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An interactive product development model in remanufacturing environment: a chaos-based artificial bee colony approach

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AN INTERACTIVE PRODUCT DEVELOPMENT MODEL IN REMANUFACTURING ENVIRONMENT: A CHAOS-BASED ARTIFICIAL BEE COLONY APPROACH

by

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This research is dedicated to my parents; father Mr. Ram Naresh Prasad, and my mother Mrs. Sanichari Devi, both of whom taught me to adopt simplicity in life, dedication to work, and devotion to society, in pursuit of excellence and lifelong happiness.

PUBLICATION THESIS OPTION

This thesis is composed of two papers which were reformatted in the style used by the university.

The first paper titled “Modeling the Value of a Product at the Design & Functional Levels: Self-Guided Algorithms & Control Approach” is presented Paper I, and the second paper titled “Economical Impact of RFID Implementation in Remanufacturing: A Chaos-based Interactive Artificial Bee Colony Approach” is presented in Paper II.

ABSTRACT

This research presents an interactive product development model in remanufacturing environment. The product development model defined a quantitative value model considering product design and development tasks and their value attributes responsible to describe functions of the product. At the last stage of the product development process, remanufacturing feasibility of used components is incorporated. The consummate feature of this consideration lies in considering variability in cost, weight, and size of the constituted components depending on its types and physical states.

Further, this research focuses on reverse logistics paradigm to drive environmental management and economic concerns of the manufacturing industry after the product launching and selling in the market. Moreover, the model is extended by integrating it with RFID technology. This RFID embedded model is aimed at analyzing the economical impact on the account of having advantage of a real time system with reduced inventory shrinkage, reduced processing time, reduced labor cost, process accuracy, and other directly measurable benefits.

Consideration the computational complexity involved in product development process reverse logistics, this research proposes; Self-Guided Algorithms & Control (S-CAG) approach for the product development model, and Chaos-based Interactive Artificial Bee Colony (CI-ABC) approach for remanufacturing model. Illustrative Examples has been presented to test the efficacy of the models. Numerical results from using the S-CAG and CI-ABC for optimal performance are presented and analyzed. The results clearly reveal the efficacy of proposed algorithms when applied to the underlying problems.

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NOMENCLATURE

NOMENCLATURE OF PAPER I

Symbol	Description
s	Stages
n	Components
m	Models
f	Functions
am	Alternative Mechanisms
KDC_s	Knowledge Discovery coefficient for PDP stage '*s*'
WMC_s	Waste Minimization Coefficient for PDP stage '*s*'
IN	The importance of need for the product or services
A(t)	The availability of the product or services to the customer, relative to the customer needs date
CO_s	Cost of Ownership of PDP stage '*s*'
a_t	Availability coefficient for Development time
KDF_{1s}	Knowledge Discovery factor for "Performance" at PDP stage '*s*'
KDF_{2s}	Knowledge Discovery factor for Information retained in mapping "Form" at PDP stage 's'
KDF_{3s}	Knowledge Discovery factor for time spent reformatting data in mapping "Form" at PDP stage '*s*'
KDF_{4s}	Knowledge Discovery factor for "Fit" at PDP stage '*s*'
KDF_{5s}	Knowledge Discovery factor for complexity of information in mapping "Function" at PDP stage '*s*'
KDF_{6s}	Knowledge Discovery factor for time spent handling the information in mapping "Function" at PDP stage '*s*'
RRF_{1s}	Waste Minimization factor for "Risk" mapping at PDP stage '*s*'
RRF_{2s}	Waste Minimization factor for failure iteration in mapping "Risk" at PDP stage '*s*'
RRF_{3s}	Waste Minimization factor for "Schedule times" mapping at PDP stage '*s*'
RRF_{4s}	Waste Minimization factor for Development Costs at PDP stage '*s*'
RRF_{5s}	Waste Minimization factor for "Timeliness" at PDP stage '*s*'

RRF_{6s} Waste Minimization factor for time accessed in mapping “Timeliness” at PDP stage ‘*s*’

z_{im} Binary variable for selecting the idea “i” for the model “m”

$z_{am,m}$ Binary variable for selecting the alternative mechanism “am” for the function “f” of the model “m”

z_n^{Std} Binary variable for standardizing component “n” in the model family

z_n^{Cus} Binary variable for customizing component “n” in the model family

VAs Total value added at PDP stage ‘s’

NOMENCLATURE OF PAPER II

Symbol	Description
p	Product Type
a	Part-type
e	Echelons
t	Time Periods
N_{at}	The total number of part ’a’ required by the manufacturer in time the period ‘t’
S_{pt}	The total number of product type ‘p’ supplied by the manufacturer in the time period ‘t’
PCC_p	The processing capacity of collection centre of product type ‘p’.
PCD_p	The processing capacity of disassembly centre of product type ‘p’
PCR_a	The processing capacity of refurbishing centre of part ‘a’
DP_{at}	The total number of part ‘a’ obtains after disassembling at disassembly centre in the time period ‘t’’
RR_p	A parameter referring to the upper bond rate of directly reusable product ‘p’ sorted at collection centre.
DR_a	A parameter referring to the lower bond of disposal rate of part ‘a’
CC_p	The collection cost per unit of returned product type ‘p’
OCR_p	The operating cost of reusable product ‘p’
OCD_p	The operating cost for disassembling per unit of product ‘p’
OCR_a	The operation cost for refurbishing per unit of part ‘a’
DC_a	The disposal cost per unit of disposable Part ‘a”

SCC_p The set-up cost for return product ‘p’ at collection centre

SCD_p The set-up cost for disassembling collected product ‘p’

SCR_a The set-up cost for refurbishing disassembled part ‘a’

$PCES_a$ The purchasing cost per unit of part ‘a’ from supplier at time ‘t’

ICC The idle cost of the collection centre

ICD The idle cost of the disassembly centre

ICR The idle cost of the refurbishing centre$UT_{e,p/a}$ The unloading time per unit product ‘p’/part ‘a’ at echelon ‘e’

$RT_{e,p/a}$ The receiving time per unit product ‘p’/part ‘a’ at echelon ‘e’

$AT_{e,p/a}$ The put-away time per unit product ‘p’/part ‘a’ at echelon ‘e’

$LT_{e,p/a}$ The loading time per unit product ‘p’/part ‘a’ at echelon ‘e’

$PT_{e,p/a}$ The picking time per unit product ‘p’/part ‘a’ at echelon ‘e’

NU_{et} The numbers of product ‘p’/part ‘a’ unloaded at echelon ‘e’ in time period ‘t’

NR_{et} The numbers of product ‘p’/part ‘a’ received at echelon ‘e’ in time period ‘t’

NA_{et} The numbers of product ‘p’/part ‘a’ put away at echelon ‘e’ in time period ‘t’

NL_{et} The numbers of product ‘p’/part ‘a’ loaded at echelon ‘e’ in time period ‘t’

NP_{et} The numbers of product ‘p’/part ‘a’ picked at echelon ‘e’ in time period ‘t’

$EUT_{e,p/a}$ The percentage efficiency increment in unloading time per unit product ‘p’/part ‘a’ at echelon ‘e’

$ERT_{e,p/a}$ The percentage efficiency increment in receiving time per unit product ‘p’/part ‘a’ at echelon ‘e’

$EAT_{e,p/a}$ The percentage efficiency increment in put-away time per unit product ‘p’/part ‘a’ at echelon ‘e’

$ELT_{e,p/a}$ The percentage efficiency increment in loading time per unit product ‘p’/part ‘a’ at echelon ‘e’

$EPT_{e,p/a}$ The percentage efficiency increment in picking time per unit product ‘p’/part ‘a’ at echelon ‘e’

$UT'_{e,p/a}$ The unloading time per unit product ‘p’/part ‘a’ after diffusion of RFID at echelon ‘e’

$RT'_{e,p/a}$ The receiving time per unit product ‘p’/part ‘a’ after diffusion of RFID at echelon ‘e’

$AT'_{e,p/a}$ The put-away time per unit product ‘p’/part ‘a’ after diffusion of RFID at echelon ‘e’

$LT'_{e,p/a}$ The loading time per unit product ‘p’/part ‘a’ after diffusion of RFID at echelon ‘e’

$LT'_{e,p/a}$ The picking time per unit product ‘p’/part ‘a’ after diffusion of RFID at echelon ‘e’

NDP_{pt} The number of disassembled product ‘p’ at time‘t’

NR_{at} The number of refurbishing part ‘a’ at time ‘t’

NH_{at} The number of disposable part ‘a’ at time ‘t’

NP_{at} The number of purchased part ‘a’ from external supplier at time ‘t’

VR_{at} The binary variable for set-up of refurbishing part ‘a’ at time ‘t’

VD_{pt} The binary variable for set-up of disassembly product ‘p’ at time ‘t’

VC_{pt} The binary variable for set-up of collected product ‘p’ at time ‘t’

1. INTRODUCTION

The last century witnessed manufacturing advances at an extraordinary rate as a direct outcome of increased customer requirements, which has had a pronounced effect on the system's complexity. Customers have come to expect reliable products that offer trouble-free use and a full range of desired functions. This expectation has made it necessary for manufacturers to pay close attention during each stage of product development in order to produce high-quality, useful, reliable products that embody all of the functionality that customers desire. Achieving these goals, however, increases the economic burden of manufacturing, which may cause some firms to fail due to the accompanying high price of the product in the market. The economic success of manufacturing firms depends on their ability to identify the needs of customers and to quickly create products that meet those needs and that can be produced at low cost. Both the customers' and the manufacturers' needs must be considered from the beginning of the product design and development process. The manufacturing firm must also consider its direct, adverse environmental impact as an inevitable byproduct of production. Regarding this concern, the government has introduced take-back legislation that forces manufacturers to collect and dispose of any hazardous products. In addition to the environment and legislation, profit is another important reason to deal with byproducts. Generally, while the byproduct has been removed due to the technological obsolescence of any of its contents, it still contains significant value. Though direct reuse is infeasible in most cases, retrieving reusable components is an important and economical recovery option. Thus, for legislative, environmental, and economic reasons, remanufacturing has emerged as a promising field of research in the last decade. This research presents the following aspects of remanufacturing, and the Product Development Process (PDP).

1. A new value model at design and functional level in PDP.
2. Introduction of remanufacturing feasibility in PDP.
3. Designing of a generic remanufacturing framework to provide a way to measure the economical merits of Radio frequency Identification (RFID) adoption at various reverse echelons.

PAPER I

MODELING THE VALUE OF A PRODUCT AT THE DESIGN & FUNCTIONAL LEVELS: SELF-GUIDED ALGORITHMS & CONTROL APPROACH

ABSTRACT

During the design and development stages of a new product, value and reliability optimization is a prime concern of the manufacturer. Previous research conducted in this domain has been limited to either the qualitative aspects of value definition, or value quantification considering time, cost, serviceability and the importance of the product. However, the value attributes, such as performance, form, fit, function, risk, schedule, and timeliness, are other important parameters responsible for mapping the two generic tasks of knowledge discovery (KD) and risk reduction (RR) in the product development process (PDP). This research presents a quantitative value model that considers product design and development tasks and their value attributes responsible for defining the product's functions. Another beneficial feature of this formulated model is that it considers the remanufacturing feasibility of used components for prototyping and performance testing at the system testing stage. The used components vary in cost, weight, and size based on their types/versions and physical state.

Furthermore, in consideration of the computational complexity involved in the PDP, this research proposes an efficient computational technique, the Self-Guided Algorithms & Control (S-GAC) Approach, which takes its governing traits from the basic meta-heuristics of GA, PSO, and SA. The proposed algorithm can efficiently predict and select a better algorithm from a given set for more adequate exploration of the entire search space.

Illustrative examples of a complex, multi-state, series-parallel system are presented to compare the performance of S-GAC with other random search techniques. S-GAC significantly outperformed PSO, SA, and GA in terms of the solution quality and rate of convergence. The results clearly reveal the efficacy of the proposed algorithm when applied to the two underlying problems.

1. INTRODUCTION

The recent technological advancement in the manufacturing scenario has been a direct outcome of increased customer requirements and therefore has a pronounced effect on the system complexity. This yields to a problem of a new dimension for serving customers who satisfied with the reliable and trouble-free use of the product composed of a full range of desired functions. This expectation has made it necessary for manufacturers to pay close attention during each stage of product development in order to produce high-quality, useful, reliable products that embody all of the functionality that customers desire. Achieving these goals, however, increases the economic burden of manufacturing, which may cause some firms to fail due to the accompanying high price of the product in the market. The economic success of manufacturing firms depends on their ability to identify the needs of customers and to quickly create products that meet those needs and that can be produced at low cost. From the perspective of a for-profit manufacturer, successful product development results in products that can be produced and sold profitably [Ulrich and Eppinger, (2011)]. Thus, considering the perspectives of both the user and the manufacturer regarding what makes a product valuable, the larger adoption of the desired functions at minimum cost is considered a successful strategy for improving a new product's success.

A new PDP comprehends a set of activities beginning with market opportunity and ending in the production, sale, and delivery of a product [Hallstedt, (2008)]. According to Roozenburg and Eekels (1995), Roozenburg (2006), and Barkley (2008), a PDP consists of all the steps that precede a new product entering the market (or the implementation of a new production process), such as basic and applied research, market research, project planning, requirement engineering, logical design, detail design, system testing, user acceptance testing, production, distribution, marketing planning, sales, and after sales service. These are the major steps, though they can be executed in a different order, and steps can be added or removed depending on the product type, customer requirements, production-related constraints, etc. Figure 1 depicts the framework of a PDP.

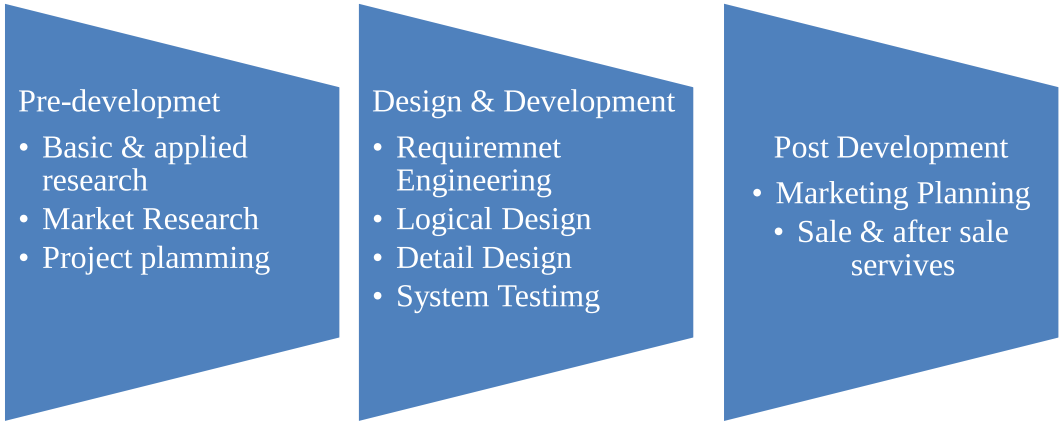

Figure 1. Overview of a New Product Development Problem

This research focuses on the design and development stages of the PDP to quantify the value of a newly developed multi-state system. The model formulated in this study considers the requirement engineering, logical design, detail design, and system testing stages, which will be elaborated upon to provide some background and different views of the terminology.

Requirement engineering: In this stage, the manufacturer identifies the target market for the product under development and conducts research, forecasting, and surveys to determine future trends and consumers' functional requirements for the product. Then, ideas are generated and screened to meet the form, function, and features of the product. In the literature, this stage is also referred to as *concept development* or *idea generation* and *idea screening*.

Logical Design: In the logical design stage, the most suitable mechanism by which to perform the function selected in the requirement engineering stage is identified, as are a set of alternative mechanisms with a built-in capability to execute a specific function in a different manner. A comparative justification analysis of each mechanism is performed, and the one with the best objective value is selected.

Detail Design: The detail design stage frames the product architecture and categorizes the product's components as standardized or modularized. Standardized components are developed on a single platform, while modularized components require multiple platforms.

System Testing: The system testing stage begins with the construction of a prototype for testing the performance of the strategically developed product. The testing is performed under various operating conditions to identify whether changes are required for the final product. A set of experiments conducted under each condition reveals how the reliability varies and accordingly predicts the system's reliability in an actual working environment.

These four stages are highly critical and make up approximately 75% of the total cost of the PDP. Thus, extra care is required when selecting parameters for the quantification of value model during these stages in order to optimize the product's value.

1.1. REASERCH AIM AND OBJECTIVE

In this research, we attempt to formulate a mathematical model during the PDP in which the value function includes the perspectives of both the users and the manufacturers. A particular benefit of this model is that it can map KD and WR parameters to define the value function at different PDP stages. In order to create a realistic value model that can closely meet both user and manufacturer requirements, the KD and WR factors are made variable with upstream to downstream design and development stages. When initiating the requirement engineering stage, the KD factor is more crucial to value adding than the subsequent logical design, detail design, and system testing stages. Similarly, the increasing influence of the risk reduction factor is set along the downstream PDP process. At the system testing stage, a multi-state series parallel product prototype is developed and tested in a remanufacturing environment. The product consists of components of different versions and physical states, which leads to the incorporation of used product and thus to the launching of remanufactured products into the market. The model also accounts for the optimal reliability factor while simultaneously minimizing other conflicting parameters, such as product cost, weight, and volume.

The product development problem studied in this research involves enormous computational complexity. The addition of remanufacturing activities into the product development model adds more difficulty to the problem to be solved in polynomial time. As deterministic methods either make it more difficult to solve the problem in polynomial time or fail to solve it with higher dimensions, various AI-based random search techniques have been proposed in the literature, such as Genetic Algorithm (GA) (Gen and Chang, 1997), Artificial Immune System (AIS) (Dasgupta et al., 2002), and Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995). This research proposes a Self-Guided Algorithms and Control (S-CAG) approach for problems of the type previously defined. The proposed algorithm is real time in the sense that it utilizes an adaptive method to allocate computational resources among a set of algorithms during its runtime in order to achieve superior performance on the underlying problem. The approach does not rely upon any complex prediction model (either on the problem domain or on algorithm behavior) and is capable of achieving performance better than the pure algorithms constituting it. The efficacy of the proposed optimization strategy is tested over a complex, multi-state, series parallel system in order to test the performance of S-CAG against that of the individual algorithms (GA, SA, and PSO).

1.2. ORGANIZATION OF THE PAPER

The remainder of the paper is organized as follows. Section 2 presents a review of the literature concerning the problem domain and solution methodology. An overview of the problem description and mathematical modeling are presented in Section 3. Section 4 details the functioning of the proposed approach. The results and a discussion of those results are provided in Section 5, followed by concluding remarks and directions for future research.

2. LITERATURE REVIEW

This section contains a review of some important considerations and challenges in the product development process (PDP).

2.1. QUANTIFYING VALUE IN THE PDP

The initial quantification of a product's value in the PDP has been cited by Slack (1999), Browning (2000), Smith (2000), Krishanna et al. (2001), and others. Browning (2000) and Browning et al. (2002) defined the value of a product in terms of its benefits to the user in association with its price. Chase (2000) comparatively assessed the performance of products with different prices. The performance measure is quantified by the ability of the product to satisfy customers' needs.

Manufacturers may view a product's value differently than the product's users (Middleton and Sutton, 2005). According to Krishanna et al. (2001, 2008) and Krishnan and Ramachnadran (2008), in addition to performance and price, manufacturers also consider production time as a major factor. Furthermore, Higgins et al. (1998), Browning (2003), McManus (2004), Slack (2006), and Higgins and Reimers (2007) emphasized the economic value model, into which the direct cost (weighted average cost in PDP) and indirect cost (capital employed by the firm) are incorporated for realism.

Considering the concerns of both the manufacturer and the user, some researchers have developed value models for the PDP over the last decade. Kettunen (2006) proposed a value-based product development model that categorizes value as either development value or phase value. The development value is established during the product development phase and hinges on customer requirements, while the phase value is established when the product is prototyped and tested. This model delivers initial value projections with some associated execution costs to the manufactures. Browning (2003) and Browning and Ramasesh (2007) defined value based on the product's status as a high-quality product or service released on time to the customers, in addition to the consequent sales and revenue. Recently, Hasan et al. (2010) introduced fundamental aspects of value from the perspective of economic theory and described product value relationships from the business, product, and project perspectives.

Table 1: Value Attribute for PDP

Type	Attribute	Units	Symbols
Performance	Performance metrics	% increase in value due to task	P_m
	Overall performance	% increase weighted due to customer requirement	P_o
Risk	Risk Specification	% decrease of value due to task	R_s
	Overall Risk	% decrease weighted to customer requirement	R_o
	Predicted failure iteration	Number	R_f
Schedule	Set up time	Hours	T_s
	Cycle time	Hours	T_c
	Integration time	Hours	T_i
	Dissemination time	Hours	T_d
	Total time	Hours	T_t
Cost	Fixed Overhead cost	$	C_o
	Variable cost	$	C_v
	Total cost	$	C_t
	Future cost development	$	C_{fd}
	Future cost manufacture	$	C_{fm}
	Future cost operation	$	C_{fm}
	Future cost support	$	C_{fs}
	Future cost retirement	$	C_{fr}
	Total future cost	$	C_{ft}
Form	Information retained	% of information capture	I_r
	Time spent reformatting data	Hours	T_{rd}
Fit	Necessity of information	% of information actually used	I_n
	Depth of information	% of information that is needed	I_d
Function	Complexity of Information	(1-10)	I_c
	Time spent handling the information	Hours	T_{hi}
Timeliness	Time before first access	Hours	T_{fa}
	Time before last access	Hours	T_{la}
	Time accessed	#	#

2.2. PRODUCT DEVELOPMENT PROCESS

PDPs are unlike typical business and production processes in several ways. Instead of repeatedly performing the same action, product development seeks to create a design that has not existed before (Browning, 2002). In this creative and iterative process, designers start with a design, find it deficient in several ways, learn more about the problems, and then improve the design to eliminate the deficiencies (Braha and Maimon (1997), Verganti (1997), and Suwa et al. (2000)). The available product development literature identifies Knowledge Discovery (KD) and Risk Reduction (RR) as the two most generic tasks in the PDP [Browning (2003); Krishnan, Ramachandran (2008), and and Yadav (2010)]. KD refers to the process of learning and evolving the related information in the development stages of the product. It is frequently referred to in the literature as design knowledge or design freedom [Mistree et al. (1990)], information evolution [Krishnan et al. (1999)], and idea generation.RR, another generic task in the PDP, is concerned with product realization. It covers the activities and processes necessary to bring a product into physical existence. In the early stages of the PDP, the potential for design failure is high, and manufacturers face penalties in terms of schedule, cost, and time [Levardy and Browning (2009)]. As the design work proceeds through the subsequent stages of the PDP, the penalties faced by manufacturers increase.

Chase (2000) advocated that designers can proceed with KD and RR tasks by adding or deleting PDP activities. Krishnan and Ramachandran (2008) categorized these activities as value-added or non-value-added. An activity that yields some useful information leading to certainty about the ability of the design to meet requirements is called a value-added activity, whereas activities that yield uncertainty and establish the risk of materializing the design concepts are called non-value-added activities. The researchers (Krishnan and Ramachandran, 2008) further categorized non-value-added activities a necessary waste (Muda 1) and unnecessary waste (Muda 2); these should be minimized or eliminated from the PDP.

When an activity leads to the discovery of some knowledge, the quality of that discovery and the risk associated with it are extremely difficult to determine (Browning et al. (2002)). Chase (2000), Browning et al. (2002 and 2006), Browning and Honour (2008), Levardy and Browning (2009), and Yadav (2010) defined KD and RR factors in terms of the following parameters: performance, form, fit, function, risk, schedule, cost, and timeliness. Different metrics are associated with each of these parameters, as summarized in Table 1. The value attributes of performance, form, fit, and function determine the quality of information or knowledge discovered during a PDP activity. On the other hand, risk, schedule, cost, and timeliness determine the range of the penalty to be incurred if the developed ideas and models fail; thus, these are RR measures.

A comprehensive overview of the literature reveals that no studies, to the best of our knowledge, have investigated the qualitative value of using a model to map value attributes at different stages in the PDP. This paper attempts to fill this gap and discusses how value is added during the various product development stages through particular activities and their attributes.

2.3. PRODUCT DEVELOPMENT STAGES

System testing is performed once the product's architecture and design have been created. A prototype is developed to test and predict the performance and reliability of the product with the functions conceived of during the earlier stages. Two prototyping methods have been reported in the literature: alpha prototyping and beta prototyping [Clifta and Vandenboschb (1999); Barkley (2008), and Ulrich and Eppinger (2011)]. Alpha prototyping is conducted to evaluate whether the product will work as designed and satisfies the desired customer functions. In beta prototyping, the testing is conducted on products similar to the final product. The typical goal of beta prototyping is to determine whether the product can perform the functions at the core of its architecture.

The literature pertaining to the system testing stage of the PDP reveals that research has been limited to developing prototypes with components having the same physical state. However, in reality, there may be different types of components with different physical states. Different combinations of types and states of a component add different degrees of value to the final product.

In order to improve the robustness of the developed product, this research considers aforementioned facts and formulates a mathematical model that maximizes the product's value while simultaneously minimizing its cost and weight. Additionally, this research considers the size of the product as having a significant impact on product design and development in the PDP.

2.4. LITERATURE RELATED TO SOLUTION METHODOLOGY

Recently, artificial intelligence techniques such as GA, AIS, PSO, etc. have been used extensively to optimize computationally complex problems categorized as NP-hard. These algorithms are marked by their short response time and high-quality solutions to the problems of real dimensions. Algorithm selection involves choosing the best algorithm from the predefined set to run on a given problem instance (Rice, 1976). Lagoudakis and Litman (2000) applied a Markov decision process with reinforcement learning to algorithm control. Boyan and Moore (2000) attempted to correlate problem features with performance in an effort to improve the search procedure. Carchare and Beck (2005) applied a machine learning approach and introduced the term *low knowledge control* for optimizing scheduling problems.

In this research, the investigators define a relative improvement factor for each pure algorithm during runtime and thereby propose the Self-Guided Algorithms and Control (S-CAG) approach for the underlying value-based product development model.

This research strives to fill some of the gaps discussed previously and presents the following contributions:

1. Models the value of a product at the design and functional levels.
2. Incorporates remanufacturing capabilities at the system testing or prototyping stage.
3. Introduces a new variant of artificial intelligence techniques.

3. PROBLEM DESCRIPTION

Certain product development approaches that apply to products that are not totally different from each others have drawn the attention of researchers and practitioners; these include independent, platform-based, standardized, and niche product development [Krishnan and Zhu (2006)]. The objective of this research is to develop a value model for a platform-based product development approach in which the manufacturer aims to incorporate economical remanufacturing at the last stage of the PDP.

3.1. MATHEMATICAL MODELING

In this section, a mathematical model for the PDP is formulated to maximize product value while simultaneously minimizing the cost, weight, and size of the developed product. First, all of the notations and decision variables used in this mathematical model will be presented. Then, the value objectives will be explained, followed by the integrated normalized objective function, and, finally, all of the related constraints.

3.1.1. Notations. The notations listed in the nomenclature are used throughout this paper.

3.1.2. Value Model Formulation. Considering the perspectives of the customers and the manufacturers at a qualitative level in the PDP, Slack (1999), Browning (2003), and Browning and Honour (2007) defined product value as:

$$\text{Value} = \frac{IN * AB * A(t)}{Co} \tag{1}$$

Where,

IN = The importance of the need for the product or service. The value of "*IN*" is fully determined by the customer.

AB = The value of "*AB*" is determined by how well the PDP is executed.

Co = The cost of ownership, which is a function of product and service attributes, as well as the efficiency of the PDP.

A(t) = The availability of the product or service to the customer, relative to the customer's need date.

Because knowledge discovery (KD) and risk reduction (RR) are the two most generic tasks in the PDP [Krishnan and Ramachandran (2008)], both must be responsible for deciding how effectively the product development stages are designed. Thus, Yadav (2010) defines AB as a function of KD and RR:

$$AB = f\,(KD, RR) \tag{2}$$

During the design and development stages, Browning et al. (2002) Browning (2008), and Yadav (2010) suggested the following uneven influence of KD and RR parameters:

1. In the earlier stages of the PDP, KD has a major influence on value creation.
2. As the PDP progresses, the manufacturer faces a higher penalty for product failure.

Considering these facts about KD and RR, this research defines *AB* in different PDP stages as defined in Yadav (2010):

PDP Stage 1: Requirement Engineering ($s = 1$)

$$AB_s = KDC_s \cdot\ (KD)^x + RRC_s \cdot\ (RR)^z \tag{3}$$

PDP Stage 2: Logical Design ($s = 2$)

$$AB_s = KDC_s \cdot\ (KD)^y + RRC_s \cdot\ (RR)^y \tag{4}$$

PDP Stage 3: Detail Design ($s = 3$)

$$AB_s = KDC_s \cdot\ (KD)^z + RRC_s \cdot\ (RR)^x \tag{5}$$

Where

$$x > y > z \geq 1 \tag{6}$$

Further, Slack (1999) advocated that A(t) should provide the dependency for the timing of the product or service. Thus, we define A(t) as:

$$A(t) = a_{tc} \,/ \sum \text{All time attributes defined for } PDP \tag{7}$$

After modifying Equation 1 with the parameters from Equations 2-7, the following new value model is defined:

PDP Stage 1: Requirement Engineering ($s=1$)

$$VA_s = \frac{\{KDC_s \cdot (KD)^x + RRC_s \cdot (RR)^z\} \cdot IN \cdot A(t)}{CO_s}; \quad \forall\, s=1 \tag{8}$$

PDP Stage 2: Logical Design ($s = 2$)

$$VA_s = \frac{\{KDC_s \cdot (KD)^y + RRC_s \cdot (RR)^y\} \cdot IN \cdot A(t)}{CO_s}; \quad \forall\, s=2 \tag{9}$$

PDP Stage 3: Detail Design ($s = 3$)

$$VA_s = \frac{\{KDC_s \cdot (KD)^z + RRC_s \cdot (RR)^x\} \cdot IN \cdot A(t)}{CO_s}; \quad \forall\, s=3 \tag{10}$$

Conceptualizing value attributes from Chase (2000), Browning et al. (2002, 2006), Browning, and Honour (2008), and Levardy, Browning (2009), and Yadav (2010) into generic product development tasks, this paper defines KD and RR as:

$$KD = KDF_{1s}(P_{ms} + P_{os}) + KDF_{2s}I_{rs} + KDF_{3s}I_{rds} + KDF_{4s}(I_{ns} + I_{ds}) + KDF_{5s}I_{cs} + KDF_{6s}I_{his} \tag{11}$$

$$RR = \left\{ \begin{array}{c} RRF_{1s}(R_{ss} + R_{os}) + RRF_{2s}P_{fis} + RRF_{4s}(C_{os} + C_{vs} + C_{fds} + C_{fms} + C_{fss} + C_{frS}) \\ + RRF_{3s}(T_{ss} + T_{cs} + T_{is} + T_{ds}) + RRF_{5s}(T_{fas} + T_{las}) + RRF_{6s}T_a \end{array} \right\} \tag{12}$$

3.1.3. Constraints.

PDP Stage 1: Requirement Engineering Constraints

$$z_{i,m} = \begin{cases} 1, & \text{if idea } i \text{ is selected for model } m \\ 0, & \text{Otherwise} \end{cases} ; \quad \forall \quad \begin{array}{c} i=1,\ldots,I \\ m=1,2 \end{array} \tag{13}$$

$$\sum_{i=1} z_{i,m} = 1 \ ; \ \forall \quad m = 1,2 \tag{14}$$

PDP Stage 2: Logical Design Constraints

$$z_{am,m} = \begin{cases} 1, & \text{if alternative/mechanism am is selected} \\ & \text{for function } f \text{ of model } m \\ 0, & \text{Otherwise} \end{cases} \ ; \ \forall \quad \begin{matrix} am = 1,\dots,AM \\ f = 1,\dots,F \\ m = 1,2 \end{matrix} \tag{15}$$

$$\sum_{f\in} z_{am,m} = 1 \ ; \ \forall \quad \begin{matrix} f = 1,\dots,F \\ m = 1,2 \end{matrix} \tag{16}$$

PDP Stage 3: Detail Design Constraints

$$z_n^{Std} = \begin{cases} 1, & \text{if component } n \text{ is commonalized} \\ 0, & \text{Otherwise} \end{cases} \ ; \ \forall \quad n \in VCOM \tag{17}$$

$$z_n^{Cus} = \begin{cases} 1, & \text{if component } n \text{ is customized/differentiated} \\ 0, & \text{Otherwise} \end{cases} \ ; \ \forall \quad n \in VCOM \tag{18}$$

$$z_n^{Std} + z_n^{Cus} = 1 \ ; \ \forall \quad n \in VCOM \tag{19}$$

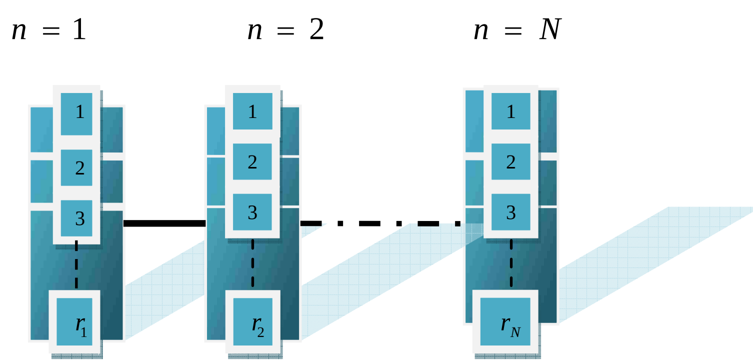

Figure 2: Multi-State Series-Parallel System

3.2. VALUE MODEL FORMULATION FOR SYSTEM TESTING STAGE

The PDP model considers a series–parallel multi-state system having n components and each component is configured with r_i number of components of same type and state parallel. A series–parallel system with the aforementioned scenario is shown in Figure 2. In order to formulate a comprehensive mathematical model of the system presented above, following points have been assumed to provide a generic view of the underlying model.

3.2.1. Assumptions.

1. All the components and system have Q possible states, namely, 1, 2…, Q.
2. There are T types of components available in the market. The cost, weight, size and state probability distribution of each type $t_i((1 \le t_i \le T))$ are specified.
3. The state and type (version) of all components in the subsystem are identical and mutually statistically independent.
4. Cost of the components is independent of its physical state, but its type.

3.2.2. Value of a Physical System. There are T versions (Types) of choices available for the components in the system where each component and system may be in Q possible states. According to Barlow and Wu (1978), the state of a parallel system is equal to the state of the best component in the system while the state of a series system is equal to the state of the worst component in the system. Thus, the state of the parallel–series system shown in Figure 2 is,

$$\psi(x) = \min_{1 \le i \le C} \max_{1 \le j \le r_i} \alpha_{ij} \tag{20}$$

Where, α_{ij} is the state of component *j* in subsystem *i*.

Using the equation (20), the probability of the system is in state “q” or above can be evaluated as follow (Shukla et al. 2009),

$$Pr\left(\psi\left(x\right)\geq q\right)=\prod_{i=1}^{N}\left[1-\left(1-\sum_{q=1}^{Q}p_{iq}\right)^{r_i}\right] \quad (21)$$

Where, p_{il} is the probability of a component i in state q.

Then, the value (U) of the multi-state series-parallel system (in state q) can be mathematically formulated as,

$$U_s=\sum_{q=1}^{Q}u_q\cdot Pr\left(\psi\left(x\right)=q\right) \qquad \forall\ s=4 \quad (22)$$

Where, u_q is the value function of the state q, and it is known for that state under consideration.

Cost, Weight, and Size of a system: Due to different versions of components available in the market the cost, weight and weight-volume have different values with respect to the corresponding component and have been formulated as (Bachlaus et al., (2006), Pandey et al., (2007), Limborg and Kochs (2007)),

$$C=\sum_{i=1}^{N}C_i\left(t_i\right)\left[r_i+\exp\left(0.25r_i\right)\right] \quad (23)$$

$$W=\sum_{i=1}^{N}W_i\left(t_i\right)\cdot r_i\cdot\exp\left(0.25r_i\right) \quad (24)$$

$$P=\sum_{i=1}^{N}P_i\left(t_i\right)\cdot r_i^{2} \quad (25)$$

Where, $C_i\left(t_i\right)$, $W_i\left(t_i\right)$ and $P_i\left(t_i\right)$ are the cost, weight and size of the individual components respectively, whereas, C, W and P are that of the complete system. r_i, and N represents the number of redundancy and number of components/subsystems.

3.3. A WEIGHTED OBJECTIVE FUNCTION

The value, cost, weight and size of the system, are the key factors in defining the objective of the system. The weighted objective function encompassing these objectives with corresponding weighting factors, is formulated as,

$$\max \quad V = \sum_{s=1}^{S} (VA_s + U_s) \tag{26}$$

And

$$\min C(r,t),\ W(r,t),\ P(r,t) \tag{27}$$

$$Max\ \phi(r,t) = \left\{ \begin{array}{l} wf(V) - wf(C(r,t)) - \\ wf(W(r,t)) - wf(P(r,t)) \end{array} \right\} \tag{28}$$

Subject to,

$$\begin{array}{l} C(r,t) \le C,\ W(r,t) \le W,\ P(r,t) \le P, \\ 0 < r; i = 1,2,...,R,\ 0 < t; i = 1,2,...,T \end{array} \tag{29}$$

Where, $\phi(r,t)$ is the weighed objective function of variables version vector $t = (t1, t2,\ldots, tT)$ and redundancy vector $r = (r1, r2,\ldots,rR)$. wf_U , wf_C, wf_w and wf_p are the weight priority associated with of system utility, system cost, system weight and system size respectively. Constraints C_0, W_0 and P_0 ensure that the cost, weight and weight-volume of the system can't exceed this limit respectively. Here, T and R are number of types for the system and number of redundancy in the subsystem.

4. SOLUTION METHODOLOGY

The product development problem is computationally complex in nature and belongs to the class of NP-Hard problems (Chen, 1992) and therefore, the model formulated in this research involves enormous computational complexity. Utilizing deterministic methods, these problems are either more difficult to be solve in polynomial time or fail to solve with higher dimensions. Therefore, subsequently, evolutionary meta-heuristics have been evolved as robust optimization techniques to effectively solve complex optimization problems. In recent years, Artificial Intelligent (AI) based random search algorithms utilizing some analogies with the natural or social systems have been applied to obtain optimal/near optimal solution. A few of such techniques found in the literatures that include Simulated Annealing (SA) (Kirkpatrick et al., 1983), Ant Colony Optimization (ACO) (Dorigo, 1992), Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995), Genetic Algorithm (GA) (Gen and Chang, 1997), Artificial Immune System (AIS) (Dasgupta et al., 2002), Artificial Bee Colony (ABC) (Karaboga, 2005) etc. Continuous improvements in past few years have spectacularly reduced the time of response of these metaheuristics along with substantial increase in solution quality. Determination of optimal number of redundant components is a computationally complex process which requires the analysis of all possible combinations of components at the subsystem level. Considering the computational complexity involved over the problem at hand, this research proposes a new meta-heuristic having its roots in canonical AI techniques; GA, PSO and SA.

4.1. OVERVIEW OF GENETIC ALGORITHM

Genetic algorithm (GA) is an artificial random search technique motivated by Darwinian’s evolution theory. Facilitated with ergodic and stochastic nature it has been invented by John Holland (1975). As of today, it is considered as very important tool in the area of research such as Scheduling problem (Dvis 1985, Gupta et al 1993, Lee And Choi 1995); Traveling salesman problem (Grefenstette et al. 1985); Pattern classification (Bandyopadhyay et al 1995); Real time control problem in manufacturing system (Lee et al 1997); Cellular manufacturing (Gupta et al 1996); Assembling line problem (Ponnambalam et al 2000); Disassembling line problem (NcGoven and Gupta 2005) etc.

Coding starting with GA requires a set of randomly generated solution candidates namely population. Each individual solution candidate called string or chromosome is evaluated by fitness test function. To incline toward favorable chromosome, population inters in loop. Loop plays the role of termination toward optimal or near optimal solution via Recombination and Selection. The process of efficient implementation of GA on underlying problem is described below.

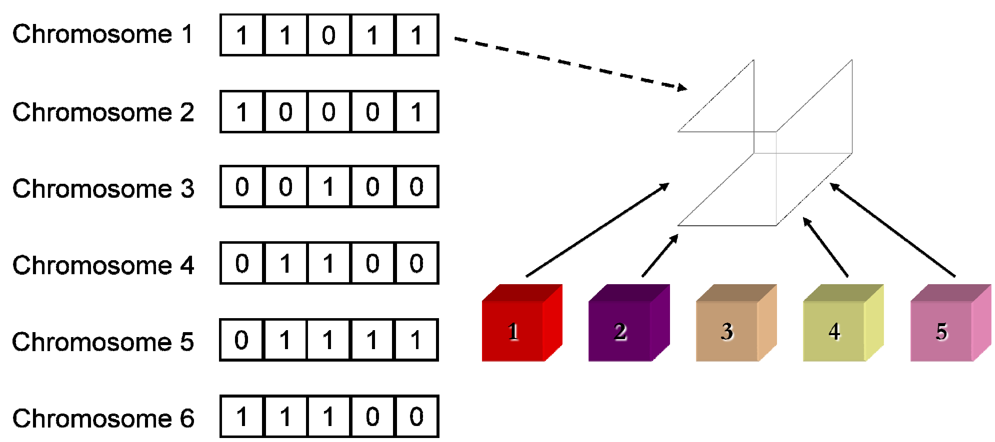

Figure 3. Population Generation in Genetic Algorithm

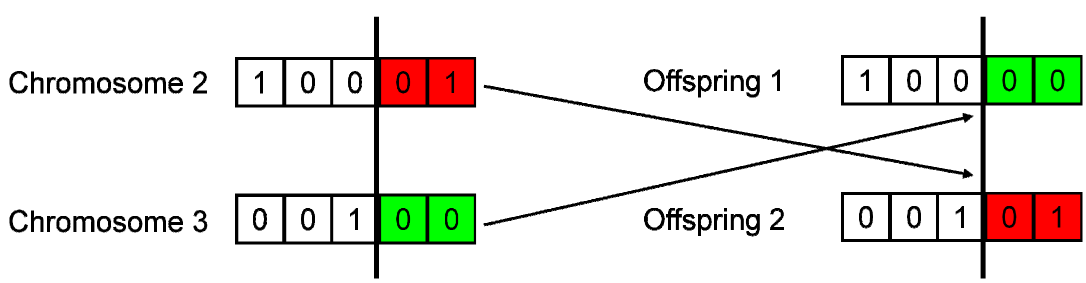

Figure 4: Crossover in Genetic Algorithm

4.1.1. Representation and Initial Population. As mentioned above, initial population is generated by random numbers. In order to create a string of work functions or obeying precedence relation among them is a tedious work. To retrain from this difficulty we generate a string representing all functions by corresponding real integer value such that each joint assigns a unique function. This string is altered at least half times the string length by interchanging randomly selected two elements in the sting. The key idea behind this to offer equal weighted to all element arrange their position randomly. The procedure is repeated until a population created. Coding of the solutions is done in the manner as shown in figure 3.

4.1.2. Recombination. Recombination imitates good balance between exploitation and exploration. It comprises two operations Crossover and Mutation.

4.1.3. Crossover. It is a crucial operation, which creates new offspring by interchanging information between two randomly selected parent chromosomes. There are many methods have been proposed for crossover operation such as, partial-mapped crossover (PMX), order crossover (OX), heuristic crossover, cyclic crossover (CX), Position-based crossover etc. [Cen and Chang, (1997)]. We use Two- Point cut crossover, which creates two off-springs by two parent chromosomes. The parents are randomly selected with crossover probability. A clear picture of this operation is shown in figures 4, and 5.

4.1.4. Mutation. Mutation provides exploitation by change one or more element in chromosome to prevent the solution from local optimal. A number of mutation operation have been proposed like, inverse mutation, displacement mutation, reciprocal exchange mutation etc (Cen and Chang). To create new genetic material we use inverse mutation works as swapping in the in chromosomes. The position of chromosome is determined by the aid of chaotic variable (details are given in Figure 6). Now, there are 8 cells in the strings. Suppose chaotic variable suggest that cell no. 3rd and 6th should be interchanged. The mutation scheme takes care of biasing the search into more useful sub space and hence, it carries out the exploitation of search space. The detailed procedure of the Genetic Algorithm is given in Figure 7.

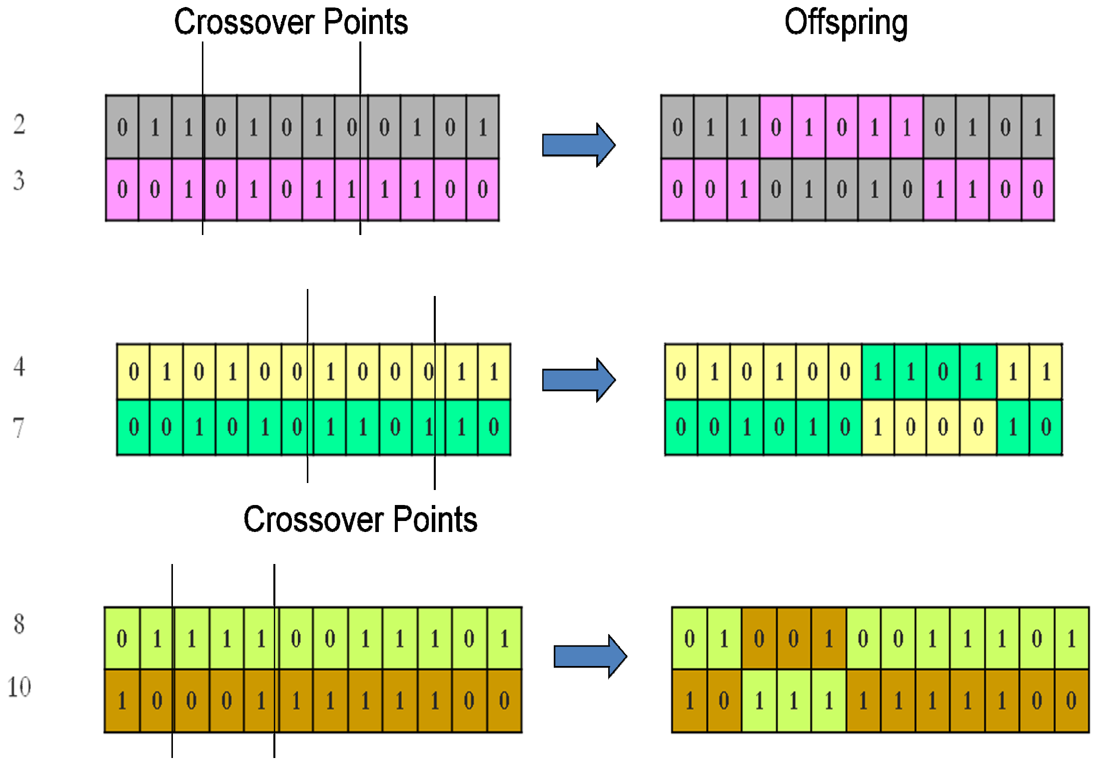

Figure 5: Offspring Generation in Genetic Algorithm

4.1.5. Reproduction. Before going to next iteration new population is generated by the good solutions. Here Tournament selection is preferred that selects half of the fitter solution from unrecompensed population and another half from recombined.

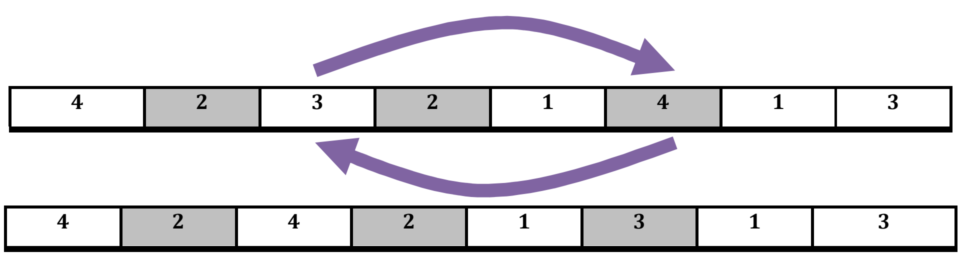
Figure 6: Mutation in Genetic Algorithm

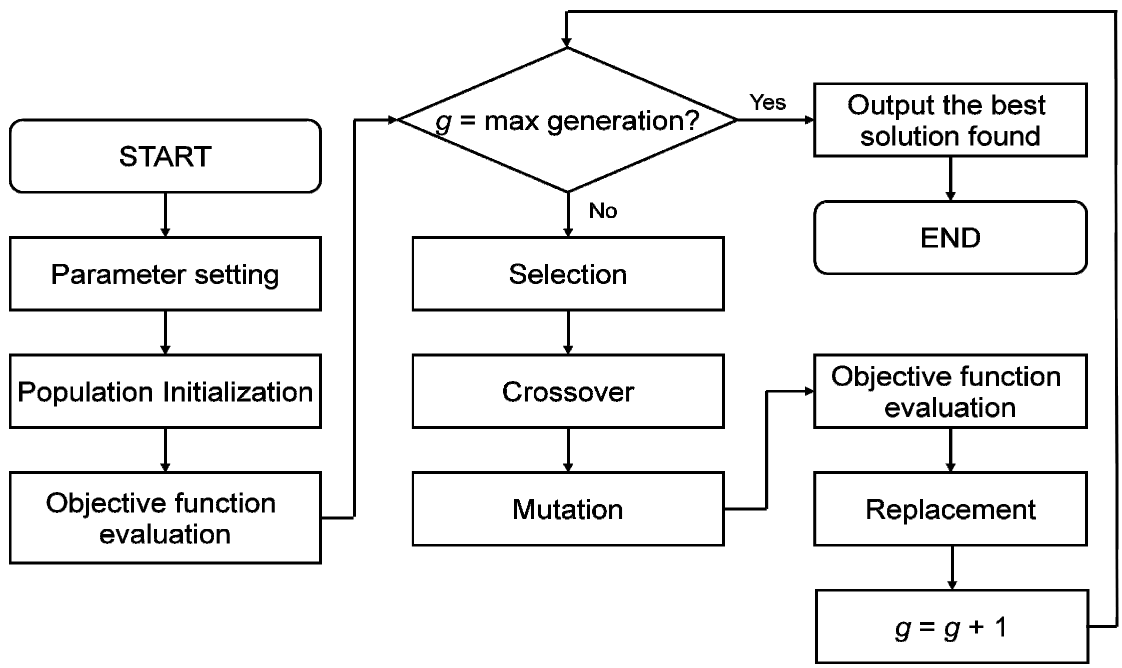

Figure 7: Pseudo Code of Genetic Algorithm (GA)

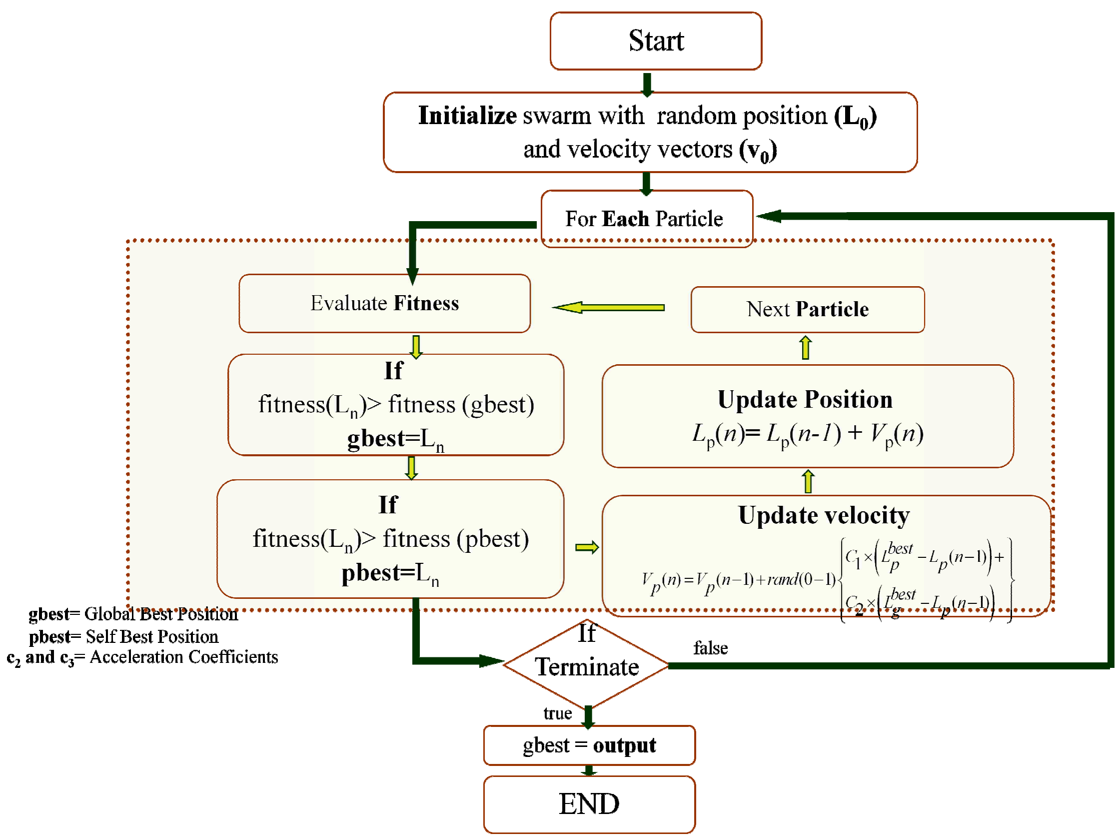

Figure 8: Pseudo Code of Particle Swarm Optimization

4.2. OVERVIEW OF PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization (PSO) is a population based stochastic optimization technique, developed by Kennedy and Eberhart (1995). The idea behind the development of PSO was to simulate the social foraging behavior of living organisms classified as swarms. However, several striking features of PSO transform it into a promising evolutionary metaheuristic. To illustrate, in the context of PSO, the population is called a swarm and each members of swarm is referred as particles. In order to reach at the desired destination, the particles of the swarm head with a restrained velocity in the search space. During the search, particles utilize their cognitive and collaborative ability to move towards their own best position and the best position explored by swarm so far, respectively. Kennedy and Eberhart (1995) developed an equation (equations (30)) for changing the velocity of each particle and thereby according to this updated velocity the position of individual particle is altered (equations (31)).

$$V_p(n) = V_p(n-1) + rand(0-1)\left\{\begin{array}{l} C_1 \times \left(L_p^{best} - L_p(n-1) \right) \\ + C_2 \times \left(L_g^{best} - L_p(n-1) \right) \end{array}\right\} \tag{30}$$

$$L_p(n) = L_p(n-1) + V_p(n) \tag{31}$$

Where, $V_p(n) \in [V_{\min}, V_{\max}]$ represents the velocity of individual particle $p(=1,2,...,P)$ at n^{th} iteration. C_1 and C_2, respectively, denote cognitive and collaborative ability of particles called accelerations coefficients. $rand(0-1)$ is a randomly generated value between 0 and 1. L_p represents position of particle p; L_p^{best} and L_g^{best} are used to denote the best position found so far (up to n^{th} iterations) for an individual particle and for the whole swarm (global best), respectively. The detailed procedure of the PSO is given in Figure 8.

4.3. OVERVIEW OF SIMULATED ANNEALING

The Simulated Algorithm (SA) belongs to class of stochastic optimization methods that mimic nature skills as Neural Networks and Genetic Algorithms in the sense in exploring and providing optimal solutions. It was first proposed by Kirkpatrick et al., (1983), inspired from thermodynamic process of cooling (annealing) of molten metal to attain the lowest free energy state. In a generic SA, the foremost and essential step is the generation of initial solution randomly.

First, the algorithmic parameters like maximum and minimum temperature, maximum number of iterations etc. are initialized, which is followed by the generation of initial solution given by, $L_0 = \left(L_{0,1}, L_{0,2,}, \ldots, L_{0,q}\right)^T$ by using the formula,

$$L_{0,i} = a_i + \left(b_i - a_i\right) \times H_{ki} \quad (32)$$

Where, $i=1, 2,\ldots, q$; q is the number of variables in objective function; a_i and b_i are the limits in which the value of corresponding variable lies; and, $L_{0,i}$ is the value of i^{th} variable at 0^{th} iteration.

After determining the initial solution, a new solution $M_p = \left(M_{p,1}, M_{p,2}, \ldots, M_{p,q}\right)^T$ is generated in each iteration by the formula,

$$M_{p,i} = L_{p,i} + \alpha \times \left(b_i - a_i\right) \times H_{k_p} \quad \ldots (33)$$

Where, $M_{q,i}$ denotes new solution of i^{th} variable at q^{th} iteration; α is a variable given as $\alpha = \alpha \times e^{-\beta}$ in each iteration; and β is a constant. This is followed by the calculation of change in energy level as $\Delta E = f\left(M_q\right) - f\left(L_q\right)$, with $f\ (M_q)$ and $f\ (L_q)$ corresponds to the fitness value of new and initial solution. If ΔE is negative then the new solution is accepted for next iteration; whereas if the change in energy level is positive then solution is accepted with probability $\exp\left(-\Delta E/T\right)$ to accept the inferior solution. The value of temperature counter is continuously decreasing by annealing schedule $T = \alpha T$, where α is a constant. The above procedure is continued until the pre-specified minimum temperature is not achieved and the best solution is given as the output. In the above procedure, it can be experimentally verified that after few iterations, value of α becomes insignificant and thus deteriorates the exploration of search space.

Figure 9 clarifies the decreasing characteristics of α (Values adopted from Mingjun and Huanwen 2004). The detailed procedure of the Genetic Algorithm is given in Figure 10.

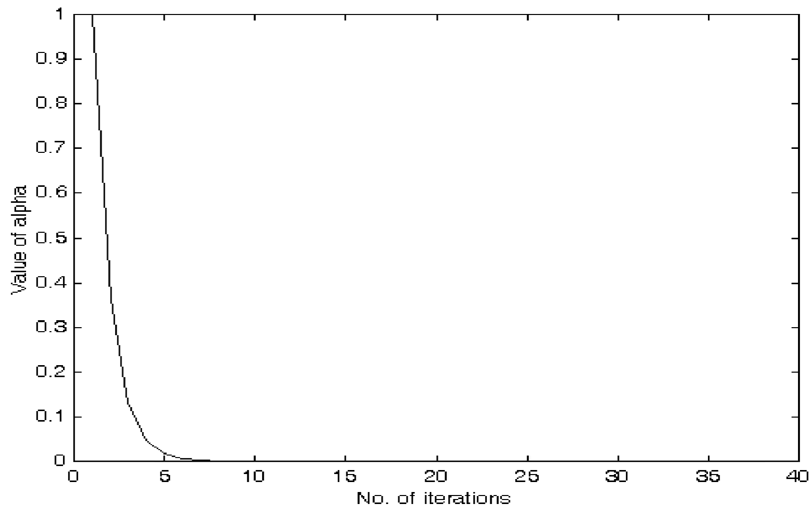

Figure 9: Variation in Value of α (alpha) With No. of Iterations

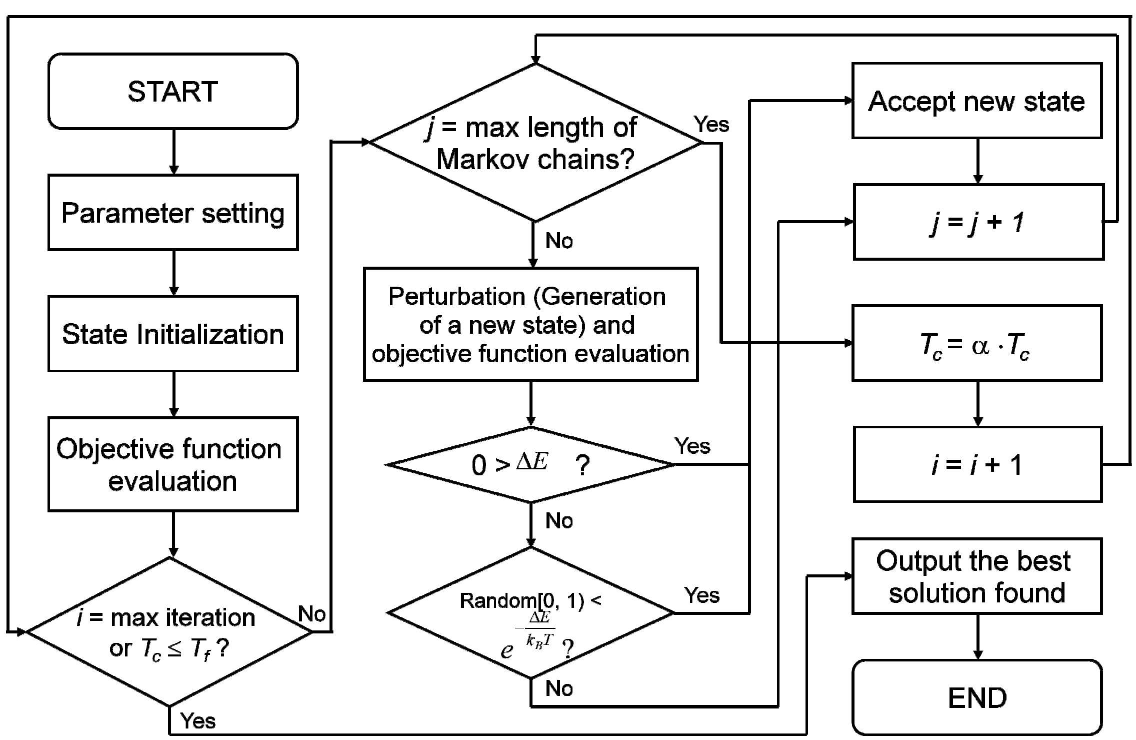

Figure 10: Pseudo Code of Simulated Annealing

4.4. PROPOSED METHODOLOGY

The proposed algorithm (Self-Guided Algorithms & Control (S-CAG) Approach) is a hybrid metaheuristic which derives its governing traits from the three aforementioned algorithms; GA, SA, and PSO. The key idea behind comprising of these algorithms is not only to provide a global component of search space but also a special local search component, which is employed to enhance the search results.

The seeking of a fruitful solution starts with random search of attaining global maximum in a multimodal function with unknown number of maxima rely generally upon the stochastic search in the individual AI techniques such as the aforementioned algorithm; GA, SA, and PSO. However, significant variation among the final outputs produced by these techniques is evident by the greater standard deviation in the results generated by the same algorithm with different random seeds. This may some time lead to inefficacy of the random search technique by producing results entrapped in the local maxima. Hence, certain measures must be incorporated into the solution methodology which makes it capable enough to generate results with acceptable standard deviation. In this paper, we propose an optimization framework comprising of a set of stochastic search algorithms. We observed following two characteristics of the proposed methodology:

1. Producing results with greater proximity towards global optimum than the pure algorithms under consideration.
2. Producing results with smaller standard deviation.

The computational complexity of the aforementioned problem paves the way for development of a search technique that efficiently predicts and selects a better algorithm from a given set and adequately explores the entire search space. Schematic representation of the algorithm flow is depicted in figure 11.

In general, superiority of a search strategy is judged by its relative performance over other metaheuristics by the principal of winner takes all (Rice, 1976). However, an algorithm producing better results on one problem instance may not guarantee to produce similar results in all other cases.

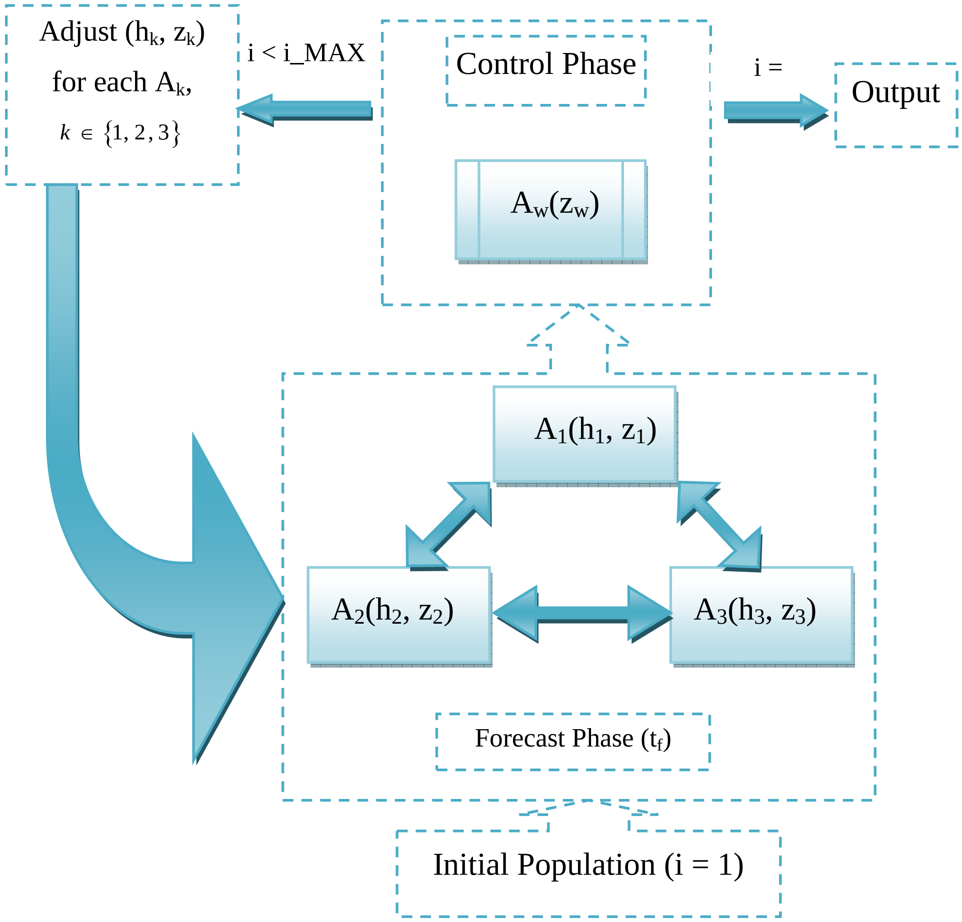

Figure 11: Overview of Proposed S-CAG

Therefore, any single optimization strategy may not prove itself to be versatile enough for having universal applicability in terms of generating better averaged results. Hence, the Self-Guided Algorithms and Control poses an issue of significant relevance in current optimization technology. In view of above considerations, the authors propose a Self-Guided Algorithms & Control (S-CAG) search strategy as an adaptive method for allocation of computational resources among a set of algorithms to achieve a superior performance on the underlying model. The approach followed in this paper does not rely upon any complex prediction model (either on problem domain or on algorithm behavior) and performs iteration wise selection of the algorithms. In the proposed technique, the metaheuristics compete among themselves for both their selection and control.

Given a time limit z, S-CAG ranks each algorithm during runtime in the order in which they have to operate on the problem instance. The time z is further broken into a short forecast phase (Z_f) and control phase (Z_c) such that,

$$Z = Z_f + Z_c \tag{34}$$

The forecast phase (Z_f) predicts which algorithm should be utilized for remaining of the control time $Z - Z_f = Z_c$. We represent the information flow within the real-time optimization based strategy as shown in the figure 11. $A_l\left(h_l + Z_l\right), l = \{1, 2, 3\}$, represents an algorithm from the predefines set, h_l and Z_l being its corresponding rank and time for which the algorithm runs during the forecast phase. A_l is the winner algorithm that is predicted to perform better in the control phase and Z_w is the time for which it is run. It is clear from figure 11 that $Z_w = Z_c$. The winner algorithm among the three is decided by the Relative Improvement Factor (RIF_l) calculated during the forecast phase via a real-time algorithm selection procedure.

In order to circumvent the loss of computations carried out during the forecasting phase, the results produced by one algorithm is passed on directly to the other algorithm sequentially. Instead of computing absolute improvement in results for each algorithm over a common static population, a relative improvement factor (RIF_l) is utilized over a dynamic population received by previous algorithm. This RIF_l is defined mathematically according to,

$$RIF_l = \begin{cases} 0; & if \sum\limits_{m=1}^{n}\left(\left(ibs_m - bs_m\right)\big/ bs_m\right) = 0 \\ \dfrac{\left(ibs_l - bs_l\right)\big/ bs_l}{\sum\limits_{m=1}^{n}\left(\left(ibs_m - bs_m\right)\big/ bs_m\right)} & ; otherwise \end{cases} \tag{35}$$

Here, ibs_l is the best solution produced in the current iteration and bs_l is the best solution over which the algorithm operated upon. The runtime for each algorithm is equally distributed (Z_f / n) among them during the forecast period. During initialization, the ranks have been randomly assigned to each algorithm which are later updated according to the rank factor hf_l (as shown in eq. 12) such that greater the value of hf_l, better the corresponding rank.

$$hf_k = \{n - h_l(i-1)\} \times RIF_l \tag{36}$$

Where, $h_l(i-1)$ represents the rank of the algorithm A_l in the previous iteration. Any conflicts in rf_l (arising due to equality of rank factors of two or more algorithms) are broken by randomization of ranks.

As a part of this research, GA, SA and PSO were selected to operate sequentially in each iteration according to their corresponding ranks. Pseudo codes for these three algorithms are presented in Appendix A-C.

5. ILLUSTRATIVE EXAMPLES

The following two illustrative examples demonstrate the efficacy of the proposed model.

5.1. EXAMPLE 1: CHAIR WITH 4 COMPONENTS

An exhaustive study of the design and development of a chair is conducted in this section. Additionally, the relevant information pertaining to the value of the developed system coupled with its functional performance is explained. In this example, the manufacturer plans to develop a few different models of a chair, each having 4 components.

The idea generation process for the design and development of the chair is detailed in Table 2. The range of value attributes contributing to the selection of the ideas; functions, standardization, and modularization of the chair appear in Table 3. Furthermore, Table 4 includes an exhaustive list of alternatives/mechanisms for each function desired in the chair. Table 5 lists the probability distribution of all four states corresponding to each type of component, $p_{i1} - p_{i4}$, in the system testing stage. Moreover, the utility of the components with respect to their existing state is listed in Table 6. Finally, Table 7 provides the numerical values of the other parameters defined in the nomenclature.

5.2. CNC MACHINE WITH 10 COMPONENTS

This example is similar to Example 1 in terms of its objectives and constraints, but the product contains 10 components. The input data for idea generation in this problem has been tabulated in Table 8. An exhaustive list of alternatives/mechanisms for each CNC function appears in Table 9. Table 10 lists the probability distribution of all four states corresponding to each type of component, $p_{i1} - p_{i4}$, in the system testing stage. The functions are further categorized as fixed or variable, and their corresponding components are listed below. The remainder of the variable data is the same as defined in Example 1.

$$\text{FUN} = \left\{ \begin{array}{c} \text{Tool/Spindle rotation, Paller support, Job holding, Body cover,} \\ \text{Coolant spray, Program control, Lighting, Safety, Noise control,} \\ \text{Heat sink, Sealing, Tool holding, Work support, Coding/Programming,} \\ \text{Motor power support, Chuck function, Health monitoring, Chip handling} \end{array} \right\}$$

$$\text{F-FUN} = \left\{ \begin{array}{c} \text{Tool/Spindle rotation, Program control, Tool holding,} \\ \text{Motor Power support, Chuck function, Coding/Programming} \end{array} \right\}$$

$$\text{V-FUN} = \left\{ \begin{array}{c} \text{Paller support, Job holding, Body cover, Coolant spray,} \\ \text{Lighting, Safety, Noise control, Heat Sink, Sealing,} \\ \text{Work Support, Health monitoring, Chip handling} \end{array} \right\}$$

$$\text{COM} = \left\{ \begin{array}{c} \text{Bed, Spindle, Turret, Tailstock, Motor, Chuck/Collect,Vice,} \\ \text{Door, Controller screen, Sprincler, Pendant, Pump, Fixture,} \\ \text{Host computer, Axis drive, Lighting, Sound damper, Heat Sinker} \end{array} \right\}$$

$$\text{F-COM} = \left\{ \text{Bed, Spindle, Turret, Tailstock, Motor, Chuck/Collect, Controller screen} \right\}$$

$$\text{V-COM} = \left\{ \begin{array}{c} \text{Vice, Door, Sprincler, Pendant, Pump, Host computer,} \\ \text{Fixture, Axis drive, Lighting, Sound damper, Heat sinker} \end{array} \right\}$$

Table 2: Idea Generation for Sitting Chair Design & Development

S. No	Functions	I1	I2
1	Sitting	+	+
2	Back Supporting		*
3	Stand Support	+	+
4	Arm support	*	*
5	Movement		
6	Rolling	*	

Table 3: Range of Value Attributes

Type	Attribute	Range
Performance	Performance metrics (P_m)	20-50
	Overall performance (P_o)	0.10-0.30
Risk	Risk Specification (R_s)	0.5-0.20
	Overall Risk (R_o)	0.5-0.30
	Predicted failure iteration (R_f)	0.3-0.10
Schedule	Set up time (T_s)	0.10-0.30
	Cycle time (T_c)	0.30-0.12
	Integration time (T_i)	0.30-0.60
	Dissemination time (T_d)	0.60-0.24
	Total time (T_t)	0.13-0.450
Cost	Fixed Overhead cost (C_o)	0.35-0.10
	Variable cost (C_v)	0.50-0.40
	Total cost (C_t)	0.85-0.50
	Future cost development (C_{fd})	0.10-0.30
	Future cost manufacture (C_{fm})	0.50-0.10
	Future cost operation (C_{fo})	0.35-0.70
	Future cost Support (C_{fs})	0.70-0.30
	Future cost retirement (C_{fr})	0.10-0.25
	Total future cost (C_{ft})	0.12-0.25
Form	Information retained (I_r)	0.10-0.70
	Time spent reformatting data (T_{rd})	0.20-0.12
Fit	Necessity of information (I_n)	0.20-0.80
	Depth of information (I_d)	0.50-0.85
Function	Complexity of Information (I_c)	1-10
	Time spent handling the information (T_{hi})	0.1-0.60
Timeliness	Time before first access (T_{fa})	0.20-0.10
	Time before last access (T_{la})	0.5-0.15
	Time accessed (#)	3-10

Table 4: Exhaustive List of Alternatives/Mechanism for Each Function of a Sitting Chair Design & Development

Functions	**Alternative Mechanism for achieving the function**		
(+)Sitting	Metal Sheet	Wooden Sheet	Plastic Sheet
Back Supporting	St. Support	Curved support	Inclined Support
(+)Stand Support	Single stand	Triple Stand	4 arm stand
Arm support	Connected to sheet	Connected to back support	
Movement	Frictional Movement	Gear movement	
Rolling	Free rolling	Forward rolling	Locked rolling

Table 5: Characteristics of the Components

N_i	t_i	p_{i1}	p_{i2}	p_{i3}	p_{i4}	$C_i(t_i)$	$w_i(t_i)$	$P_i(t_i)$
1	1	0.140	0.350	0.350	0.160	1.150	12	1
	2	0.487	0.240	0.038	0.235	0.630	5	2
	3	0.190	0.074	0.186	0.550	0.900	8	3
	4	0.038	0.350	0.180	0.432	0.550	10	4
	5	0.480	0.060	0.290	0.170	0.740	12	2
2	1	0.215	0.180	0.025	0.580	0.875	10	2
	2	0.300	0.250	0.250	0.200	0.250	12	4
	3	0.074	0.550	0.186	0.190	0.545	17	1
	4	0.450	0.250	0.250	0.050	0.975	14	3
3	1	0.240	0.400	0.110	0.250	0.826	3	5
	2	0.150	0.400	0.045	0.405	0.550	8	1
	3	0.235	0.240	0.038	0.487	0.790	16	3
	4	0.160	0.452	0.038	0.350	0.545	13	3
	5	0.255	0.230	0.450	0.065	0.780	5	4
	6	0.200	0.100	0.300	0.400	1.120	7	3
4	1	0.100	0.450	0.250	0.200	0.875	10	2
	2	0.040	0.300	0.320	0.340	0.494	15	3
	3	0.080	0.320	0.320	0.280	0.790	12	2
	4	0.074	0.186	0.550	0.190	0.380	14	4
	5	0.038	0.240	0.235	0.487	0.620	6	1

Table 6: Utility of the system of state q

q	1	2	3	4
U_q	20	50	90	70

Table 7: Value of Defined Parameters

KDC_s = $ 4.0
WMC_s = $ 3.0
IN = 7
$A(t)$ = 0.004
CO_s = $ 120000
a_t = 1000 Hour
KDF_{1s} = 0.0016 Per Product value
KDF_{2s} = 0.0080
KDF_{3s} = 0.0012 Hour^{-1}
KDF_{4s} = 0.0070
KDF_{5s} = 0.0090
KDF_{6s} = 0.0050 Hour^{-1}
WMF_{1s} = 0.0018 Per Product value
WMF_{2s} = 0.0011
WMF_{3s} = 0.0014 Hour^{-1}
WMF_{4s} = 0.0050 \$$^{-1}$
WMF_{5s} = 0.0060 Hour^{-1}
WMF_{6s} = 0.0040
x=3, y=2, z=1

Table 8: Idea Generation for CNC Design & Development

S. No	Functions	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
1	Tool/spindle Rotation	+	+	+	+	+	+	+	+	+	+
2	Pallet support		*		*	*					*
3	Job Holding	+	+	+	+	+	+	+	+	+	+
4	Body Cover	*	*			*		*			*
5	Coolant spray				*	*		*			*
6	Program control	*					*				*
7	lighting	*		*				*		*	*
8	Coding/ Programming	+	+	+	+	+	+	+	+	+	+
9	Noise Control		*	*		*				*	
10	Sensor	*	*			*	*	*		*	
11	Sealing			*	*				*	*	
12	Tool Holding	+	+	+	+	+	+	+	+	+	+
13	Work Support			*			*		*	*	
14	Motor Power support	+	+	+	+	+	+	+	+	+	+
15	Chucking	+	+	+	+	+	+	+	+	+	+
16	Heat sink		*				*	*	*		
17	Chip handling	*			*				*		
18	Safety			*	*		*		*		

Table 9: Exhaustive List of Alternatives/Mechanism for Each Function of A CNC Machine

Functions	Alternative Mechanism for achieving the function							
Tool/Spindle Rotation	fixed collet spindles			manual quick change spindles		automatic tool change spindles		brush types Spindle
Pallet support	Hard Polymer Router	Woodworking Router	Steel Router	CI Router	Light Stone Router	Heavy Stone Router	Granite Router	Ceramic router
Job Holding	Vice	Automated fixture	Magnet	Arm with grip	cotter	clamps	fasteners	Jigs
Body Cover	Hard polymer	Lead plating	Steel enclosure	Kevlar	Ceramic Proof coating	composite	Force field	Reactive armor
Coolant spray	Sprinkler	Pump	nozzle	pipe				
Program control	Pendent	Controller Screen	MPG	CNC CAT	Remote controller	Lath handler	Optical Encoder	CNC Mach3
lighting	bulb	tube bulb						
Programming	computer	MDI processor	Controller	Cable Tape	Embedded System	Smart wire DT	LAB view compact RIO	
Noise Control	Sound damper	Muffler	Acoustic Material	Noise Collector	Damper	Lubricant		
Heat sink	Liquid coolant	Mist air	Radiator	Fan	Exhaust Pipes		Fins	Thermo cooling
Sealing	EM shield	Plastic coating	Compartment		Sealant	PVC	Gasket	Jelly Barrier
Tool Holding	4 tools Turret	5 tools Turret	6 tools Turret	7 tools Turret	8 tools Turret	9 tools Turret	10 tools Turret	
Work Support	ROHM Tailstock	PSI LCENTL	Sunwin	PSI	Sherline	Amico Tailstock	Amico Tailstock	MT2 Tailstock
Motor support	NEMA	TB6560	Autek 4	MAKINO	LEBLOND	hossen	Amico	DIY CNC
Chucking	ER-Collets	Newbie	Dremel	Steelex	Bosch	TECHNIKS	Sherline	Hardinge
Sensor	Temperature sensor	Thermal Stress Sensor	Mechanical sensor					
Chip handling	Magnet	Vacuum	scoop	net	velcro	Suction cup		
Safety	gloves	goggles	shoes	Leather	Earplug			

Table 10: Characteristics Of The Components

N_i	Sub-systems/ Components	t_i	p_{i1}	p_{i2}	p_{i3}	p_{i4}	$C_i(t_i)$	$w_i(t_i)$	$P_i(t_i)$
1	Magnet Pallet	1	0.140	0.350	0.350	0.160	1.150	12	1
		2	0.487	0.240	0.038	0.235	0.630	5	2
		3	0.190	0.074	0.186	0.550	0.900	8	3
		4	0.038	0.350	0.180	0.432	0.550	10	4
2	Turret	1	0.215	0.180	0.025	0.580	0.875	10	2
		2	0.300	0.250	0.250	0.200	0.250	12	4
		3	0.074	0.550	0.186	0.190	0.545	17	1
3	Motor Power components	1	0.240	0.400	0.110	0.250	0.826	3	5
		2	0.150	0.400	0.045	0.405	0.550	8	1
		3	0.235	0.240	0.038	0.487	0.790	16	3
		4	0.160	0.452	0.038	0.350	0.545	13	3
		5	0.255	0.230	0.450	0.065	0.780	5	4
		6	0.200	0.100	0.300	0.400	1.120	7	3
4	Scoop	1	0.100	0.450	0.250	0.200	0.875	10	2
		2	0.040	0.300	0.320	0.340	0.494	15	3
		3	0.080	0.320	0.320	0.280	0.790	12	2
		4	0.074	0.186	0.550	0.190	0.380	14	4
		5	0.038	0.240	0.235	0.487	0.620	6	1
5	PVC	1	0.172	0.158	0.309	0.361	0.079	2	1
		2	0.183	0.376	0.284	0.157	0.832	12	3
		3	0.045	0.294	0.147	0.514	0.152	9	2
		4	0.181	0.164	0.304	0.351	0.793	4	5
		5	0.080	0.103	0.316	0.501	0.228	6	1
6	Brush types Spindle	1	0.321	0.194	0.132	0.353	0.982	14	1
		2	0.091	0.059	0.077	0.773	0.121	13	4
		3	0.133	0.327	0.321	0.219	0.189	13	5
		4	0.175	0.442	0.303	0.080	0.782	8	3
7	ER-Collets	1	0.131	0.420	0.360	0.089	0.560	4	4
		2	0.583	0.123	0.091	0.203	0.726	11	2
		3	0.709	0.078	0.187	0.026	0.673	2	5
		4	0.447	0.149	0.168	0.236	0.124	12	3
		5	0.100	0.076	0.241	0.583	0.480	13	1
		6	0.212	0.249	0.289	0.250	0.254	8	2
8	Leather jacket	1	0.075	0.029	0.401	0.495	0.579	13	1
		2	0.268	0.131	0.417	0.187	0.108	14	4
		3	0.103	0.561	0.150	0.186	0.743	14	1
		4	0.103	0.378	0.330	0.189	0.453	10	3
		5	0.056	0.222	0.055	0.667	0.650	1	3
9	Heavy Stone Router	1	0.429	0.173	0.286	0.112	0.708	8	4
		2	0.514	0.319	0.130	0.037	0.146	1	5
		3	0.459	0.052	0.331	0.158	0.252	12	2
10	Controller Screen	1	0.750	0.081	0.052	0.117	0.578	8	3
		2	0.314	0.166	0.287	0.233	0.863	8	4
		3	0.056	0.120	0.245	0.579	0.742	15	1
		4	0.432	0.183	0.174	0.211	0.119	6	4
		5	0.298	0.168	0.378	0.156	0.344	13	2
11	Nozzle	1	0.447	0.149	0.168	0.236	1.524	15	4
		2	0.172	0.158	0.309	0.361	1.55	17	6

Table 11: Optimal Values & Ideas Achieved At Requirement Engineering Stage For Sitting Chair Family

	Model 1	Model 2
Idea Selected	I2	I1
Functions	(+)Sitting	(+)Sitting
	Back Supporting	---
	(+)Stand Support	(+)Stand Support
	Arm support	Arm support
	---	---
	---	Rolling
Values Added	242.879	185.14
Total Values Added	428.029	

6. RESULT AND DISCUSSION

This section outlines the results obtained by implementing the proposed Self-Guided Algorithm and Control Approach over Value based a new product development model problem. For comparative purpose Particle Swarm Optimization (PSO), Simulated Annealing (SA) and Genetic Algorithm (GA) algorithms have also been used in addition to proposed S-CAG.

6.1. PARAMETER SETTING

The algorithms have been coded in C++ and compiled program is run on a system specification of Dell Notebook with Intel ® Core ™ i5-2.40GHz and 4 GB RAM. The first step in the implementation of a search technique to any problem is the representation of search space and tuning the various parameters of each algorithm. For the underlying model, integer encoding in used and length of the string is set to match the problem requirements. For example, in system testing stage, the length of string is 12: the first four digits represent the number of components (r_1 - r_4), next four digits are used to represent its corresponding type (t_1 - t_4) and the last four digits denote the existing state of the subsystems. After extensive experimentations the value of the tuning parameters are decided. For GA the population size, crossover rate and mutation rate are set to be 20, 0.25 and 0.10 respectively. Moreover, in order to find out optimal control parameters of SA, number of rejected solution, temperature and steps in which temperature is reduced were inspected by varying in the range of 1 - 5, 200 - 1000 and 5 - 15, respectively. Likewise, for PSO swarm size and acceleration coefficients are chosen to be 10 and 2.0 respectively.

Moreover, for S-CAG, Z_f is the time required for each iteration of the pure algorithm under consideration and was computed dynamically during the run of each algorithm separately under S-CAG. Therefore, each single iteration of S-CAG constituted of Z_f such that there were 5 runs of each pure algorithm during prediction phase. Similarly, Z_c was chosen such that there were 20 runs of the winner algorithm during the control phase. The ranks of the algorithms were initialized randomly. In case of tuning parameters utilized in S-CAG for individual pure algorithms, same parameter settings have been undertaken as reported for GA, SA and PSO.

Table 12: Optimal Values & Mechanism Achieved At Logical Design Stage For Sitting Chair Design & Development Family

Functions	Model 1	Model 2
	Mechanism selected for each function	
(+)Sitting	Wooden sheet	Plastic sheet
Back Supporting	Curved Support	Curved Support
(+)Stand Support	Single stand	---
Arm support	Connected to back support	Connected to back support
Rolling	---	Locked rolling
Values Added	(496+578+248+635)	(734+356+498+478)
Total Values Added	1957+2066=4023	

Table 13: Standardization & Customization of Variable components at Physical Design stage for CNC family

	Customized Components	
Standardized Components	Model 1	Model 2
Curved back Support	Wooden sheet	Plastic Sheet
Arm Connected to back support	Single type stand	Locked roller
Values Added	1,05,869 + 1,13, 126	
Total Values Added	2,18,995	

6.2. RESULT ANALYSIS FOR EXAMPLE 1

The ideas, functions and components selected in requirement engineering and logical design stages are listed in tables 11 and 12. The tables also include value adding in the both stages. Table 13 summaries the architecture of the product platform. It provides a clear picture which components to be standardize and which to be modularized during platform development time.

Comparative study of the proposed solution methodology (S-CAG) and their canonical version; PSO, SA, and GA for first illustrative example, sitting chair with four components, have been provided in Table 13. It includes value added to product at system testing stage. The results obtained In this case, equal priority has been given to the each design metrics and the values of wf_U, wf_C, wf_W and wf_p are considered to be 1 for simplicity. In this case, results obtained by the best performing algorithm (S-CAG) have also been stated in the table 14.

Figure 12 illustrates the convergence rate of solution with the number of function evaluations when algorithms are applied in the illustrative example. The following inference can be drawn from Figure 12 that initially SA has faster convergence rate but with the increase in number of iterations, its convergence rate becomes almost constant whereas, S-CAG and PSO both of them initially converges with the same rate and finally S-CAG in the long run gains the advantage of adaptive algorithm selection and yields better solutions in both the cases. Hence, from above discussion it can be concluded that S-CAG demonstrated superior results in context of computational time and convergence rate both.

Table14: Comparative Results By Applying Different Algorithm

	GA	PSO	SA	S-CAG
$\phi(x)$	2.52653	2.52323	2.51612	2.50997
U	916.13	910.903	917.121	905.689
C	26.8176	29.3608	28.4782	28.6294
W	917.674	1022.95	984.197	996.575
P	301	283	301	370
Components(r)	(3,2,2,1)	(1,2,3,3)	(2,1,3,2)	(1,2,1,2)
Type(t)	(4,2,6,5)	(4,1,2,5)	(4,1,2,5)	(4,1,2,5)
State	(4,3,2,1)	(4,4,1,2)	(1,1,3,2)	(4,3,4,4)

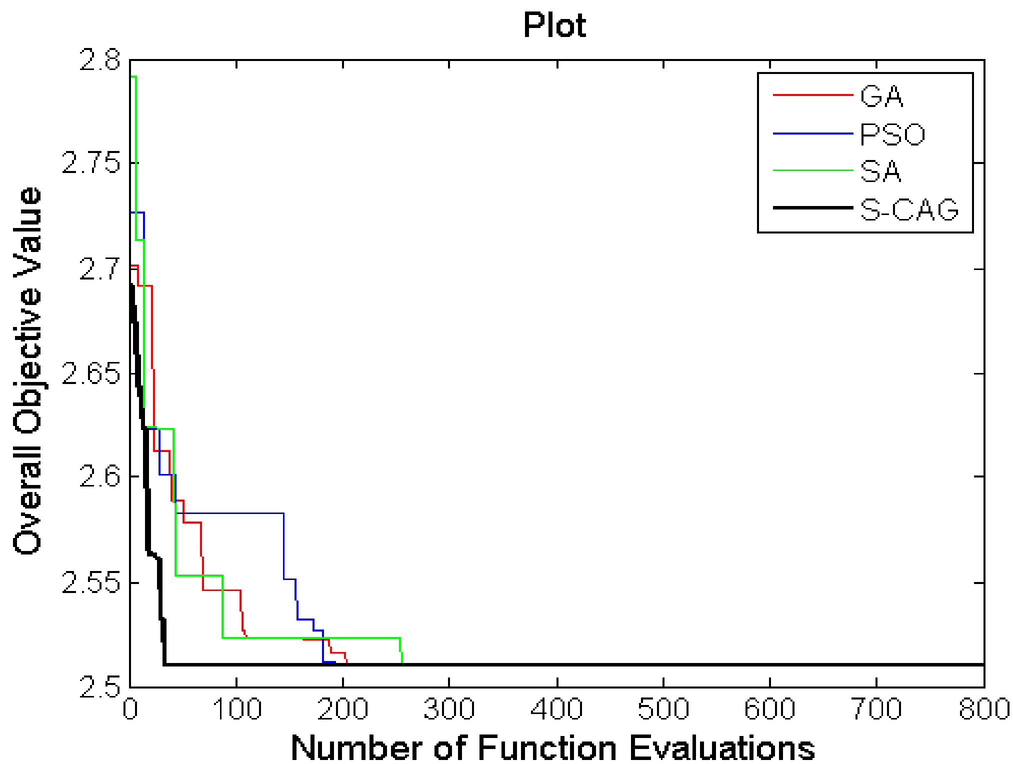

Figure 12: Variation and Search Characteristics of GA, PSO, SA and Proposed S-CAG

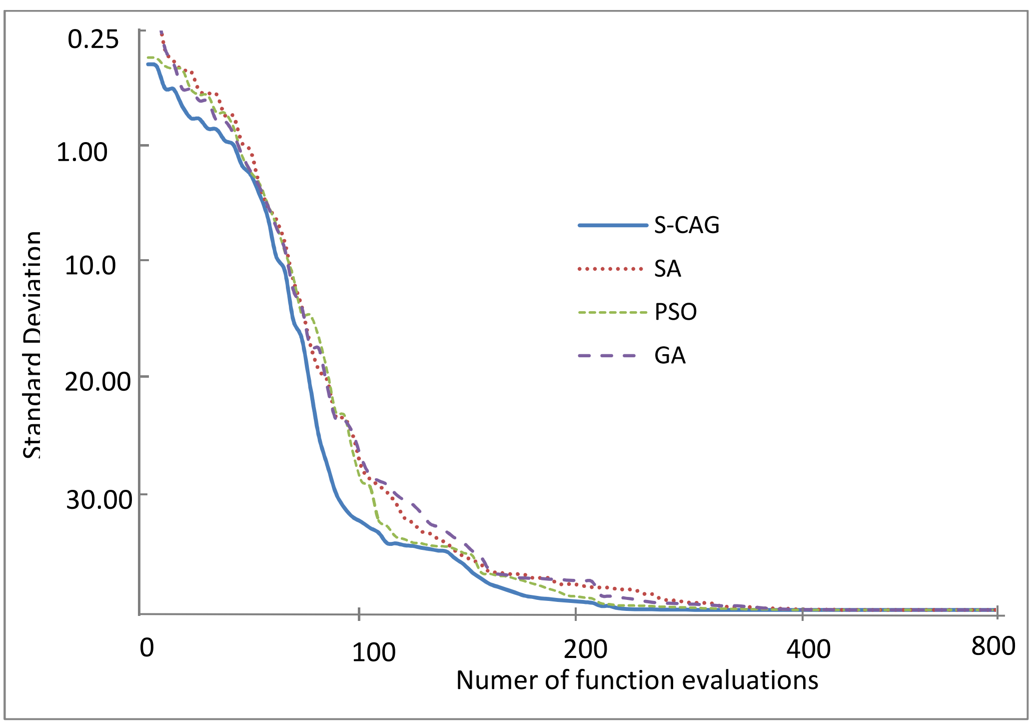

Figure 13: Standard Deviation Comparison of the Proposed Algorithm

Furthermore, in order to check the scalability and effectiveness of the proposed method, a comparative standard deviation graph at different generations for all algorithms is plotted in Figure 13. The trend of smaller standard deviation of S-CAG at every generation than the other algorithms reveals that the proposed solution methodology provides an adaptive allocation of computational resources between exploration and exploitation of the search space. In addition, it supports the basic theory behind the formulation of the proposed algorithms. Hence, from the above discussion it can be concluded that S-CAG demonstrated both superior results in the context of solution quality and convergence rate.

Table 15: Optimal Values & Ideas Achieved At Requirement Engineering Stage For CNC Family

	Model 1	Model 2
Idea Selected	I4	I8
Functions	(+) Tool/spindle Rotation	(+) Tool/spindle Rotation
	Pallet support	---
	(+) Job Holding	(+) Job Holding
	---	---
	Coolant spray	---
	---	---
	---	----
	(+) Coding/ Programming	(+) Coding/ Programming
	---	---
	---	---
	Sealing	Sealing
	(+) Tool Holding	(+) Tool Holding
	---	Work Support
	(+) Motor Power support	(+) Motor Power support
	(+) Chucking	(+) Chucking
	---	Heat sink
	Chip handling	Chip handling
	Safety	Safety
Values Added	5284.27	6721.62
Total Values Added	12005.89	

6.3. RESULT ANALYSIS FOR EXAMPLE 2

The ideas, functions and components selected in requirement engineering and logical design stages are listed in tables 15 and 16. The tables also include value adding in the both stages. Table 17 summaries the architecture of the product platform. It provides a clear picture which components to be standardize and which to be modularized during platform development time.

Table 16: Optimal Values & Mechanism Achieved At Logical Design Stage For CNC Family

Functions	Model 1	Model 2
	Mechanism selected for each function	
(+) Tool/spindle Rotation	Brush types Spindle	Manual quick change spindle
Pallet support	Heavy Stone Router	---
(+) Job Holding	Magnet	Magnet
Body Cover	---	---
Coolant spray	Nozzle	---
Program control	---	---
lighting	---	---
(+) Coding/ Programming	Controller Screen	Pendent
Noise Control	---	---
Sensor	---	---
Sealing	PVC	PVC
(+) Tool Holding	8 tools Turret	8 tools Turret
Work Support	---	ROHM Revolving Tailstock
(+) Motor Power support	MAKINO	MAKINO
(+) Chucking	ER-Collets	Bosch
Heat sink	----	Mist air
Chip handling	scoop	scoop
Safety	Leather jacket	shoes
Values Added	(448+498+324+510+491+465+ 572+452+ 531+386+404)	(467+678+546+432+486+ 452+ 605+635+478+489+601)
Total Values Added	5081+5851=10,932	

Table 17: Standardization & Customization of Variable components at Physical Design stage for CNC family

Standardized Components	Customized Components	
	Model 1	Model 2
Magnet Pallet	Brush types Spindle	Manual quick change spindle
Turret	Heavy Stone Router	Pendent
Motor Power components	Nozzle	Tailstock
Scoop	Controller Screen	Bosch
PVC	ER-Collets	Mist air
	Leather jacket	Shoes
Values Added	1,05,869 + 1,13, 126+ 1, 72, 064 + 98, 972+ 1, 03, 426	
Total Values Added	5, 93,457	

7. CONCLUSION AND FUTURE WORK

This study aimed to develop a model by which to determine the value of a product at the design and functional levels. The model was formulated to maximize the value of the product while minimizing its cost, weight, and size. In this research, a four-stage (components) problem was considered to map the remanufacturing component into the PDP. In order to tackle the underlying problem, a novel approach, Self-Guided Algorithms & Control (S-CAG), was proposed and implemented successfully. The proposed algorithm has been shown to significantly outperform many existing optimization strategies prevalent in the literature, with faster convergence.

The following directions for future research are suggested to interested readers: (i) include more realistic reliability considerations, such as the field and service data (in the form of survey results) into the value computation, (ii) evaluate the reliability of the developed products, and (iii) apply the S-CAG strategy to optimize other computationally complex problems.

8. BIBLIOGRAPHY OF PAPER I

Ulrich, K.T., Eppinger, S. D.. 2011. Product design and development. McGraw-Hill, New York.

Hallstedt, S. 2008. A foundation for sustainable product development. Doctoral thesis, Blekinge Institute of Technology, Karlskrona, Sweden.

Roozenburg, N. F. M. and J. Eekels. 1995. Product Design: Fundamentals and Methods. Chichester, England: John Wiley & Sons Ltd.

Browning, T. R., Fricke, E., and Negele, H.. 2006. Key Concepts in Modeling Product Development Processes. Systems Engineering, 9(2), 104-128.

Browning, T.R., Deyst, J.J., Eppinger, S.D., and Whitney, D.E. 2002. Adding Value in Product Development by Creating Information and Reducing Risk. IEEE Transactions on Engineering Management, 49:443–58.

Browning, T. R.. 2003. On customer value and Improvement in product Development process. Systems Engineering, 6(1), 49-61.

Browning, T. R., and Honour, E. C.. 2008. Measuring the Life-Cycle Value of Enduring Systems, Systems Engineering, 11 (3), 187-202.

Levardy, V. and Browning, T. R. 2009. An Adaptive Process Model to Support Product Development Project Management, IEEE Transactions on Engineering Management, VOL. 56, NO. 4, November 2009.

Barkley, B. T.. 2008. Project Management in New Project Development. New York: McGraw-Hill.

Smith, J.. 2000. Measuring Value in Product Development. The Lean Aerospace Initiative Working Paper Series;WP00-05. MIT, Cambridge, MA.

Middleton, P. and Sutton, J. (2005) Lean Software Strategies: Proven Techniques for Managers and Developers, Productivity Press.

Kettunen, P.. 2008. Rethinking Software-Intensive New Product Development: From Product Push to Value, http://www.cloudsoftwareprogram.org/rs/2237/9ed65124-0873-400e-bc8a-9c85c1f1afa8/5a5/filename/submission.pdf

Hasan, Sk. Md. N., Hasan, M. S., Mahmood, A. A., and Alam, Md. J.. 2010. A Model for Value Based Requirement Engineering. IJCSNS International Journal of Computer Science and Network Security, VOL.10 No.12,

R. Verganti, “Leveraging on systematic learning to manage the early phases of product innovation projects,” R&D Management, vol. 27, no. 4, pp. 377–392, 1997.

D. Braha and O. Maimon, “The design process: Properties, paradigms, and structure,” IEEE Trans. Syst., Man, Cybern., vol. 27, pp. 146–166, Apr. 1997

M. Suwa, J. Gero, and T. Purcell, “Unexpected discoveries and S-invention of design requirements: Important vehicles for a design process,” Design Studies, vol. 21, no. 6, pp. 539–567, 2000.

Chase, J.. 2000. Measuring Value in Product Development. The Lean Aerospace Initiative Working Paper Series; WP00-05. MIT, Cambridge, MA.

Clifta, T. B., Vandenboschb M. B.. 1999. Project Complexity and Efforts to Reduce Product Development Cycle Time. Journal of Business Research, Volume 45, Issue 2, Pages 187–198.

Krishnan V., and Zhu W.. 2006. Designing a Family of Development-Intensive Products. Management Science, 52(6), 813–825.

Krishnan V., Ramachandran K.. 2008. Economics models of product family design and development. C. Loch, S. Kavadias, eds. Handbook of New Product Development Management. Butterworth Heinemann-Elsevier, Oxford, UK, 87-112.

Browning T. R., 2008. A Quantitative Framework for Value, Risk and Opportunity Management in Projects. 2nd Annual UTD Project Management Symposium University of Texas at Dallas, Dallas, TX, Aug. 18-19.

Bachlaus M., Shukla N., Tiwari M. K and Shankar R., Optimization of System Reliability using Chaos-Embedded Self-organizing Hierarchical Particle Swarm Optimization., J. Risk and Reliab., 2006, 220.

Yadav S., A Value Model for Product Development Process Using Lean Principles. Master's Thesis, Missouri S&T, 2010.

Barlow Re and Wu AS., Coherent System with Multi-State Components, Math Oper., 1978, 3(4), 81-275.

Boyen, J., and Moore, A., Learning evaluation functions to improve optimization by local search, J. of Mach. Lear. Res., 2000, 1, 77-112.

Carchare, T. and Beck J. C., Applying Machine Learning to Low Knowledge Control of Optimization Algorithms, Computational Intelligence, 2005, 21(4), 372-387

Chen M. S., On the computational complexity of reliability redundancy allocation in series system, Oper. Res., 1992, 11, 309-315.

Dasgupta D. and Gonzalez G., An Immunity-Based Technique to Characterize Intrusions in Computer Networks, IEEE Tra. on Evo. Com., 2002, 6(3), 281-291.

Gen M. and Cheng R., Genetic algorithm and engineering design., A Wiley-Interscience publication, John Wiley and sons, Inc., 1997

Gen M. and Yun Y.S., Soft computing approach for reliability optimization: State-of-the-art survey, Reliab Eng and Sys Saf, 2006, 91 1008–1026.

Huang, H.-Z., Tian, Z., and Zuo, M.J. Intelligent Interactive Multiobjective Optimization Method and its Application to Reliability Optimization. IIE Tran., 2005, 37, 983-993.

Kennedy J. and Eberhart R. C., Particle Swarm Optimization in Proc. IEEE Int. Conference. Neu. Networks, 1995; 4: 1942-1948.

Kumar, V. V., Pandey, M. K., Tiwari, M. K., & Ben-Arieh, D. (2010). Simultaneous optimization of parts and operations sequences in SSMS: a chaos embedded Taguchi particle swarm optimization approach. Journal of Intelligent Manufacturing, 21(4), 335-353.

Kumar, V. V., Tripathi, M., Pandey, M. K., & Tiwari, M. K. (2009). Physical programming and conjoint analysis-based redundancy allocation in multistate systems: a Taguchi embedded algorithm selection and control (TAS&C) approach. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 223(3), 215-232.

Kumar, V., Kumar, V. V., Mishra, N., Chan, F. T. S., & Gnanasekar, B. (2010, October). Warranty failure analysis in service supply chain: A multi-agent framework. In Supply Chain Management and Information Systems (SCMIS), 2010 8th International Conference on (pp. 1-6). IEEE.

Kumar, V. V., Yadav, S. R., Liou, F. W., & Balakrishnan, S. N. (2013). A digital interface for the part designers and the fixture designers for a reconfigurable assembly system. Mathematical Problems in Engineering, vol. 2013.

Kumar, V. V., Tripathi, M., Tyagi, S. K., Shukla, S. K., & Tiwari, M. K. (2007). An integrated real time optimization approach (IRTO) for physical programming based redundancy allocation problem. In Proceedings of the 3rd International Conference on Reliability and safety engineering, Udaypur, Rajasthan, India (pp. 692-704).

Lagoudakis, M.G., and Littman, M.L., Algorithm selection using reinforcement learning, In proceedings of 17th International Conference on Machine Learning. Morgan Kaufmann, San Francisco, CA, 2000, 511-518.

Liu P., Zuo M., and Meng M., Using neural network function approximation for optimal design of continuous-state parallel–series systems. Comput Oper Res., 2003; 30(3), 339–52.

Limbourg P. and Kochs H.D., Multi-objective optimization of generalized reliability design problems using feature models-A concept for early design stages, Reliab En. And Syst Saf, 2007

Levitin G, Lisnianski A., Structure optimization of multi-state system with two failure modes. Reliab Eng Syst Saf 2001; 72(1), 75–89.

Pandey M. K., Tiwari M. K. and Zuo M. J., Interactive enhanced particle swarm optimization: A multiobjective reliability application, Inst. of MeE, Part O, J. of risk and reliability, on line available.

Rice, J., The algorithm selection problem, Advances in Computers, 1976, 15, 65-118.

Tian Z. and Zuo M. J., Redundancy allocation for multi-state systems using physical Programming and genetic algorithms, Reliability Eng. and Sys. Saf.y, 2006, 91, 1049–1056.

PAPER II

ECONOMICAL IMPACT OF RFID IMPLEMENTATION IN REMANUFACTURING: A CHAOS-BASED INTERACTIVE ARTIFICIAL BEE COLONY APPROACH

ABSTRACT

In the modern manufacturing arena, environmental and economical concerns draw considerable attention from both practitioners and researchers towards remanufacturing practices. The success of remanufacturing firms depends on how efficiently the recovery process is executed. Radio Frequency Identification (RFID) technology holds immense potential to enhance the recovery process. The deployment of RFID technology at reverse echelons has the advantage of having a real time system with reduced inventory shrinkage, reduced processing time, reduced labor cost, process accuracy, and other directly measurable benefits. In spite of these expected benefits, the heavy financial investment required in implementing the RFID system is a big threat for remanufacturing companies. This paper examines the economical impact of RFID adoption to remanufacturing. The aim of the research is to compare the basic and RFID-diffused reverse logistics model, and to quantitatively decide whether RFID implementation is economically viable. In order to meet these objectives, we have proposed a Chaos-based Interactive Artificial Bee Colony (CI-ABC) algorithm. Numerical results from using the CI-ABC for optimal performance are presented and analyzed. Comparison between the canonical Artificial Bee Colony and the Particle Swarm Optimization reveals the superiority of the CI-ABC for this application.

1. INTRODUCTION

An unprecedented increase in every field of human daily requirements has a direct effect on the burgeoning demand for consumer goods in the last decade. In addition, the customer expects trouble-free use of products over a certain period of time. Consequently, the manufacturers need to produce superior products; this expectation also leads to scientific and technological innovations. Fast emerging manufacturing paradigms have resulted in frequent dumping of products due to technological obsolescence of any components that still have a significant value. The shortening of the product's life cycle not only puts an extra demand of raw materials to manufacture a new product but also increases the threat to the environment as an inevitable by-product of this process. A growing concern about environment (pollution, global warming and traffic congestion, etc.) has led to a number of take-back legislation and European Union (EU) directives such as: End-of-Life Vehicle (ELV), Closed Substance Cycle and Waste Management Act, and Waste Electrical and Electronic Equipment (WEEE) to collect End-Of-Life (EOL) products and to properly dispose of the hazardous materials (Schultmann et al., 2006; Jung and Hwang, 2011). The economical value of EOL products has generated some interest in manufacturers and needs a better handling approach. A manufacturer can retrieve some components from an EOL product having the same utility as it was in the virgin state, at a much lower cost compared to a new one. For example, manufacturers of toner cartridges (Xerox), single-use cameras (Eastman Kodak and Fuji Film) and photocopiers (Fuji and Xerox), washing machines (ENVIE), computers (IBM) and mobile phones (ReCellular, and Greener Solutions) have profited by a huge amount through reusing durable components (Franke et al., 2006). Thus, various factors such as economical, environmental, legislative, and depletion of natural resources have led to the emergence of a promising field of research termed "remanufacturing".

Remanufacturing is a process of recapturing parts of value and proper disposal of the hazardous components from a used product. This process is performed in a cost-effective and environmentally friendly manner from the point of consumption to the point of origin of reverse logistics. There are several steps to be followed which can be executed in different order or some steps could even be ignored, depending on the product type, remanufacturing volume etc. Frequently used reverse logistics steps reported in previous studies are termed as: collection, sorting, inspection, cleaning, disassembling, repairing, refurbishing, and disposing (Charter and Gray, 2008). First, inspection operation is performed at the collection centre to justify whether the returned product is directly reusable or needs disassembling to sort out its worn-out parts. At the disassembly centre, the product is disassembled to subassembly and further to the individual part level. The good and moderate quality components are shipped to refurbishing centers to execute cleaning, repairing and replacing operations on any defective or worn out parts, whereas the unendurable ones are sent to landfills at the disposal centre.

Quantitative studies in remanufacturing addresses the various existing complexities such as; Network design (Charter and Gray, 2008; Lee and Dong, 2009), product recovery and distribution planning (Jayaraman, 2006; Pineyro and Viera, 2010), scheduling and shop floor management (Franke et al., 2006; Stanfield et al., 2006), inventory control (Konstantaras and Papachristos, 2007; and Pan et al., 2009), resource allocation (Wang and Yang 2007), routing (Blanc et al., 2006), and third party logistics (Ko and Evans, 2007; Lee et al., 2008). In addition to these, some researchers have highlighted issues related to uncertainty in demand and return rate. Hong et al. (2006) presents a scenario-based robust optimization model, “Reverse Production Systems” (RPS) that employs some electronic goods e-scraps under uncertainty. They implement an RPS model to a case study based in Georgia and linked a relation between RPS processing strategic decisions and RPS collection decisions. Salema et al. (2006) studies a design of reverse logistics network with uncertainty in demand and return, and capacity limits. They developed a mixed integer model to resolve these multi product management issues. Uncertainty in the return rate of an EOL product due to various environmental factors such as law, government policies, and environmental protection issues is considered in Bu and Xu (2008). They formulated an expiration based on above factors and have drawn a mathematical relation between return rate and environmental factors. Recently, Naeem et al. (2013) incorporated both deterministic and stochastic model to determine the optimal quantities that have to controlled for both inventories; recoverable and serviceable in remanufacturing environment. They developed a dynamic programming based model to minimize the total cost, including production cost, holding cost for returns and finished goods, and backlog cost at each period.

Utilisation of state-of-the-art Radio Frequency Identification (RFID) is experiencing an increasing popularity in logistics systems. Addressing the forward logistics problems, many researchers such as Prater et al. (2005), Chow et al. (2006), Nagi et al. (2007), and Pigni and Ugazio (2009) emphasise the adaptation of RFID technology at different echelons viz. manufacturer production sites, warehouses, distribution centres, retail stores, etc. These researchers have developed network models and discussed several benefits of RFID dissemination mainly for real time information, stock-out reduction, process accuracy, and for increasing labour efficiency. However, the cost associated with the RFID adaptation over the traditional shop floor facilities has been ignored by most of the researchers. Only a few recent papers deal with the economical impact of RFID technology on logistics. Veeramani et al. (2008), presents a framework and models for assessing the value of RFID utilization by tier-one suppliers to major retailers. Their paper argues that the RFID implementation is profitable on 5 upper echelons of the supply chain in the context of a real-life application to Wal-Mart's top 100 suppliers. Bottani and Razzi (2008) evaluate the economical impact of RFID tools on three echelons of fast-moving consumer goods in a supply chain: manufacturers, distributors, and retailers. Their assessment is made by analysing two different scenarios: non-integrated and integrated, which shows that RFID diffusion is not profitable for all scenarios. A cost analysis of an RFID integrated three-echelon supply chain is investigated by Ustundag and Tanyas (2009). They conclude that the total supply chain cost savings are increased by RFID integration.

Although resource allocation and inventory management at forward logistics echelons are similar to the reverse one, they are not exactly the same. Recycling activities differ from production procedure in time and manner such as quantity, category, cycle time, stock keeping unit, and distribution paths. Consequently, the remanufacturing process requires extra care in implementing the RFID technology than the forward supply chain. Moreover, unlike the forward logistics which has been adequately studied, the reverse logistics have not been well studied for the suitability of RFID adoption. Researchers have recently proposed the utilization of RFID in remanufacturing most of them have overlooked its cost in their mathematical models (Lee and Chan, 2009; Yoo and Park, 2009; Kumar et al., 2011; Dowlatshahi, 2012; etc.). In order to fill this gap, this study focuses on the design of a generic framework of a remanufacturing system which provides a way to measure the economical impact of RFID adoption at various reverse facility centers viz. collection, disassembling, and refurbishing.

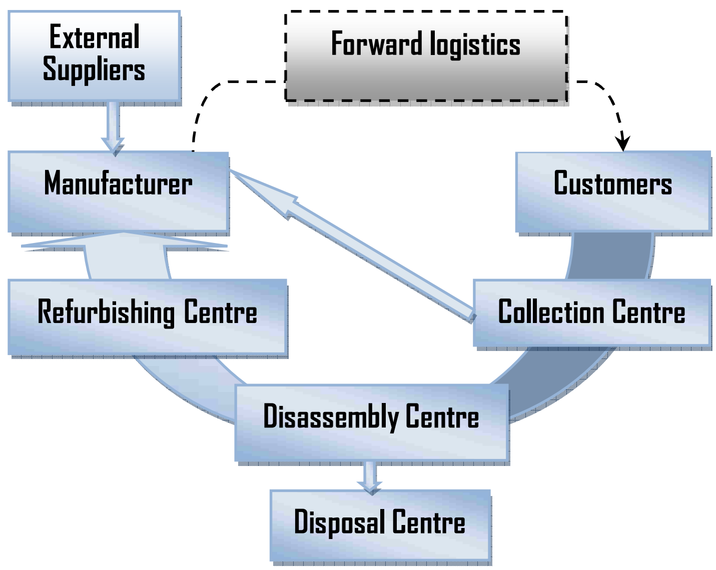

Figure 1: Reverse logistics network

It has already been proven that the remanufacturing network design problem belong to the class of NP-hard problems (Doh and Lee, 2010; Kumar et al., 2013). Hence, random search optimization techniques and their variants have been widely accepted as a more efficient optimization tool over conventional enumeration based optimization techniques; such as genetic algorithm (GA), artificial immune system (AIS), particle swarm optimization (PSO), and their variants (Chan et al., 2011; Kumar et al., 2009; Yadav et al., 2008; etc.). In addition, Artificial Bee Colony (ABC) meta-heuristic has gained adequate favour in this area of research in recent past (Lazzús, 2013; Tsai et al., 2009; Prakash et al., 2008; Kumar et al., 2004; Soleymanpour et al., 2003; etc.). Inspired by successful applications of ABC, in this paper, a new variant of the Artificial Bee

Colony algorithm (ABC) called the Chaos-based Interactive Artificial Bee Colony (CI-ABC) Algorithm is used to handle a realistically sized remanufacturing problem. The proposed CI-ABC assimilates the attributes of chaotic systems by introducing stochastic and ergodic properties in searching for the optimal or near optimal solution. Moreover, a new primitive component is combined to update the position of component for enhancing the interaction between employed and unemployed bees. The computational results indicate that the proposed CI-ABC outperforms the canonical ABC and PSO metaheuristics.

1.1. ORGANISATION OF THE PAPER

The rest of this paper is organized as follows: In section 2, modeling of a suitable objective function for a reverse logistics problem that includes the RFID cost is discussed. Section 3 presents the steps involved in implementing the CI-ABC over the illustrative examples which are discussed in section 4. The results obtained by implementing the aforementioned algorithms are discussed in detail in section 5. Finally, section 6 provides the conclusions from the study and provides directions for further research.

2. THE MODEL DEVELOPMENT

This section develops a model to systematically examine the impact of RFID technology on reverse logistics cost factors. In this sense, a general and an RFID-integrated reverse logistics model are illustrated in the subsequent sub-sections.

2.1. REVERSE LOGISTICS MODEL

Figure 1 depicts a generic reverse logistics network of the system under study. This system starts with returned products including EOL products from customers. First, the returned products are collected at a collection centre where they are sorted. Reusable products are sent back to the manufacturer after the required treatment and the rest of them are transported to the disassembly centre. At the disassembly centre, the product is disassembled to subassembly and further to the individual part level. The components of good and moderate quality are shipped to refurbishing centers for cleaning, repairing, and replacing any defective or worn parts. The unendurable ones are sent to a land fill at the disposal centre. At all three echelons (collection, disassembly, and refurbishing centers), the product/parts are processed through two warehouse processes: inbound moves and outbound moves. The inbound moves include unloading, receiving, and put-away operations during the receiving of the returned products, while outbound moves consist of two operations: picking and loading when the products are shipped to next the echelon. Table 1 summarizes the warehouse operations considered in this study.

Table 1: Main Warehouse Operations

Movement type	Operations		
Inbound Moves	Unloading	Receiving	Put-Away
Outbound Moves	Picking		Loading

In this study, the manufacturer produces a certain number of products in a certain time period by assembling the virgin and used parts which are in good condition to remanufacture. Virgin parts are purchased from external suppliers while used parts are acquired by disassembling and retrieving the valuable parts from EOL products. Thus, the model is aimed at determining the optimal revival of the used parts in an economical way. In order to articulate this concept into mathematical terms, an objective function (J) is formulated below, followed by a list of all model parameters and decision variables used in this research, which is shown in the nomenclature.

2.1.1. Objective Function. The objective function, J, is formulated as follows;

$$\text{Min}\,(J) = \text{Min}\,(J_{\text{cost}} + J_{\text{time}}) \tag{37}$$

In equation (37), the operation cost (J_{cost}) is defined as:

$$J_{Cost} = \left\{ \begin{array}{l} \sum_{t=1}^{T}\sum_{a=1}^{A} PCES_a.N_{at} + \sum_{t=1}^{T}\sum_{p=1}^{P} r.S_{pt}.CC_p + \sum_{t=1}^{T}\sum_{p=1}^{P} RR_p.r.S_{pt}.OCR_p \\ + \sum_{t=1}^{T}\sum_{p=1}^{P} (OCD_p.NDP_{pt}) + \sum_{t=1}^{T}\sum_{a=1}^{A} (DC_a \cdot NH_{at}) + \sum_{t=1}^{T}\sum_{a=1}^{A} (OCR_a.NR_{at}) \\ + \sum_{t=1}^{T}\sum_{p=1}^{P} (SCC_p.VC_{pt}) + \sum_{t=1}^{T}\sum_{p=1}^{P} (SCD_p.VD_{pt}) + \sum_{t=1}^{T}\sum_{a=1}^{A} (SCR_a.VR_{at}) \\ + \sum_{t=1}^{T}\sum_{p=1}^{P} (1-VC_{pt})ICC + \sum_{t=1}^{T}\sum_{p=1}^{P} (1-VD_{pt})ICD + \sum_{t=1}^{T}\sum_{a=1}^{A} (1-VR_{at})ICR \end{array} \right\} \tag{38}$$

This equation reflects the total manufacturing cost that consists of the cost of virgin product and the cost incurred in retrieving potential product/parts from EOL products. The first term shows the cost associated with the purchase of virgin parts to fulfill the customer demand in a time period; the second term considers the cost of collecting the end-of-use product from the final users. The collection cost of a product depends on its type and geographical region from which it was collected and aggregated on return rate ‘r’ of EOL. The third term stands for the cost charged for cleaning or repairing operations of all directly reusable products sorted out at the collection centre. The next three terms consider operating costs of the disassembly, disposal, and refurbishing centers respectively. The operations like landfill of uneconomical and hazardous parts at a disposal centre, breaking of joints to recover reusable parts at a disassembly centre, and repainting of potential parts at a refurbishing centre correspond to operation costs. The seventh, eighth, and ninth terms represent the set-up costs of collection, disassembly, and refurbishing echelons. The last three terms indicate the idle cost of reverse facilities.

The second term in (1), J_{time} represents the operational time cost and is defined as:

$$J_{time} = \sum_{e=1}^{E}\sum_{t=1}^{T}\sum_{p,a=1}^{P,A}\left\{\begin{array}{l}(UT_{e,p/a}\cdot NU_{et})+(RT_{e,p/a}\cdot NR_{et})+(AT_{e,p/a}\cdot NA_{et})\\+(LT_{e,p/a}\cdot NL_{et})+(PT_{e,p/a}\cdot NA_{et})\end{array}\right\} \quad (39)$$

This term counts the time involved in warehouse operations viz. inbound moves (Unloading, Receiving, and Put-away) and outbound moves (Picking and Loading) at echelons; collection, disassembly, and refurbishing centers. Note that the length of operational time depends on the number of items ready for movement between the two consecutive centers.

2.1.2. Normalization for Assimilation. Since the time and cost functions cannot be added directly, they are normalized in the range [0, 1]. The motive of normalization is to make them compatible with each other and to formulate a comprehensive objective function J. The normalized functions for J_{cost} and J_{time} can be defined as:

$$N\_J_{\cos t} = \frac{J_{\cos t} - LB_{\cos t}}{UB_{\cos t} - LB_{\cos t}} \quad (40)$$

$$N\_J_{time} = \frac{J_{time} - LB_{time}}{UB_{time} - LB_{time}} \quad (41)$$

Where, LB_{cost} and LB_{time} are the lower bounds of J_{cost} and J_{time} respectively, and UB_{cost} and UB_{time}, are the upper bounds.

Based on the normalized objective of cost and time J is reformulated as:

$$J = N\_J_{cost} \cdot W_C + N\_J_{time} \cdot W_t \tag{42}$$

W_C=Priority weight associated with cost objective.

W_t= Priority weight associated with time objective.

The weight priorities associated with integrated objectives are given by crisp values which are assessed by decision's maker based on relative importance of cost and time objectives. In case of more priority assigned to cost objective W_C is always greater than W_t and vice versa.

2.1.3. Constraints. The total number of parts of type 'a' obtained after disassembling the products at a disassembly centre at time period 't' depends on the Bill-Of-Materials (BOM) of the products type, is represented by equation 43.

$$DP_{at} = NDP_{pt} . \sum_{p=1}^{P} BOM_{pa}; \quad \forall a, p, t \tag{43}$$

The total disassembled parts of type 'a' at time period 't' are further sorted into disposal and refurbished parts at the disassembly centre, is represented by equation 44.

$$DP_{at} = NH_{at} + NR_{at} \quad \forall a, t \tag{44}$$

The maximum inventory level of product can be equal to the upper capacity limit of the collection centre. Thus the sum of total number of sorted for disassembling and direct reusable purpose is equal to the processing capacity of collection centre of product type ‘p’ at time period ‘t’.

$$NDP_{pt} + RP_{p}.r.S_{pt} = PCC_{p}; \quad \forall p,t \tag{45}$$

The maximum inventory level of product can be equal to the upper capacity limit of the disassembly centre:

$$NDP_{pt} = PCD_{p}; \quad \forall p,t \tag{46}$$

The maximum inventory level of parts of type ‘a’ at time-period ‘t’ can be equal to the upper capacity limit of the refurbishing centre:

$$NR_{at} = PCR_{a}; \quad \forall a,t \tag{47}$$

The numbers of product ‘p’/part ‘a’ received at echelon ‘e’ in time period ‘t’ have to be satisfy set-up constraint of different echelons. Here, *M* is a large predetermined positive number.

$$NR_{at} \le M.VR_{at}; \quad \forall a,t \tag{48}$$

$$NDP_{pt} \le M.VD_{pt}; \quad \forall p,t \tag{49}$$

$$RR_{p}.r.S_{pt} \le M.VC_{pt}; \quad \forall p,t \tag{50}$$

A parameter referring to the lower bond of disposal rate of part type ‘a’ is set to DRa in time period ‘t’ that instruct that a fraction of disassembled parts are assumed to be hazardous for that time period ‘t’. Thus, for the whole time horizon it is expressed as:

$$\sum_{t=1}^{T} NH_{at} \le DR_{a}.\sum_{t=1}^{T} DP_{at}; \quad \forall a,t \tag{51}$$

Non-negativity and binary constraints are represented by equation 52 and 53 respectively:

$$S_{pt}, DR_a, DP_{at}, NDP_{pt}, NR_{at}, NP_{at} \geq 0; \forall a, p, t \tag{52}$$

$$VR_{at}, VD_{pt}, VC_{pt} \in \{0,1\}; \quad \forall a, p, t \tag{53}$$

Table 2: Benefits from Implementing RFID Technology

Inbound Moves	
	Benefits
Unloading	• Reduction in waiting time before unloading • Increased visibility of incoming product • Real time monitoring and control • Automated services
Receiving	• Pallet labels cost • Manpower cost for labeling of pallets • Manpower cost for checking of received pallets and updating the information to control room • Manpower cost for amending data errors
Put Away	• Manpower cost for paper works • Cost of shrinkage; misplacement, spoilage, shoplifting, and organized shop floor crime • Manpower cost for general and replacement inventory counts • Manpower cost to identify pallets and locations and update the information to control room.
	Outbound Moves
Picking and Sorting	• Optimal picking routes • Reduction in bin location exception management • Cost of pallets labels • Manpower cost for amending data errors • Manpower cost to identify pallets and locations and update the information to control room. • Cost of shrinkage of picking inventory
Loading	• Improvement in loading time • Reduction in waiting time before loading • Increased data accuracy and reduction of errors in counting

2.2. RFID INTEGRATED REVERSE LOGISTICS MODEL

RFID system is a wireless technology which enables auto-identification (auto-ID) and traceability of items by transmitting radio waves between an RFID tag and a reader. A tag, which contains a microchip that stores the data, is attached on objects and broadcasts part data such as: manufacturing site, production lot, date of manufacture, expiry date, product and component type, etc. The reader receives this information and converts it into digital data to a computer system. The capability to obtain real-time information about the location and properties of tagged objects influenced various industries to deploy the RFID tool for enhancing the efficiency of their logistics processes. A large number of forward logistics players such as Wal-Mart, The U.S. Defense Department, Metro groups, and Tesco utilize RFID technology and are high profit examples. In reverse logistics, the adaptation of RFID has not been studied much; however, there is significant opportunity in the use of this process to improve operational efficiencies which is being considered in this study. The diffusion of RFID technology at reverse echelons (collection, disassembly, and refurbishing centers) enables increased inbound and outbound operational efficiency through auto-counting and precise instructions. The information and physical flow of the EOL items are presented in figure 1. Moreover, Table 2 summarizes advantages of an RFID system in warehouse operations over traditional processes.

Based on the information provided in Table 2 the cost and time objective for the RFID adopted reverse logistics model, $J_{\cos t}^{RFID}$ and J_{time}^{RFID} is defined as:

$$J_{\cos t}^{RFID} = \left(\begin{array}{l} OBJ_{\cos t} + SP_{RFID}^{C} + SP_{RFID}^{D} + SP_{RFID}^{R} \\ +Tag_{\cos t} \sum_{t=1}^{T} \left(\sum_{p=1}^{P} (r.S_{pt} + (1-RR_p).r.S_{pt}.\sum_{a=1}^{A} DP_{at}) \right) \end{array} \right) \tag{55}$$

Here, cost factors SP_{RFID}^{C}, SP_{RFID}^{D}, and SP_{RFID}^{R} are the RFID set-up costs at collection, disassembly, and refurbishing centers respectively. Excluding tag cost ($Tag_{\cos t}$), the

RFID set-up cost associates all hardware and software costs defined in Section 4. The model equally imposes the RFID set-up cost to all '*T*' time scenarios. The last term of the equation represents the cost involved in pasting RFID-tags onto all optimally assigned products at collection centers and to the parts at disassembly centers after being disassembled. The RFID tagging is not required at the refurbishing centre as they were already tagged at disassembly centre.

Now,

$$J_{time}^{RFID} = \left\{ \sum_{e=1}^{E} \sum_{t=1}^{T} \sum_{p,a=1}^{P,A} ((UT'_{e,p/a} .NU_{et}) + (RT'_{e,p/a} .NR_{et}) + (AT'_{e,p/a} .NA_{et}) + (LT'_{e,p/a} .NL_{et}) + (PT'_{e,p/a} .NP_{et})) \right\} \quad (56)$$

The J_{time}^{RFID} equation calibrates time involved in inbound and outbound moves of warehouse operations. The expressions used in Equation (56) are described below.

$$UT'_{e,p/a} = UT_{e,p/a} \cdot (1 - EUT_{e,p/a}); \qquad \forall\, a,\ e,\ p \quad (57)$$

$$RT'_{e,p/a} = RT_{e,p/a} \cdot (1 - ERT_{e,p/a}); \qquad \forall\, a,\ e,\ p \quad (58)$$

$$AT'_{e,p/a} = AT_{e,p/a} \cdot (1 - EAT_{e,p/a}); \qquad \forall\, a,\ e,\ p \quad (59)$$

$$LT'_{e,p/a} = LT_{e,p/a} \cdot (1 - ELT_{e,p/a}); \qquad \forall\, a,\ e,\ p \quad (60)$$

$$PT'_{e,p/a} = PT_{e,p/a} \cdot (1 - EPT_{e,p/a}); \qquad \forall\, a,\ e,\ p \quad (61)$$

Again, in order to formulate a compatible overall objective function, (J^{RFID}), $J_{\cos t}^{RFID}$ and J_{time}^{RFID} are normalized in the range of 0 to 1.

$$N\_J_{\cos t}^{RFID} = \frac{J_{cost}^{RFID} - LB_{\cos t}^{RFID}}{UB_{\cos t}^{RFID} - LB_{\cos t}^{RFID}} \quad (62)$$

$$N\_J_{time}^{RFID} = \frac{J_{time}^{RFID} - LB_{time}^{RFID}}{UB_{time}^{RFID} - LB_{time}^{RFID}} \tag{63}$$

where $LB_{\cos t}^{RFID}$ and LB_{time}^{RFID} are the lower bounds of $J_{\cos t}^{RFID}$ and J_{time}^{RFID}, and $UB_{\cos t}^{RFID}$ and UB_{time}^{RFID} are the upper bounds.

Thus, the aim of this research is to

$$Min\ (J^{RFID}) \tag{64}$$

where $J^{RFID} = N\_J_{cost}^{RFID} \cdot W_C^{RFID} + N\_J_{time}^{RFID} \cdot W_t^{RFID}$

W_C^{RFID}=Priority factor associated with cost objective.

W_t^{RFID}= Priority factor associated with time objective.

2.2.1. Constraints. Apart from Constrains 7 to 17, a non-negativity constraint 65 which cannot exceed the value of one numerically is assumed in this study. That is,

$$EUT_{e,p/a}, ERT_{e,p/a}, EAT_{e,p/a}, ELT_{e,p/a}, EPT_{e,p/a} \in [0,1]; \quad \forall a, e, p \tag{65}$$

3. SOLUTION METHODOLOGY

The determination of an optimal solution in the reverse logistics problems is a computationally complex process since it requires vast exploration and exploitation of search space. Since this problem is NP-hard, artificial intelligence-based random search techniques have gained favor in this area of research (Kim et al., 2008). Inspired by successful applications of the Artificial Bee Colony meta-heuristic over a closed loop logistics model by Kumar et al. (2010), an improved version of Artificial Bee Colony (ABC) algorithm, known as Chaos-based Interactive Artificial Bee Colony (CI-ABC) algorithm, is used in this study. The following subsections present the proposed methodology in brief.

3.1. AN OVERVIEW OF ARTIFICIAL BEE COLONY

The ABC algorithm is a recently developed (Karaboga, 2005) swarm intelligence technique based on the natural food searching behavior of bees. In a D-dimensional search space, each solution (S_{xy}) is represented as;

$$S_{xy} = \{S_{x1}, S_{x2}, \ldots, S_{xD}\} \quad (66)$$

Here, x = 1,…, SP is the index for solutions of a population and y = 1,.., D is the optimization parameters index.

The probability value which is based on the individuals’ fitness value to summation of fitness values of all food sources and decides whether a particular food source has potential to get status of a new food source is determined as;

$$P_g = f_g / \sum f_g \quad (67)$$

Where, f_g and P_g are the fitness and probability of the food source ‘g’ respectively.

After sharing the nectar information between the existing onlookers and employed bees, in case of higher fitness than that of the previous one, the position of the new food source is calculated as following:

$$V_{xy}(n+1) = S_{xy}(n) + [\varphi_n \times (S_{xy}(n) - S_{zy}(n))] \tag{68}$$

where z =1, 2,.., SP is a randomly selected index and has to be different from *x*. $S_{xy}(n)$ is the food source position at n^th^ iteration, whereas $V_{xy}(n+1)$ is its modified position in $(n+1)^{th}$ iteration. φ_n is a random number in the range of [-1, 1]. The parameter S_{xy} is set to meet the acceptable value and is modified as;

$$S_{xy} = S^{y}_{\min} + ran(0,1)(S^{y}_{\max} - S^{y}_{\min}) \tag{69}$$

In this equation, $S^{y}_{\max}$ and $S^{y}_{\min}$ are the maximum and minimum y^{th} parameter values.

Although the employed and scout bees nicely exploit and explore the solution space, the original design of the onlooker bee's movement only considers the relation between the employed bee food source, which is decided by the roulette wheel selection, and a food source having been selected randomly (Tsai *et al.*, 2009). This consideration reduces the exploration capacity and thus induces premature convergence. In addition, the position updating factor utilizes a random number generator which shows a tendency to generate a higher order bit more random than a lower order bit (Kumar *et al.*, 2010).

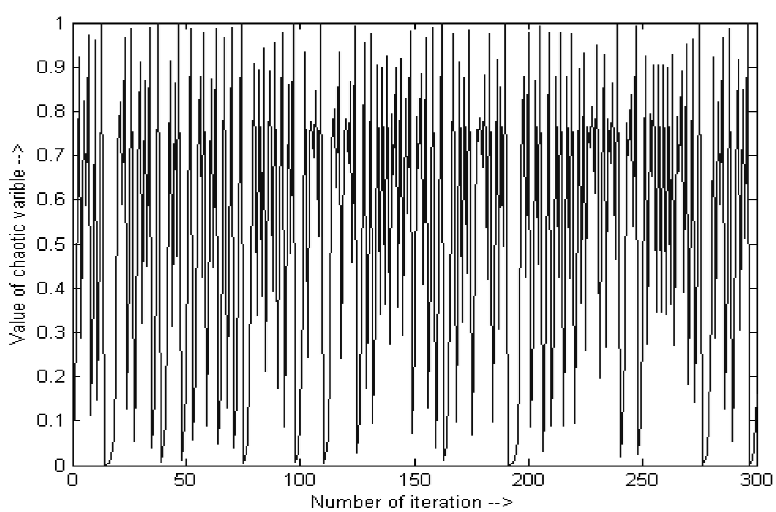

Figure 2: Logistic mapping

3.2. CHAOS-BASED INTERACTIVE ARTIFICIAL BEE COLONY LGORITHM

In order to avoid the aforesaid shortcomings and enhance the searching capacity of the canonical form of the ABC, a new variant called the Chaos-based Interactive Artificial Bee Colony (CI-ABC) algorithm, has been proposed. This algorithm is described next.

3.2.1. Basic of Chaotic Systems. A non-linear system is said to be chaotic if its evolution is very sensitive to the initial conditions and has an infinite number of different periodic responses (Yuan et al., 2002). The ability to generate unbiased random numbers increases the use of chaotic sequences over random number generators in recent years. There are considerable numbers of chaotic operators possessing ergodic and stochastic properties and are reported in literature (Luo and Shen, 2000; Yang and Chen, 2002). In this paper, a "Logistics" (Parker and Chua, 1989) chaotic system is used to replace the random function in the equation (70), which is formulated as:

$$C_{n+1} = \lambda . C_n (1 - C_n); \; C_n \in (0, 1); \quad n = 1, \ldots, N \tag{70}$$

where C_n is the value of the chaotic variable at nth iteration and λ is the bifurcation parameter of the system. Figure 2 shows the chaotic graph of the logistic map. This graph has been plotted for 300 iterations with initial values of $C_0 = 0.01$ and $\lambda = 4$.

3.2.2. Proposed CI-ABC. In order to enhance the exploration capacity of foraging bees, the equation for updating new position (equation 68) has been modified by adding a new factor which incorporates more perturbation on the food source position S_{xy}.

The concepts can be mathematically represented as;

$$V_{xy}(n+1) = S_{xy}(n) + [C_n \times (S_{xy}(n) - S_{zy}(n)) + C_n \times (S_{xy}(n) - S_{wy}(n))] \tag{71}$$

where $C_n \in [-1, 1]$ stands for the chaotic value obtained from equation (70) at nth iteration. $w \in \{1,...,W\}$,

where $C_n \in [-1, 1]$ stands for the chaotic value obtained from equation (70) at nth iteration. $w \in \{1,...,W\}$, an index refers to the bee having the largest nectar amount. It is the best global position found by any employed bee so far. The index w may be to x or z, depending on whether the x or z index referred bees achieved best position in the population.

The newly added term brings diversification in the search and facilitates each bee to interact with a higher number of neighborhoods. Another advantage of this term is to help get better convergence toward the goal of the bees. For easy comprehension, a flow chat of the proposed algorithm (CI-ABC) has been detailed in Figure 3.

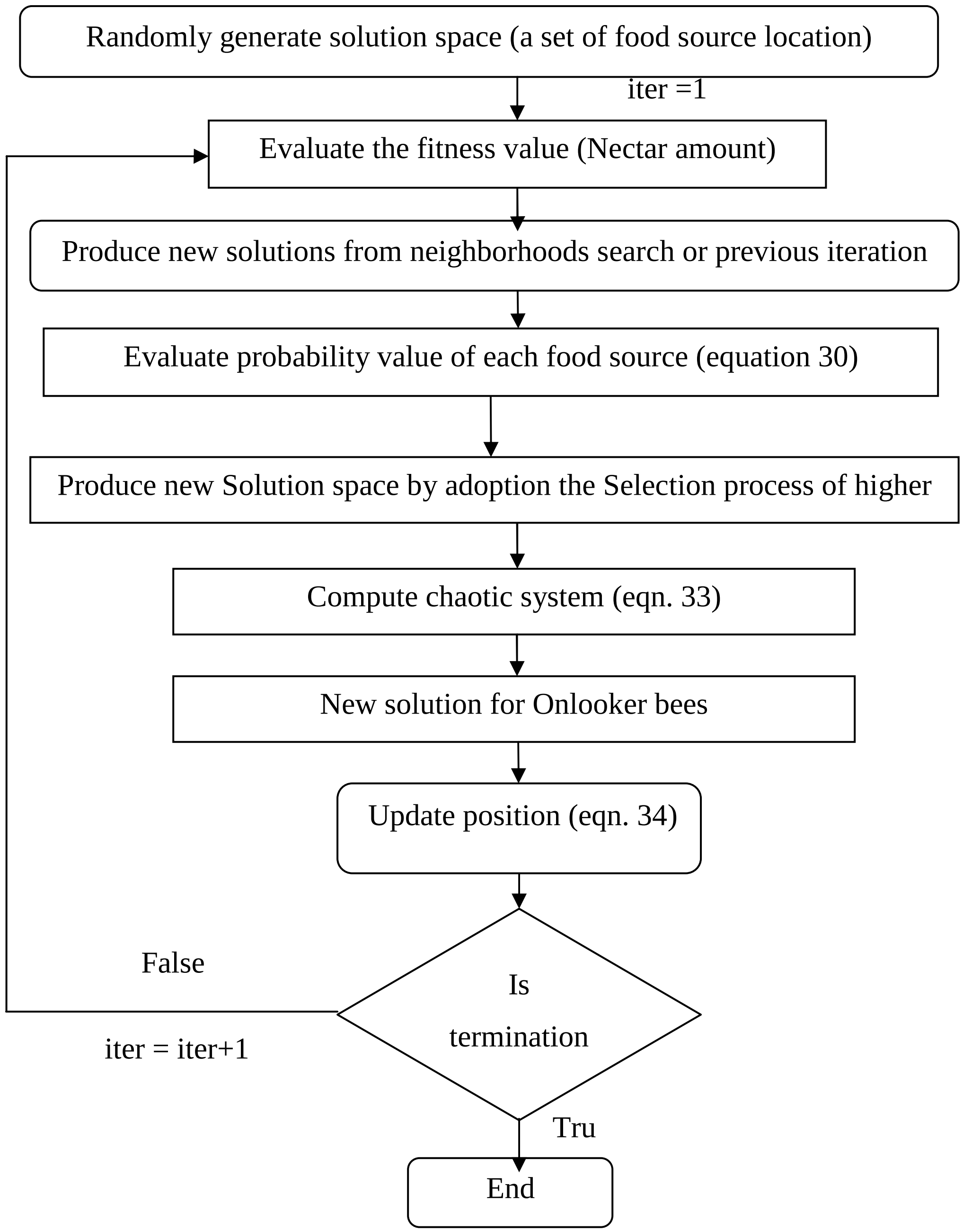

Figure 3: Flowchart of the proposed CI-ABC algorithm

4. ILLUSTRATIVE EXAMPLES

This section presents a numerical example to check the efficacy and scalability of the proposed algorithm. The dimension of the test cases has been varied irregularly with a view to show flexibility in an underlying model. The planning horizon for demand and supply of products considered is taken in six time periods (T=6). Table 3 summarizes the numbers of product that are to be manufactured according to their own production plan under 6 time periods. The test beds conceived in this paper have to manufacture 8 different numbers of product-types. Table 4 shows Bill-Of-Material (BOM) of each product by which part-types are assembled to a product. The BOM can have a maximum of 9 different part-types for each individual product.

The unit purchasing cost from external supplies is set to be 20, 25, 22, 32, 25, 33, 68, 25, and 35 dollars for part-type 1 to 9 respectively. Furthermore, the idle costs of the echelons; collection, disassembly, and refurbishing centers are fixed at 2900, 2500, and 2700 dollars respectively.

The return rate '*r*' is limited by the environmental factors which have a maximum of 0.90 for any scenario. The test case set an upper fraction of EOL products going to be directly reusable is 0.25 (DR_p= 0.25; $\forall$ 'p') and the lower bound for the disposal rate for all part types in each time period is 0.30 (RR_p= 0.30; $\forall$ 'p'). The set-up costs for each product/Part-type are set as: collection centre (SCC_p=\$0.2; $\forall$ 'p'), disassembly centre (SCD_p=\$0.4; $\forall$ 'p'), and refurbishing centre (SCR_a=\$0.25; $\forall$ 'a'). Furthermore, the upper limit of product-types and part-types to be operated at three centers is listed in table 5. Table 6 summarizes the operating costs on these echelons. Owing to integrity with time objectives of the paper, the parameters related to implementing RFID at different reverse logistics echelons are outlined in Table 7. The costs of RFID adoption encompass hardware and software costs. For the RFID-hardware set-up, different technical devices such as tags, RFID mobile reader, shock-proof shielding gates, and RFID printer are taken into account. Unitary costs have been derived from Bottani and Rizzi (2008) and are listed in Table 8. The proposed procedure is used in conjunction with the above data on different cases.

The next section describes the numerical results from the proposed CI-ABC on the reverse logistics problems.

Table 3: Manufacturing Plan of Product in Different Scenarios

	p=1	p=2	p=3	p=4	p=5	p=6	p=7	p=8
t=1	13759	13823	16702	12271	8721	13023	3289	9917
t=2	14562	12026	11011	16388	11902	10060	8871	8794
t=3	8401	5988	9429	9832	9862	4821	14024	14290
t=4	12452	14200	7793	11012	2291	6428	11191	12375
t=5	9372	13063	10503	2310	13027	5826	7728	9943
t=6	10067	8823	12985	8621	14738	12221	7998	10727

Table 4: BOM; Number of Part-Types for Assembling

	p=1	p=2	p=3	p=4	p=5	p=6	p=7	p=8
a=1	5	1	10	4	5	3	6	3
a=2	6	0	0	6	3	9	6	6
a=3	1	10	0	2	4	5	3	7
a=4	4	2	9	8	9	8	8	2
a=5	6	8	9	10	7	8	10	7
a=6	9	8	4	1	3	2	7	8
a=7	2	6	8	6	6	9	2	9
a=8	0	9	9	2	0	7	6	3
a=9	7	3	0	6	8	4	6	8

Table 5: Processing Capacity of Reverse Echelons

Product-type(p)/Part-type (a)	1	2	3	4	5	6	7	8	9
Collection Centre (PCC_p)	15000	15000	15000	15000	15000	15000	15000	15000	
Disassembly Centre (PCD_p)	10000	8500	9000	7000	7500	7500	8000	8000	
Refurbishing Centre (PCR_a)	195000	178000	169000	177000	187000	157500	105000	105000	181000

Table 6: Operating Costs of Product-Types and Part-Types at Reverse Echelons (in $)

Product-type(p)/Part-type (a)	1	2	3	4	5	6	7	8	9
Collection cost (CC_p)	7	7	11	8	6	3	5	7	
Cleaning (OCR_p)	3.0	1.5	1.5	3.5	4.5	1.5	1.2	2.5	
Disassembling (OCD_p)	2.0	0.5	0.75	1.5	1.8	2.2	3.2	0.75	
Refurbishing (OCR_a)	1.4	0.75	0.3	0.75	0.9	1.2	2.5	1.8	0.75

Table 7: Inbound and Outbound Moves Time for Product and Part-Types (in Min.)

	Unloading ($UT_{e,p/a}$)	Retrieving ($RT_{e,p/a}$)	Put-away ($AT_{e,p/a}$)	Loading ($LT_{e,p/a}$)	Picking ($PT_{e,p/a}$)
Processing time	2.2	1.5	1.8	2.5	1.75
Percentage efficiency increment after adopting RFID					
	$EUT_{e,p/a}$	$ERT_{e,p/a}$	$EAT_{e,p/a}$	$ELT_{e,p/a}$	$EPT_{e,p/a}$
% increment	0.75	0.75	0.50	0.85	0.65

Table 8: Costs of RFID Equipment (1€=1.3$)

Hardware and software equipment	Costs (€)
RFID tag (€/tag)	0.15
label (€/label)	0.035
Printer of logistics (€/time period)	400.00
RFID reader (€/time period)	300.00
RFID gate (€/time period)	425.00
Equipments of a RFID truck (€/time period)	800.00
Software and implementation projects (€/time period)	30,000.00

5. RESULTS AND DISCUSSION

This section is devoted to report and analyze the effect of different values of CI-ABC approach parameters on its performance. In order to check the efficacy of the proposed algorithm, canonical ABC and PSO algorithms are also tested on the illustrative example. The algorithms have been coded in C++ and executed on an Intel® core™ i5 CPU M @ 2.4 GHz and 4GB of RAM.

5.1. PARAMETERS SETTINGS

Extensive experimental tests were carried out to see the effect of different values of the parameters on the performance of all three algorithms. The population size has been varied in the range of 10-100 in steps of 10, and it was observed that the CI-ABC algorithm obtains best results with a population size of 70. It was also observed that although lesser population size reduces the computational time, it fails to achieve an optimal solution, and vice versa, in the case of higher population size. Thus, the population size of 60 was facilitated to obtain optimal solutions in a reasonable computational time. Similarly, the parameters value that assisted in finding optimal or near optimal solutions in case of PSO, and ABC, are presented in Table 9.

For the evaluation of the objective function, experiments have been performed for 50 runs, and the lower and upper bounds of set cost and time objectives are calculated. Since the operation time changes with varied integration of RFID technology to reverse logistics, the cost and time limits for each case comes out to be different, as shown in table 10.

Table 9: Optimal Tuning Parameters

Parameters	PSO	ABC	CI-ABC
Random number generator	[0, 1]	[-1,1]	Logistics system
Size of solution space	40	60	60
Acceleration coefficients	2.0	-	-
Chaotic parameter (λ)	-	3.0	3.0

Table 10: Lower and Upper Bounds of Cost and Time Objectives

Upper bounds		Lower bounds	
UB_{cost}	$2.89*10^{19}$	LB_{cost}	$7.83*10^{8}$
UB_{time}	$1.07*10^{7}$	LB_{time}	$8.41*10^{4}$
UB^{RFID}_{cost}	$6.98*10^{25}$	LB^{RFID}_{cost}	$5.19*10^{10}$
UB^{RFID}_{time}	$4.48*10^{4}$	LB^{RFID}_{time}	$9.12*10^{2}$

5.2. THE ENCODING SCHEMA

Integer coding is followed for the string representation so that each echelon and external supplies centre is assigned the value of a unique positive integer. A set of solution candidates equal to the number of the employed bees are generated. Each string segment denotes an individual reverse facility centre (collection, disassembly, refurbishing, and disposal) and external supplier. In order to assign the value of return rate in different scenarios, a separate string is followed which comprises integer values. For example, in the following 5-tuple string representation, <213; 189; 985; 24; 94>, integers represents the number of products/parts assigned to collection, disassembly, refurbishing, disposal, and external supplier centre in a certain time period respectively.

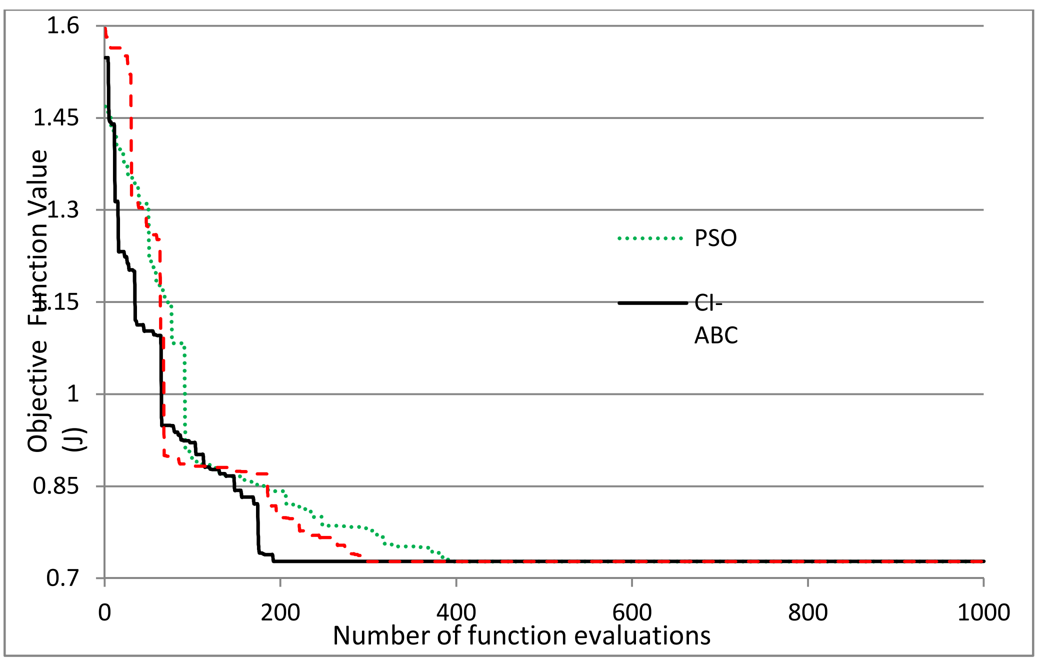

Figure 4: Solution Convergence Rate

5.3. PERFORMANCE COMPARISON

The proposed algorithm has been applied to the illustrative example underlined in the previous section. Equal priority has been assigned to both time and cost objectives. First, the results obtained from the basic reverse logistics model (equation 42) are given in Table 11. Also, for an easy appraisal, normality values of time (N_J_{time}) and cost (N_J_{cost}) have been outlined in Table 11. On the basis of the results marked in Table 11, it is evident that, although CI-ABC produced the same quantitative results as ABC and PSO, it significantly outperforms the both when compared in terms of computational time and the number of function evaluation. In front of 192th function evaluation for the CI-ABC, PSO terminates at 398th. Figure 4 illustrates the convergence rate of solution with the number of function evaluations when algorithms are applied in the illustrated example. The following inference can be drawn from Figure 4: CI-ABC has the fastest convergence rate. However, PSO terminates better than CI-ABC in the middle, but with the increase in number of iterations, its convergence rate becomes almost constant.CI-ABC and ABC both initially converge with the same rate, and CI-ABC, in the long run, yields better solutions over others.

Table 11: Results on Reverse Logistics Model

	PSO	ABC	CI-ABC
Objective function value (J)	0.7275	0.7275	0.7275
Normalized Cost (N_J_{cost})	0.4013	0.3822	0.3778
Normalized Time (N_J_{time})	0.3262	0.3253	0.3507

Table 12: The Number of Product to Go to Direct Reuse

	p=1	p=2	p=3	p=4	p=5	p=6	p=7	p=8
t=1	972	1238	1337	627	126	1526	1521	1087
t=2	1091	1224	1421	771	273	1421	1471	1201
t=3	1273	1379	1554	509	93	979	1009	997
t=4	928	1127	1328	512	145	1437	1406	1213
t=5	975	1325	1378	476	76	1584	1213	1203
t=6	1013	1243	1287	518	205	1174	1313	1078

In the process of getting the optimal objective value, the assigned numbers of parts/products to reverse facility centers are listed in Tables 12-14. Table 12 represents the reusable product to go to the manufacturer directly after minor cleaning operation. Table 13 summarizes the product quantities needed to disassemble for sorting into recoverable and disposable parts. Furthermore, the rest of the required parts purchased from external suppliers to fulfill the customer's demands are listed in Table 14.

Table 13: The Number of Disassembled Product

	p=1	p=2	p=3	p=4	p=5	p=6	p=7	p=8
t=1	6224	8031	1016	6127	5221	7117	1101	6124
t=2	7079	8500	7723	6724	7334	6101	4017	5778
t=3	5441	7023	5747	5981	5281	2814	4121	6908
t=4	8108	6092	5391	6123	1019	3421	3789	7001
t=5	7719	8500	5378	1223	7493	3871	2121	6193
t=6	6873	7179	7273	5211	7197	6884	2298	6276

Table 14: The Number of Parts to be Purchased from External Supplies

	a=1	a=2	a=3	a=4	a=5	a=6	a=7	a=8	a=9
t=1	12223	10270	7521	6541	4215	4216	103	4013	1267
t=2	13107	11177	8795	5719	5073	5217	219	4271	1547
t=3	9287	9271	6281	5929	4587	4791	3	5978	1987
t=4	10018	8439	6547	5786	4991	6289	0	4774	678
t=5	9129	88271	5489	6020	5298	5665	78	1719	910
t=6	1174	7541	5545	5627	5303	5217	21	2191	1103

5.4. IMPACT OF RFID TECHNOLOGY

In order to analyze the impact of RFID diffusion in reverse echelons, the proposed algorithm is implemented on the RFID integrated reverse logistics model (equation 64). In contrast to the objective value (0.7275) of the basic reverse logistics model, the minimal objective value is evaluated by the CI-ABC as 0.7859. The figure reveals that the RFID-enabled scenario is uneconomical under the given data in Section 4. The result, however, reflects improvement in operational time performance by reducing the time objective by 53.3 %; it increases the overall cost objective by 34.6%. The "hiking in cost" objective is primarily due to huge investments in software and hardware equipment at different echelons of reverse logistics. Consequently, the cost of RFID tags put heavy economical load in tagging the returned parts/product. It can be concluded that, €0.15/unit tag is still too high to enable the diffusion of RFID in reverse logistics. Nevertheless, such costs are widely compensated by time saving in inbound and outbound moves. The benefit of time saving in unloading, receiving, put-away, picking, and loading operations are achieved from a dramatic shortening of time required to perform replenishment cycle and inventory counts.

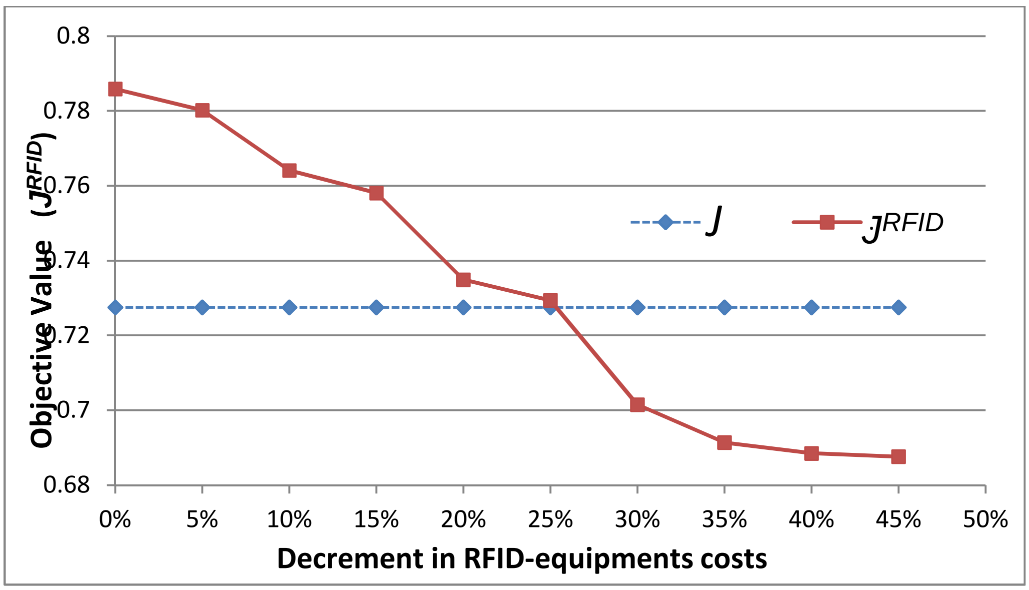

Figure 5: Sensitivity Analysis of the RFID-Equipments

The above finding of RFID-based reverse logistics model depended on a number of parameters that we assumed to be constant in the illustrative example. However, in corporate reality, the different quality of RFID hardware and software that is utilized, significantly affects the installation cost of RFID technology in reverse logistics. For this reason, sensitivity analysis is performed for RFID equipments, capacity of reverse echelons, and the parameter related to chaotic generator.

5.4.1. RFID Equipment Costs. It can be examined from the objective values of basic reverse logistics model and RFID-based reverse logistics model, that the latter is uneconomical due to the high cost of adoption of an RFID project. At present, the cost of RFID implementation comprises the major investment in hardware, application software, middleware, tags, and the cost of integrating the RFID system with the legacy systems. Tag costs represent a major cost factor as they have to be supplied in high quantities. In market, the costs of these tags vary significantly which refer bulk or small orders of tags purchased. As the research aim is to utilize high quantities of tags at collection, disassembly, and refurbishing centers, an analysis is performed by varying the investment cost of all hardware and software defined in Table 8 for the successful diffusion of RFID technology. Since the tags are utilized in high quantities, we investigate the impact of RFID equipment at two different stages. Firstly, excluding the tags, Figure 5 gives the sensitivity of all hardware and software costs an objective value. Furthermore, the impact of RFID tags is depicted in Figure 6.

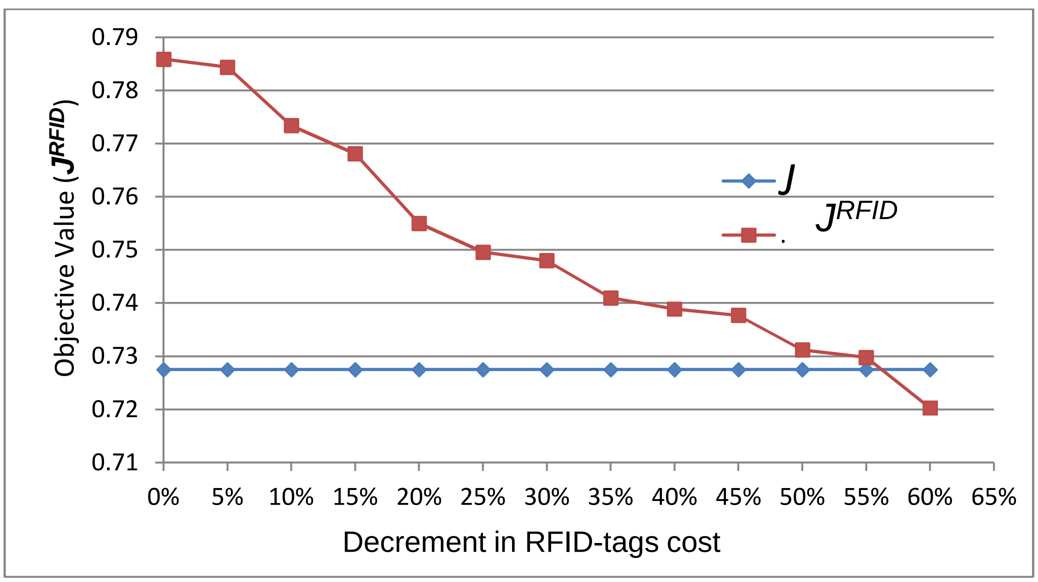

Figure 6: Sensitivity Analysis of the RFID-Tags

As expected, Figures 5 and 6 shows that the price depreciation of RFID hardware and software creates great influence on remanufacturing. Though the implementation of RFID technology is uneconomical at present equipment prices, it will create a favorable environment for remanufacturers in the near future. It is easily noticed from the figures that a 55 % decrement tag's price and a 25% decrement in other RFID equipment, produce same the objective of the basic reverse logistics model. In this scenario, the hike in objective value arises due to RFID-equipment costs is easily compensated by the operational time reduced after RFID installation.

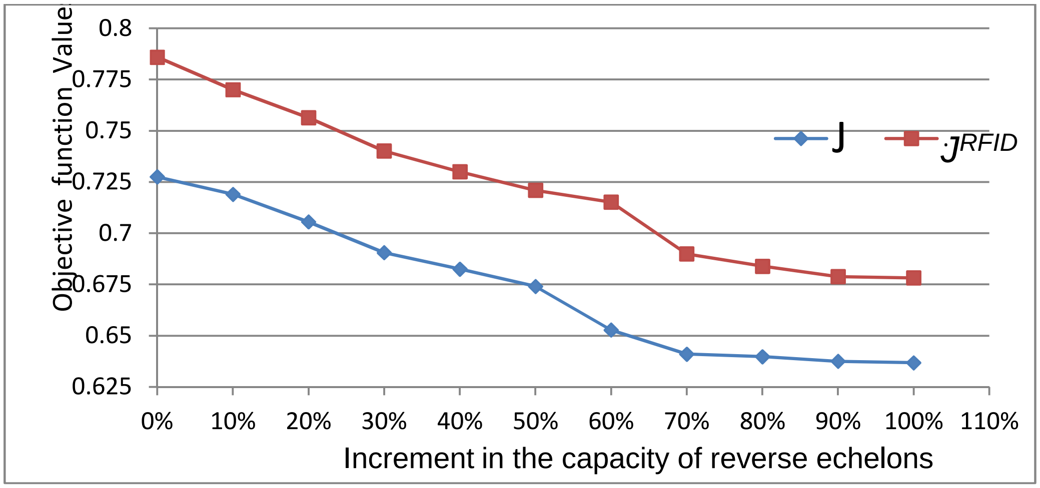

Figure 7: Sensitivity Analysis of the Reverse Echelons Capacity

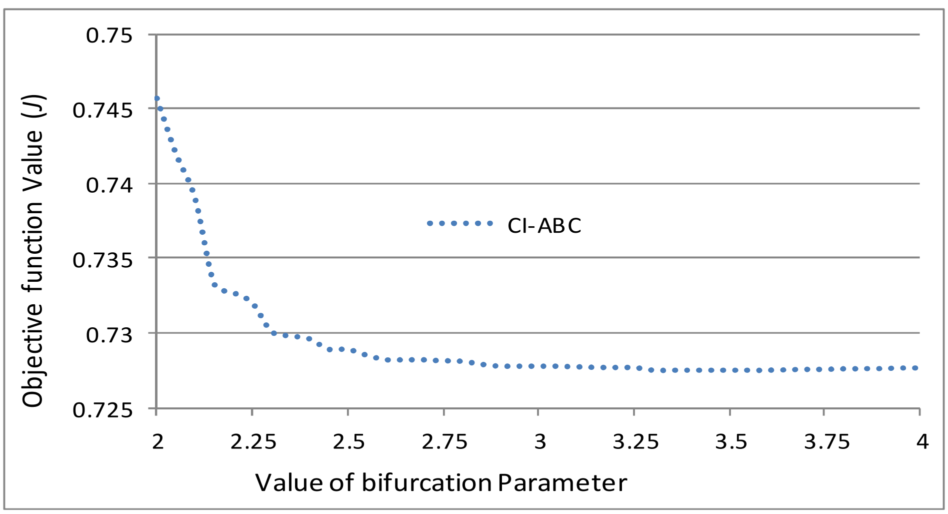

Figure 8: Impact of Bifurcation Parameter on Objective Value

5.4.2. Capacity of Reverse Echelons. The successful implementation of any new technology relies on how effectively it is utilized by the system on which it is applied. In this research, the adoption of RFID has been proposed at reverse echelons that encompass RFID equipment, such as tags, readers, fixed and mobile devices, and related software. As mentioned above, the RFID tags only variable parameter is a quantity that depends on the optimal assignment of parts/products to the echelons. Thus, the capacity of reverse echelons is an important influential factor in the proposed model.

In order to investigate the effect of operational capacity over solution quality, the upper capacity limit of three echelons viz. collection, disassembly, and refurbishing centers varies by an even percentage amount. The result has been drawn in Figure 7.

From Figures 7, it is analyzed that the objective value decreases with the increscent in capacity up to a certain level. Above this level the value became constant and the manufacturer is not getting any additional profit for extension of the centers. Such a result reveals that RFID implementation is favorable at the centers having a very high capacity limit. In this case, only RFID tags put additional costs, while the other equipment costs are the same for the echelons having lower operational capacity.

5.5. EFFORT ANALYSIS FOR RFID ADOPTION

The variation in demand of a new product and the returning of a used one are considered on seasonal basis in six time-horizons (T=6). The duration of an individual time period can be assumed in an hour, day, or month depending on the flow of the products. However, the maximum limit of operating products on the reverse echelons is not only controlled by such consideration, but also by the capacity of the corresponding echelon. A centre can only allow the maximum number of products to be operated which is minimum from the maximum capacity limit and maximum flow of EOL products in a time period.

As the underlying model consists of cost and time objectives for different activities, a trade-off analysis of both is difficult to execute with the constraints discussed above. In order to examine a correlation, the inventory level defined in the equations 45, 46, and 47 are eliminated from the model. Moreover, the time periods are considered as order numbers (T=1 is order number 1 and so on), so that the product-types/ parts-type of any order can be operated just after the previous one. The result shows that the saving in time for in-bound and out-bound moves is 15.6%, 20.3%, 17.2%, 11.3%, 21.7%, and 15.3% for order numbers 1 to 6 respectively. Similarly, the extra burden on cost objectives are 8.6%, 7.7%, 8.1%, 11.3%, 6.8%, and 8.1%. A correlation that can be set from here is that the adoption of RFID technology is economically viable in the long run for remanufacturers. Since there is no inventory limit at the echelons, a sufficient number of refurbished products/parts are ready for re-use at low cost, which will reduce the burden on new parts from the external supplier.

5.6. IMPACT OF CHAOS PARAMETER LAMBDA (λ) ON THE SOLUTION

In the proposed CI-ABC, the bifurcation parameter λ is used with the numerical value 3.5 to generate chaotic variables using equation (70). The computational experiments are performed by varying the value of λ between 2 and 4 in Figure 8, and establishing that the solution quality increases with the increase in the value of λ. It can also be seen from Figure 8 that, as λ attains value of 3, this comes in the region of the chaotic regime. Actually, this is the location of the first bifurcation and the logistic equation becomes super stable at this point. As the growth rate exceeds 4, all orbits zoom to infinity and the modeling aspects of this function become useless. Hence, this is the reason why the value of λ stops at 4 and for this value the chaotic system performs best.

5.7. LIMITATION OF PROPOSED CI-ABC

The following aspects are relevant to the performance of the algorithm.

1. Problem implementation: A decision maker is required only to evaluate the generated seed solutions and compare the estimated objective values. Thus, the cognitive load is not very arduous and it is not too complex to use CI-ABC in solving real problems. However, evaluation of the generated solutions and determining their preference values is a key issue.

2. Parameter effect: The algorithm moves towards the global best position by adjusting the trajectory of each bee towards its own best position and the nectars' best position. The determination of the employed and unemployed (Onlooker, and Scout)

bees and probability function are critical factors. Also, the chaotic function requires careful estimation.

3. Convergence: The decision maker’s preference model guides the search to explore the discrete Pareto front of seed solutions. Albeit, the algorithm performed very well to converge to the near optimal solutions. In each of the cases that use Linear value, Quadratic value, L-4 metric value, and the Tchebycheff value functions the percentage scaled deviation remains about 1 % to 2%.

6. CONCLUSION AND FUTURE REMARKS

Implementing RFID technology in remanufacturing is primly concerns to abandonment of outdated recovery processes. It can contribute to real-time quality information and increased efficiency in reverse logistics. Through this research, the authors have demonstrated that the RFID technology can effectively improve inventory control, operational efficiency, and data visibility at reverse echelons, i.e., at collection, disassembly, and refurbishing centres. However, the present price of RFID equipment (hardware and software) is still one of the main cost factors when implementing RFID. We studied an illustrative example on a basic and a RFID-based reverse logistics model to quantitatively decide whether RFID technology is feasible and economically viable. In order to execute this task, the paper proposes a new variant of artificial bee colony algorithm, namely the Chaos-based Artificial Bee Colony (CI-ABC) approach. The analysis showed that the RFID-enabled scenario is uneconomical at present equipment prices but it has a potential to create a favorable environment for remanufacturers in the near future. For the comparative analysis of the proposed CI-ABC algorithm it was compared with ABC, and PSO algorithms, over a problem instances. The comparison shows that the proposed algorithm outperforms others in terms of computational time and rate of convergence.

The paper put forwards a number of future research directions for interested researchers. Future research can be aimed at: (i) Checking the improvement in process accuracy; (ii) Sensitivity analysis of various cost factors such as operational, disposal, and inspection can be considered; (iii) Application of the proposed model to a real remanufacturing corporation; and (iv) Utilizing the multi-objective techniques for solving the problems.

7. BIBLIOGRAPHY OF PAPER II

Blanc I. L., Krieken M. V., Krikke H., and Fleuren H., 2006, Vehicle routing concepts in the closed-loop container network of ARN a case study, OR Spectrum, 28, 53-71.

Bottani E., and Rizzi A., (2008), Economical assessment of the impact of RFID technology and EPC system on the fast-moving consumer goods supply chain, Int. J. Production Economics, 112, 548–569.

Bu X. and Xu S., 2008, The profit model in reverse logistics under the different environmental factors, IEEE Int. conference on service operations and logistics, Beijing, China, 1215-1220.

Charter M. and Gray C., 2008, Remanufacturing and product design. Int. J. Product Development, 6(3/4), 375-392.

Doh H-H and Lee D-H, 2010, Generic production planning model for remanufacturing systems. Proc. IMechE Part B: J. Engineering Manufacture, 224(1), 159-168.

Dowlatshahi S.. 2012, A framework for the role of warehousing in Reverse Logistics. International Journal of Production Research, 50(5), 1265–1277.

Franke C., Basdere B., Ciupek V., and Seliger S., 2006, Remanufacturing of mobile phones-capacity, program and facility adaptation planning. The international journal of management science, 34, 562 – 570.

Hong I H., Assavapokee T., Ammons J., Boelkins C., Gilliam K., Oudit D., Realff M. J., Vannícola J. M., and Wongthatsanekorn W., 2006, Planning the e-Scrap Reverse Production System Under Uncertainty in the State of Georgia: A Case Study. IEEE Transactions on Electronics Packaging Manufacturing, 29 (3).

Jayaraman V., 2006, Production planning for closed-loop supply chains with product recovery and reuse: an analytical approach. International Journal of Production Research, 44(5), 981–998.

Jung K. S., Hwang H.. 2011, Competition and cooperation in a remanufacturing system with take-back requirement. Journal of Intelligence Manufacturing, 22:427–433.

Karaboga D., 2005, An idea based on honey bee swarm for numerical optimization. Technical Report-TR06, Erciyes University, Engineering Faculty, Computer Engineering Department.

Karaboga D. and Basturk B., 2007, A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. J Glob Optim., 39, 459–471.

Kim M-C., Kim C. O., Hong S. R., Kwon I. H., 2008, Forward–backward analysis of RFID-enabled supply chain using fuzzy cognitive map and genetic algorithm, Expert Systems with Applications, 35, 1166–1176.

Ko H. J. and Evans G. W., 2007, A genetic algorithm-based heuristic for the dynamic integrated forward/reverse logistics network for 3PLs, Computers & Operations Research, 34 (2), 346–366.

Konstantaras I. and Papachristos S., 2007, Optimal policy and holding cost stability regions in a periodic review inventory system with manufacturing and remanufacturing options. European Journal of Operational Research, 178, 433-448.

Kumar V. V., Chan F. T. S., Mishra N., and Kumar V., 2010, Environmental Integrated Closed loop Logistics Model: An Artificial Bee Colony Approach, 8th International conference on SCMIS, 6-8 October 2010, Hong Kong.

Kumar V. V., Pandey M. K., Tiwari M. K., and Ben-Arieh D., 2010, Simultaneous optimization of parts and operations sequences in SSMS: a chaos embedded Taguchi particle swarm optimization approach, Journal of Intelligent Manufacturing, 21(4), 335-353.

Kumar, V.V., Tripathi M., Pandey M. K., Tiwari M. K., 2009. Physical programming and conjoint analysis-based redundancy allocation in multistate systems: a Taguchi embedded algorithm selection and control (TAS&C) approach. In: Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 223 (3), 215–232.

Kumar R., Tiwari M. K., and Shankar R.. 2003, Scheduling of Flexible Manufacturing Systems: An Ant Colony optimization Approach, Proc. IMechE: Part B: Journal of Engineering Manufacture, 217(10), 1443-1453.

Kumar V. V., and Chan F. T. S.. 2011. A Superiority Search and Optimisation Algorithm to Solve RFID and an Environmental Factor Embedded Closed Loop Logistics Model. International Journal of Production Research, 49 (16): 4807–4831.

Kumar, V. V., Liou, F. W., Balakrishnan, S. N., & Kumar, V. (2013). Economical impact of RFID implementation in remanufacturing: a Chaos-based Interactive Artificial Bee Colony approach. Journal of Intelligent Manufacturing, 1-16.

Lazzús J.A.. 2013. Hybrid particle swarm-ant colony algorithm to describe the phase equilibrium of systems containing supercritical fluids with ionic liquids. Communications in Computational Physics, 14 (1), 107-125.

Lee D. H., Bian W., Dong M., 2008, Multiproduct Distribution Network Design of Third-Party Logistics Providers with Reverse Logistics Operations. Journal of the Transportation Research Board, 26-33.

Lee C.K.M., Chan T.M., 2009, Development of RFID-based Reverse Logistics System. Expert Systems with Applications, 36, 9299–9307.

Lee D. H. and Dong M., 2009, Dynamic network design for reverse logistics operations under uncertainty. Transportation Research Part E, 45, 61–71.

Luo C. Z., Shao H. H., 2000, Evolutionary algorithms with chaotic perturbations. Control Decision, 15, 557–560.

Naeem M. A., Dias D. J., Tibrewal R., Chang P. C., Tiwari M. K.. 2013, Production planning optimization for manufacturing and remanufacturing system in stochastic environment. Journal Intelligence Manufacturing, 24, 717-728.

Ngai E.W.T., Cheng T.C.E., Au S., and Lai K.H., 2007, Mobile commerce integrated with RFID technology in a container depot, Decision Support Systems 43 (1), 62–76.

Neslihan O. D., and Hadi G., 2008, A mixed integer programming model for remanufacturing in reverse logistics environment. Int J Adv Manuf Technol, 39, 1197–1206.

Pan Z., Tang J., Ou L., 2009, capacitated dynamic lot sizing problems in closed-loop supply chain. European Journal of Operational Research, 198, 810–821.

Parker T. S., and Chua L. O., 1989, Practical numerical algorithms for chaotic system. Berlin, Germany: Springer-Verlag.

Pigni, F., Ugazio, E., (2009), Measuring RFId Benefits in Supply Chains. In: Proceedings of the Fifteenth Americas Conference on Information Systems, San Francisco, California.

Pineyro P. and Viera O., 2010, The economic lot-sizing problem with remanufacturing and one-way substitution, Int. J. Production Economics. 124, 482–488.

Prakash A., Tiwari M. K., and Shankar R.. 2008, Optimal job sequence determination and operation machine allocation in flexible manufacturing systems: an approach using adaptive hierarchical ant colony algorithm, Journal of Intelligent Manufacturing, 19 (2), 161-173.

Salema M. I. G., Barbosa-Povoa A. P. and Novais A. Q. (2006), An optimization model for the design of a capacitated multi-product reverse logistics network with uncertainty, European Journal of Operation Research, 179 (3), 1063-1077.

Schultmann F., Zumkeller M. and Rentz O. (2006), Modeling reverse logistic tasks within closed-loop supply chains: An example from the automotive industry, European Journal of Operational Research, 171 (3), 1033–1050.

Soleymanpour D.M., Vrat P., and Shankar R.., Ant colony optimization algorithm to the inter-cell layout problem in cellular, manufacturing, European Journal of Operational Research, 157(3), 592-606.

Stanfield P. M., King R. E., and Hodgson T. J., 2006, Determining sequence and ready times in a remanufacturing system. IIE Transactions. 38, 597–607.

Tsai P.W., Pan J.-S., Liao B.-Y., and Chu S.-C., 2009, Enhanced artificial bee colony optimization," International Journal of Innovative Computing, Information and Control, 5(12).

Ustundag A., and Tanyas M., 2009, The impacts of radio frequency identification (RFID) technology on supply chain costs, Transportation Research Part E: Logistics and Transportation Review, 45 (1), 29–38.

Veeramani D., Tang J., & Gutierrez A., 2008, A framework for assessing the value of RFID implementation by tier-one suppliers to major retailers. J. Theor. Appl. Electron. Commer, Res., 3(1), 55-70.

Wang I. L. and Yang W. C, 2007, Fast Heuristics for Designing Integrated E-Waste Reverse Logistics Networks. IEEE Transactions on Electronics Packaging Manufacturing, 30(2), 147-154.

Yadav S. R., Dashora Y., Shankar R., Chan Felix T.S, and Tiwari M.K., 2008, An interactive particle swarm optimization technique for selecting a product family and designing its supply, International Journal of Intelligent Systems Technologies and Applications, 31 (3-4), 168-186.

Yang L., Chen T., 2002, Application of Chaos in Genetic Algorithms, Communication Theoretical Physics, 38, 168–72.

Yuan X. H., Yuan Y. B. and Zhang Y. C., 2002, A hybrid chaotic genetic algorithm for short-term hydro system scheduling. Mathematical Compu. Simulation, 59, 319–327.

SECTION

2. CONCLUSION

The first part of this study develops value of a product at design and functional level. The model has been formulated with the view of maximizing value of the product and minimizing product cost, product weight and product size simultaneously. In this research, a four stage (components) problem has been considered to map the remanufacturing facility in to product development process. The second part of this research examines the economical merits of RFID adoption at remanufacturing echelons. Through this research, the authors have demonstrated that the RFID technology can effectively improve inventory control, operational efficiency, and data visibility at reverse echelons, i.e., at collection, disassembly, and refurbishing centers. However, the present price of RFID equipment (hardware and software) is still one of the main cost factors when implementing RFID.

In order to tackle the underlying models, a novel approach, Self-Guided Algorithms & Control, has been proposed and implemented successfully in PDP value model, and a Chaos-based Interactive Artificial Bee Colony approach to RFID based Remanufacturing models respectively the first and the second part of the thesis. The proposed algorithms have been shown to significantly outperform many existing optimization strategies prevailing in the literature and offer a faster convergence.

Following directions for the future research are suggested to interested readers: (i) inclusion of more realistic reliability considerations such as including the field and service data (in form of survey results) in value computation, (ii) Reliability evaluation of the developed products, (iii) application of S-CAG and CI-ABC strategies for optimizing other computationally complex problems, (iv) Application of the proposed model to a real remanufacturing corporation; and (v) Utilizing the multi-objective techniques for solving the problems.

APPENDIX A

PSEUDO CODE of PSO

Randomly generate the initial particles and velocity

While (iter < max_iter)

for (i = 1 to number of particles)

Calculate the fitness value for each particle.

Update the self-best position of ith particle

End for

Update the global best position of the swarm

for (i = 1 to number of particles)

for (j = 1 to number of dimensions)

Update particle velocity

Update particle position

j = j+1

i= i+1

iter = iter + 1;

end for

end

Output: Best Solution of the problem

Appendix B

PSEUDO CODE of SA

Randomly generate a solution string Evaluation fitness function) for all solution string

Set, Initial and final temperature and Iterations at each temperature

While (Final tem. =Initial Tem.)

{

For (fixed number of iteration)

Randomly introduce a perturbation (a small change to the current solution string)

Evaluate newly generated string

Always accept the new alternative if it reduces the cost

Randomly accept some alternatives that increase the cost

End of for loop

Reduction in final temperature

}

Output: Best Solution of the problem

APPENDIX C

PSEUDO CODE of GA

Generate random population of solutions

For each individual: calculate Fitness

While (iter<iter_MAX)

{

Perform Crossover operation based on probability of crossover;

Perform Mutation operation based upon probability of mutation;

Compute Fitness;

Perform Selection operation for population of next generation.

iter++;

}

Output: Best Solution of the problem

VITA

Vishwa Vijay Kumar, son of Ram Naresh Prasad and Sanichari Devi, was born in Sitamarhi (the birth place of goddess Sita in Hindu Mythology), Bihar, India on February 7th, 1985. He received his B.Tech in Manufacturing Engineering from one of the most reputed national institutes in India named National Institute of Foundry and Forge Technology, in 2009. During his undergraduate studies, he worked with Dr. M. K. Tiwari as an undergraduate research assistant, publishing three research papers in international journals/Conference of repute like Journal of Intelligence Manufacturing, Journal of Risk and Reliability, and 3rd International Conference on Reliability and Safety Engineering.

He received his Masters in Manufacturing Engineering from Missouri University of Science and Technology in May 2014. During graduation, Vishwa worked as a Graduate Research Assistant in the Intelligent Systems Center (ISC) at Missouri S&T under Dr. S. N. Balakrishnan and Dr. Frank Liou on various research projects with Boeing and NASA. As a result of his research work at Missouri S&T, three of his papers have been published in Journal of Intelligent Manufacturing, and Journal of Mathematical Problem in Engineering and others are at different stages of review.

His research interest is in Product Design & Development, Operation Management, Statistical Modeling, Data Science, Cyber embedded Manufacturing, and Internet of things. He also serves as the reviewer for many international journals such as IEEE Transactions on Systems Man and Cybernetics, Computers & Industrial Engineering, International Journal of Systems Science, and Journal of Intelligent Manufacturing.