certain product quality. Many researchers have conducted a study evolving various defects and materials, variety set of parameter setting, differential method of optimisations in order to overcome the defects and plus, enhancing the product quality. Most of them, need an outstanding parameters and optimum setting to find a factor that contribute to a certain defect which can be determined through simulation or experimental works. The enhancement can be seen when the percentage of the defects are being calculated by showing how much the improvement has been made.

Optimisation is a problem of searching the best solutions that can be implemented to every real problem (Ghose,T, 2002). Previously, many modern optimisation techniques were carried out by past researchers to understand and explore an interaction of the process parameters in the injection moulding towards mechanical properties of moulded parts and their responses (Mahapatra and Chaturvedi, 2009, Xu *et al.*, 2012, Wang *et al.*, 2013). From those studies, they stated that there is a stringent interaction between a set of parameters processing and their responses while delivering various optimisation techniques (Manjunath and Krishna, 2012). Therefore, many researchers have made variety of works in optimising the injection moulding defects, for example, Particle Swarm Optimisation (PSO) (Xu *et al.*, 2012), Genetic Algorithm (GA) (Wang, 2012;), Artificial Neural Network (ANN) (Manjunath and Krishna, 2012), Back Propagation ANN (BPANN) (Wang *et al.*, 2013), Radial Basis Function (RBF) (Kitayama and Natsume, 2014), Taguchi Method (Ćurić *et al.*, 2012) Glowworm Swarm Optimisation (GSO) (Hazwan *et al.*, 2017), Support Vector Machine (SVM) (Tellaeche and Arana, 2013) and many more. The modern technique is good at local search and easy to be implemented but the convergence is initially fast but slow in the end (Mahapatra and Chaturvedi, 2009). Based on these studies, it was observed that the optimisation of shrinkage parameters using GWO algorithm have been limitedly considered by past researchers. Therefore, this study considered GWO algorithm to estimate the optimal solution for shrinkage performance.

Based on the reviews, each artificial intelligence and numerical simulation has the ability to improve the plastic injection moulding design. Even though these techniques are proven to be applicable, it is not optimal (Shi *et al.*, 2003). For GWO optimisation, it has been used for various real problems and from these result, GWO optimisation shows an outstanding performance when compared to other optimisation techniques. Some of the real problems that have used GWO optimisation are economic dispatch problems of power system (Wong *et al.*, 2014), power system in risk prevention of smart grid (Mahdad and Srairi, 2015), using GWO for decision tree classifier for gene classification (Vosooghifard and Ebrahimpour, 2015), for forecasting natural resources of time series forecasting (Mustaffa and Kahar, 2015), photonic crystal filter image (Chaman-Motlagh, 2015; Li *et al.*, 2016) and many more. For GWO optimisation, it has many advantages for solving unconstrained and constrained problems. Also, it has a high performance at an unknown search space, convenience and only needs fewer parameters (Mirjalili *et al.*, 2014). Even though, with so many advantages GWO had, still it has the drawbacks which are not fit for complex function and trapped at local optima. Because of that, it leads to a refinement of GWO optimisation either hybridisation or modification by adjusting its algorithm into many shapes of changes to fit and fix the drawbacks so that the desired problems can be solved.

Some part of the main structure of GWO algorithm such as tracking, encircling and attacking prey has been adjusted and modified based on the problem. Many researchers focusing to enhance GWO algorithm by improving the wolves' position by using probabilistic method (Gupta *et al.*, 2015), Kcentroids (Korayem and Kassem, 2015), clustering position (Sayed and Hassanien, 2015) and sequence alignment (Jayapriya and Arock, 2015). Furthermore, for balancing search agents, pattern search technique is proposed by Mahdad and Srairi, 2015, random technique introduced by Niu *et al.*, (2016) and the same technique is used by improving it with emission technique (Dudani and Chudasama, 2016). Besides, for enhance the wolves when encircling the prey, Mirjalili, 2015 used ANN technique and Saremi *et al.*, 2015 used Evolutionary Population Dynamic (EPD) to remove the poor search space so that the exploration and exploitation of GWO algorithm can be enhanced. Form these studies, it can be seen that, the focus of improving the exploration and exploitation GWO algorithm is crucial as stated as one of main disadvantages and hence there is lack of studies. Based on GWO optimisation weaknesses where it is easy to be trapped in local optima and several studies show by combining various optimisation techniques, injection moulding problem can be improved (Kapoor and Kumar, 2016). Therefore, a hybrid computational technique is recommended to solve the optimisation problem and this study proposes a hybrid Grey Wolf Optimiser Sine Cosine Algorithm (GWOSCA). However, the hybrid technique is not fully accommodating the drawback that GWOSCA algorithm had. Thus, this study attempts to develop an improved hybrid of GWOSCA to enhance the flaw of GWOSCA algorithm by improving its algorithm and achieve optimum parameters of the shrinkage performance in injection moulding process.

1.3 Problem Statement

The key to the process parameter setting that greatly affects the shrinkage must be investigated because it plays a big role in ensuring the standard of product quality. Shrinkage relationship between process parameter is difficult to understand because it is a nonlinear and implicit function (Zhao *et al.*, 2015). Because of that, it needs a metamodel-based optimisation method to execute its relationship into the explicit form of low order polynomials. Here, Response Surface Methodology (RSM) technique is proposed because of it able to express the relationship of the shrinkage and process parameter by the mathematical model which forms of quadratic polynomial with acceptable accuracy. Then, further optimisation to obtain the optimum process parameter will be deployed.

In obtaining optimum parameters for injection moulding to minimse the shrinkage, the main objectives that need to be considered are accurateness of result, dependability, and computer efficiency. Plus, with poor setting can lead to an insufficient system in accurateness and bothering the time of the execution (Mok and Kwang, 2002). Therefore, the present study proposes an improved Grey Wolf Optimiser Sine Cosine Algorithm (GWOSCA) to solve weaknesses of the standard GWOSCA algorithm and at the same time enhancing better optimum parameter results for shrinkage performance. GWOSCA algorithm was reported to have a robust search variant for various global optimisation functions (Sing and Singh, 2017). In order to benefit a better exploration capability and high speed searching of GWOSCA algorithm, the searching behavior of SCA is deployed in GWO algorithm. In this study, it focuses on GWO's problem where the working of its search agents needs a robust movement so that the searching skill can move faster with information to find their prey (optimise) (Singh and Singh, 2017). Therefore, SCA will help the movement of the grey wolf agents in GWOSCA at calculate and update fitness value phase. In the meantime, SCA will help GWO in preventing their search agents to not be trapped in local optima and will boost the robustness of the GWO, especially when all search agents are equally shared and receive information as the process is working continuously (in loop).

This study investigates an optimisation problem in injection moulding process with single performance. The product quality performance is measured based on defects. Shrinkage is one of the crucial product qualities (Fischer, 2003; Harper, 2006; Osswald and Hernandez-Ortiz, 2006) that need to be controlled by combining good parameters setting during the injection moulding process. After obtaining optimal parameters from the prediction model of the optimisation algorithm, a real conformation experiment need to be applied. This is to ensure the quality of estimating model obtained in this study is accepted to predict a real experiment. The mixture of parameters from the optimisation result is used in the injection moulding machine to produce new parts. Then, the shrinkage measurement will be determined and compared with the result from generated model.

To answer the problem statement, this study comes out with three research questions which are:

(a) How to design effective mathematical models for shrinkage performances?

(b) How effective is the proposed improved GWOSCA algorithm in approximating optimal process parameters that leads to a better shrinkage performance?

(c) How to validate the estimating model by real experiment?

1.4 Objectives

In this study, three main objectives were stated as below in contemplation of furthering the study on the shrinkage at the moulded parts produced in the plastic injection moulding process:

(a) To develop the mathematical models for injection moulding shrinkage performances.

(b) To develop an improved GWOSCA optimisation algorithm for determine optimal process parameters of shrinkage performance.

(c) To validate the estimating model solution by conducting real experiment.

1.5 Scopes

The scopes of this study are as follows:

1. Manufacturing :

(a) Shrinkage is selected as the response in this study.

(b) Autodesk Moldflow Insight (AMI) 2012 software is used for simulation analysis.

(c) Response Surface Methodology (RSM) is implemented by Design Expert Software 7.0 in obtaining the objective function for responses.

(d) Acrylonitrile Butadiene Styrene (ABS) is a material for thick plate part.

(e) 80 Tonne Nissei NEX1000 injection moulding machine was used to conduct the experiment.

(f) Part designed is according to ISO 2941-1: 1996(E).

(g) Mould designed for cavity A and B are according to ISO 3167:2002 (E).

(h) Shrinkage measurement for x and y axes are according to ISO 294-2:2001.

(i) Process parameters for shrinkage are mould temperature, melt temperature, cooling time and packing pressure.

2. Artificial intelligence:

(a) Improved Grey Wolf Optimiser Sine Cosine Algorithm (GWOSCA) is selected as the optimisation method and implemented by MATLAB 2014b.

1.6 Significance of Research

This study investigates the performance of the proposed improved GWOSCA which is to minimise the value of the injection moulding performance which is shrinkage. Then, the result of the proposed technique was compared with simulation to ensure the effectiveness of the proposed technique in estimating the shrinkage at the thick plate part before validated by real experiment. This proposed technique is considered as a new perspective in the plastic manufacturing industry research for improving the injection moulding performance and optimising the shrinkage and thus produce a good quality of product.

1.7 Summary

This chapter has discussed the background of the study, problem statement, aims, objectives, scopes, research significance and contributions. The discussions are placed in order so that the problem arises in optimizing the shrinkage at the thick plat part can be figured out.

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