A Genetic Algorithm for Optimization of Trust- Based Knowledge Sharing Adoption Model

Olusegun Folorunso

Department of Computer Science, Federal University of Agriculture, Abeokuta, Ogun State, Nigeria.

Abstract

The degree of willingness or intention to share knowledge based on trust, varies among the trustees in various organizations. However, the relationship between the knowledge sharing trust variables and the determination of optimal trust variable that contributed most in knowledge sharing (KS) has not been well researched. Meanwhile, Trust- Based Knowledge Sharing Adoption Model (TBKSAM) was developed using Technology Adoption Model to determine the needed KS trust variables. In this study, Genetic Algorithms(GA) was used to determine the optimal trust variable in KS system. However, in order to establish the relationship between the KS trust variables, multiple regression model was derived which later became fitness function for GA model. Also, the TBKSAM which shows the extent KS trust variables correspond accurately to each other was validated at 95% confidence interval. Furthermore, the degree of association between KS trust variables has been found with almost significant interaction. The optimum KS trust variables combination to the attainment of Knowledge Sharing Trust Level(KSTL) goal was implemented using MATLAB gaobj solver. A sensitivity analysis using multiple regression model and the effect of change in weight to the fitness function in aggregation method was compared to the optimal solution. It was found that the optimal solution is more stable and performed better for the combination of KS trust variables adopted in KSTL.

Keywords: Multiple regression, Genetic Algorithms, trust variables, knowledge sharing, technology adoption model.

1.0 Introduction

Recently, there has been an evolving global interest in examining the factors that contribute to the issue of knowledge sharing. From literature, few studies have been able to provide statistical validity of knowledge sharing variables in various organizations. Infact, most studies have not been able to show optimality to the variables that lead to the adoption of Trust-Based Knowledge Sharing Adoption Model (TBKSAM). This study aim is to determine the knowledge sharing variables that most represent the adoption of Knowledge Sharing Trust Level (KSTL). This study bridges the gaps for knowledge sharing between potential trustees and reduces the cases of sparsely in knowledge sharing. Meanwhile, organizations have recognized that knowledge forms the nucleus for creating and sustaining competitive advantage and thus, the need for KSTL model such as the one proposed in this work. The sharing of knowledge constitutes a major problem in the domain of knowledge management this is because, some trustees tend to monopolize their knowledge within their peer group. In this study, TBKSAM was developed using Technology Adoption Model (TAM)among the knowledge sharing trustees[1].

Meanwhile, previous works has been discussed in the adoption of soft computing techniques in evaluating knowledge sharing [1, 2, 3].

Furthermore, it appears that optimization of Trust Based Knowledge Sharing Adoption Model (TBKSAM) using genetic algorithm has not been well researched. In this paper, four KSTL trust variables were used such as: Perceived Trust Towards Benevolence (PTTB); Perceived Trust Towards Competence (PTTC); Perceived Trust Barrier for Sharing (PTBS) and External Cue Towards Trust (ECTT).

Corresponding author: Olusegun Folorunso, E-mail: folorunsoo@funaab.edu.ng, Tel.: +2348035640707

A Genetic Algorithm for... Folorunso J of NAMP

Analysis of Variance (ANOVA) was used to test the statistical validity and significance of the empirical dependencies[4]. The remaining of the paper is organized as follows. Section 2 is on literature review of papers on genetic algorithm. Section 3 covers research approach and methodology while section 4 discusses data interpretation analysis, while section 5 discusses the conclusion as well as suggestion for future work.

2.0 Literature Review

Trust is the major driving force behind the willingness to share knowledge in virtual enterprises. Therefore, from the view of the importance of trust it has become unavoidably relevant to deal with the optimization of trust variables in knowledge sharing organization. An investigation was carried out on the constituent materials in aluminum that are stronger, stiffer, and more wear-resistant using artificial neural network and genetic algorithm [5]. The feed-forward back propagation neural network model was used for predicting the characteristics of the aluminum metal. These characteristics were the crystallite size, and the lattice strain of Aluminum matrix. The aim of the optimization in this work was to specify the maximum lattice strain and the minimum crystallite size of aluminum matrix that could be acquired by adjusting the process variables. Process variables included milling time, milling speed, balls to powders weight ratio that they were given as the input of the neural network model. In this work, both modeling and optimization achieved satisfactory performance, and the genetic algorithm system proved to be a powerful tool that suitably optimize process parameters [5]. Genetic Algorithm was used for the survey of different software testing techniques to determine the cause of software failure. Genetic Algorithm was used to get the best optimal path to the software testing to save time and cost [6]. An online and intelligent energy management controller for fuel control was discussed in [7]. Based on analytic analysis between fuel-rate and battery current at different driveline power and vehicle speed, quadratic equations are applied to simulate the relationship between battery current and vehicle fuel-rate. The power threshold at which engine is turned on and optimized by genetic algorithm (GA) based on vehicle fuel-rate, battery state of charge (SOC) and driveline power demand. The algorithm for this work controlled the battery current effectively, which makes the engine work more efficiently and thus reduce the fuel-consumption. Furthermore, a Genetic Algorithm (GA) to solve the problem of the split-platform storage/retrieval system (SP-AS/RS) was invented to store containers more efficiently and to access them more quickly, more accurately and precisely [8]. The GA included a new operator to make a random string of tasks observing the precedence relations between the tasks. For evaluating the performance of the GA, 10 small size test cases were solved by using the proposed GA and the results were compared to those from the literature. Results show that the proposed GA was able to find fairly near optimal solutions similar to the existing simulated annealing algorithm. Moreover, it was shown that the proposed GA outperforms the existing algorithm when the number of tasks in the scheduling horizon increases. However, to estimate the Enterprise Resource Planning (ERP) adoption readiness, it has been discussed that organizations should consider the inter-dependency between important factors and find the optimal plan as optimization trade-off between the two objectives of maximum readiness and lowest cost [9]. The study further demonstrated how to calculate the readiness using fuzzy cognitive maps to include all the complex causal relationships between factors, and then solve the multi-objective optimization problem using evolutionary genetic algorithm for optimal improvement plans. Meanwhile, a Pareto-based multi-objective optimization model for multi-stage hot forging processes has been considered to be an elitist strategy [10]. Furthermore, a multi objective optimization of drilling process variables using genetic algorithm for precision drilling operation and finding the relationship between drilling process variable on thrust force and torgue using multiple regression model was explained in [4]. A multi objective evolutionary algorithm for job scheduling in grid environment[11] was proposed and the result were compared with a number of other optimization algorithm and it was found that their approach is efficient. A new approach in [12] was explained to solving multi objective optimization problem different from the commonly known ones by subdividing the population with respect to each overlapping pair of objective functions and their merging through genetic operations. Finally, a selective hyper-heuristic choice function based to solve multi-objective optimization problems was discussed in [13]. The approach combines the strengths of three well-known multi-objective evolutionary algorithms (NSGAII, SPEA2, and MOGA) and the result performed better than the known multi-objective evolutionary algorithm. With the contributions mentioned above, it has proven that genetic algorithm can be used in optimizing TBKSAM.

2.1 Trust-Based Knowledge Sharing Adoption Model (TBKSAM)

The aim of this model is to determine the reason why people intend to share knowledge and also to examine whether the mix of competence-based and benevolence-based trusts has effect on knowledge sharing [2].

The model in Fig. 1 considers different factors affecting knowledge sharing based on the confidence of the trusting agents, both its role as Knowledge source and Knowledge destination.



Fig. 1: Trust-Based Knowledge Sharing Adoption Model (TBKSAM)

2.1.1 Definition of Constructs

- i. **Perceived Ease of Trust (PET):** is the degree of confidence between the knowledge source and the knowledge destination [14].
- ii. **Perceived Trust Towards Attitude and Behavior (PTTAB):** is the level of trust prediction towards understanding the behavior intention of a person that will occur [15,16, 17].
- iii. **Perceived Trust Towards Competence (PTTC):** is the perception about the ability or the degree of trust in which an individual believes that another person is knowledgeable or experienced in a given subject area [18, 19].
- iv. **Perceived Trust Towards Benevolence (PTTB)**: is the degree of willingness to share knowledge or the degree of trust to which an individual will not intentionally take advantage of a certain situation.
- v. **Perceived Trust Barrier for Sharing (PTBS)**: are the biases people have in trust toward knowledge sharing [20, 21, 17].
- vi. External Cue Towards Trust (ECTT): are the external factors that affect trust and knowledge sharing [17, 22].
- vii. **Knowledge Sharing Trust Level (KSTL)**: is the degree of willingness to share knowledge, based on the TBKSAM.

However, the reliability of the model was carried out in [1] after conducting a survey. Functional dependencies of TBKSAM were achieved by reducing the KSTL variables to PTTB, PTTC, PTBS and ECTT, see(Fig. 2).



Fig. 2: Knowledge Sharing Trust Level Model

2.2 Genetic Algorithms

Genetic Algorithms (GAs) is a natural evolution algorithm based on Darwinian's theory of survival of the fittest[23]. GA begin with a set of possible fittest individuals (initial population) represented by strings of binary digits known as chromosomes. These set of possible solutions are subjected to selection process and the result of these tournament are made to undergo genetic operators such as crossover and mutation and the output from this genetic operator gives the new population that is expected to be better than the previous one. Basically, GA is used to get better solution and it's applicable in several domains that relate to improvement and optimization problem. In the context of this paper, GA will be used to get the best knowledge variable from trust-based Knowledge Sharing Adoption Model. The summary of the GA been described can be represented by the following algorithm [23]:

- Step 1 [start] initialize a random population of possible solutions to the problem.
- Step 2 [Fitness evaluation] calculate the fitness of individuals in the initial population.
- Step 3 [New population] create a new population as follow:
 - a. [selection] choose two best individual from the new population
 - b. [crossover] create new offsprings from the two best individual based on probability of crossover
 - c. [mutation] mutate the offsprings created if there is no distinct difference from their parents
 - d. [Placement] accept the new offsprings and place them in the new population.
- Step 4 [Replace] use the accepted new population for further iteration of the algorithm
- Step 5 [Test] stop to return the fittest individual if the end condition is satisfied.
- Step 6 [Loop] go to step 2.

Optimization in general term can be defined as the process of getting the best from among some set of qualitative variables. Ga can be used to define a mathematical model of fitness function describing the performance criteria of conflicting factors. Ga requires a problem setup by calling the fitness function by a function handle of the form @trust_fun where trust_fun.m is a function file that return a vector. The number of independent variables for the fitness function is also required for the problem setup. An optional constraint input textboxes is also available but may be left empty. The solver was run and the result shows that ga is necessary for the optimization of real life scenario such as the model proposed in this paper.

3.0 **Research Approach and Methodology**

3.1 **Problem Statement**

The process of Knowledge Sharing between trustees, indicate that there is need for trust variables optimization in order to have an improved and feasible KS. The research problem is to determine a statistical validity and relationship between the variables that lead to the KSTL model adoption and to find the optimal KSTL variable(s).

Research objectives include the:

- Determination of the relationship between KSTL variables. i.
- ii. Testing statistical validity and significance of the discovered relationship.
- iii. Determination of the optimal variable(s) among the KSTL variables.

3.2 **Research Hypotheses**

H₀: All the four KSTL variables does not lead to the adoption of TBKSAM.

H₁: Some KSTL variables are more likely than others in the adoption of TBKSAM.

3.3 **Data Interpretation and Analysis**

F-Test was used in testing for the goodness of fit of the model at 5% level of significance. t-Test also was used to check for the significance of individual parameter i.e (PTTB, PTTC, PTBS and ECTT) of (N=150) generated random KSTL trust variables.

From Table 1, it was observed that (p - value = 0.000) which indicates that the proposed KSTL model is significant and was a good fit. From Table 2, the p- value for each of PTTB, PTTC, PTBS and ECTT is 0.000. This indicates that each of the variables is significantly contributing to KSTL model leading to the rejection of hypothesis H_0 . The adjusted $R^2 = 0.996$, indicates that the regression model explain 99.6% variation and only 0.4% is unexplained i.e., PTTB, PTTC, PTBS and ECTT jointly explain 99.6% information about KSTL model. These factors are the best factors to be considered when explaining KSTL model. Hence, the proposed objective model is formulated in (Eq. 1). (1)

 $Z = -0.010 + 0.173 \times X(1) + 0.165 \times X(2) + 0.167 \times X(3) + 0.164 \times X(4)$

Z = KSTL

 $X_1 = PTTB$

 $X_2 = PTTC$

X₃=PTBS

 $X_4 = ECTT$

3.4 **Research Methodology**

The following steps represent the procedure taken in this work for obtaining the optimal result.

Step 1: Generate 150random values for trust variables between -1.0 and 1.0 for KSTL trust variables.

Step 2: Pre-process generated values to derive KSTL.

Step 3: Develop empirical relationship between the variables in KSTL with SPSS.

Step 4: Examine statistical truth value and significance of relationship at 95% confidence interval.

Step 5: Verify research hypothesis.

Step 6: Formulate fitness function: KSTL.

Step 7: Formulation of optimal fitness function

Step 8: Set the required options for genetic algorithm (ga).

Step 9: Start optimization by ga.

Step 10: Evaluate result both graphically and by table of fitness.

Step 11: Perform sensitivity analysis on the ga optimal result.

Table 1: KSTL Model Summary

Model					Change Statistics				
	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	0.998	0.996	0.996	0.018669740491849	0996	5590.042	6	143	0.000

Table 2: Coefficients of KSTL model

Model		Unstandardiz	zed coefficients	Standardized coefficients		
		В	Std. Error	Beta	Т	Sig.
1	(constant)	-0.010	0.007		-1.456	0.148
		0.173	0.002	0.458	83.878	0.000
	PTTB	0.165	0.002	0.423	77.017	0.000
	PTTC	0.167	0.022	0.467	85.166	0.000
	PTBS	0.164	0.022	0.402	73.613	0.000
	ECTT					

3.5 kstl-gaobj Algorithm

A KSTL-gaobj algorithm was developed and later implemented using Matlab 7.6.0. The KSTL Gaobj model determine its optimal KSTLvariable, see (Fig 3).

INPUT Parameters PTTB, PTTC, PTBS and ECTT **OUTPUT:** OptimalKSTL variable Begin 1. Initialization f random values between [-1, +1] for PTTB, PTTC, PTBS and ECTT 2. Generate the objective fitness function from regression model as illustrated in Table 2 $Z_1 = -0.010 + 0.173 * X_1 + 0.165 * X_2 + 0.167 * X_3 + 0.164 * X_4$ $// z_1 = kstl_1$, $C_i = constant$, $X_{i=}$ PTTB, PTTC, PTBS, ECTT 3. call the fitness function into gaobj as @trust_fun.m 4. set GA options in MATLAB 5. Generate initial population 6. Evaluate individual by ranking 7. perform tournament selection perform crossover and mutation operation of winners of step 7 8. 9. Evaluate migrated offsprings 10. selection process 11. if (stopping criteria == true) 12. else step 7 13. Evaluate solution 14. for i = 1 to n of input variables do 15. *if fitness for any individual variable* < 0 *do* 16. new pop = fittest individuals > 017. end if 18. end for 19. end if End.

Fig 3: kstl- gaobj algorithm

4.0 Ga- optimization (gaoptim)

This section will illustrate and show the various MATLAB Output and the M- file definition. The fitness optimization problem is solved to obtain solutions by genetic algorithm in MATLAB on a Pentium dual core 2.4GHZ with 4GB of ram. A fitness function can be formulated in the format shownin (Eq. 2).

function $z = trust_fun(x)z = -(-0.010 + (0.173*x(1)^{1}) + (0.165*x(2)^{1}) + (0.167*x(3)^{1}) + (0.167*x($

(2)

 $(0.164*x(4))^{1};$ Where z = KSTL model

It is to be noted that minus sign is added to the original fitness function generated to represent maximization problem. This is because we want to maximize the knowledge variables to get the best optimal variable(s) that can lead to the adoption of KSTL.

After the writing of the M-file as shown in the M-code above the fitness functionz is saved in a folder along MATLAB (directory on the computer system). The function is then called into the ga environment by a function handle. All other parameters of the ga are set as shown below and the results of the iteration is as shown in Table3.

- i. Population type: double vector
- ii. Population size: 100
- iii. Creation function: constraint dependent
- iv. Selection: Tournament with size = 4
- v. Crossover fraction = 0.8, mutation fraction 0.2
- vi. Mutation: Adaptive feasible
- vii. Crossover: Intermediate with 1.0 ratio
- viii. Migration direction: forward with fraction of 0.2 and interval of 20
- ix. Termination criteria: generations, time limit, fitness limit, stall generation and function tolerance all set as default.
- x. Display to command window: Diagnose
- xi. Evaluate fitness function: in serial

A Genetic Algorithm for... Folorunso J of NAMP

Fig 4 shows the screen shot for the first case of the ga final values shown in Table3 along with the selected options as generated in the optimization tool in Matlab.

File Problem Solve: ge-Genetic Algorithm Population Problem Population type: Double vector Problem Population type: Double vector Number of variables: 4 Double vector Constraints: bit Double vector Linear requalities: Acg: beg: Double vector Nonlinear constraint function: bit Double vector Double vector Nonlinear constraint function: bit Double vector Double vector Nonlinear constraint function: bit Discretion function: Discretion: Discretion function: Discretion: Discretion: </th <th>ik Help colder Population colder Population robler Population robler Population robler Population type Population Population type Population Population type Population Population type Population Population type Constraints Image Linear requalities: Acg Linear requalities: Acg Lower Upper Integer variable indices: Image unret teation Image Upper tand wiew results Specify: Integer variable indices: Specify: Upper teations function Specify: Integer variable indices: Specify: Upper teations function view: results Specify: Integer variable indices: Specify: Upper teations function view: results Specify: Integer variable indices: Specify: Upper teations function view: result endices Specify: Integer variable indices: Specify: Upper teati</th> <th>File Help Problem Files Files Files Solver ge-Genetic Algorithm Problem Files Files Files Constraints: Linear requalities: Aeg beg Linear requalities: Aeg beg Inter requalities: Inter requalities: Aeg beg Inter requalities: Boundo: Lower: Upper Intial scores: Use default: Intial scores: Use default: Specify: Intial range: Use default: Specify: Commit territion: Intial range: Use default: Specify: Specify: Intial range: Optimizator territies: Specify: Intial range: Specify: Specify: Specify:<</th>	ik Help colder Population colder Population robler Population robler Population robler Population type Population Population type Population Population type Population Population type Population Population type Constraints Image Linear requalities: Acg Linear requalities: Acg Lower Upper Integer variable indices: Image unret teation Image Upper tand wiew results Specify: Integer variable indices: Specify: Upper teations function Specify: Integer variable indices: Specify: Upper teations function view: results Specify: Integer variable indices: Specify: Upper teations function view: results Specify: Integer variable indices: Specify: Upper teations function view: result endices Specify: Integer variable indices: Specify: Upper teati	File Help Problem Files Files Files Solver ge-Genetic Algorithm Problem Files Files Files Constraints: Linear requalities: Aeg beg Linear requalities: Aeg beg Inter requalities: Inter requalities: Aeg beg Inter requalities: Boundo: Lower: Upper Intial scores: Use default: Intial scores: Use default: Specify: Intial range: Use default: Specify: Commit territion: Intial range: Use default: Specify: Specify: Intial range: Optimizator territies: Specify: Intial range: Specify: Specify: Specify:<
Problem Options Problem Problem Fitness function: @trust_fun Outpuistion type: Outple vector Number of variables: 4 Constraints: bg Linear equalities: Acg Bounds: Lower Upper Upper Nonlinear constraint function: Upper Integr variable indices: Upper Integr variable indices: Upper Optimation running: Optimation running: Optimation running: Stat Stat St	oblem Options color color <th>Problem Setup and Results Options Solver ge- Genetic Algorithm Population Problem Fitness function: @trust fun Number of variables 4 Population type Constraints: bit @population size Linear equalities: Ac bit Bounds Lower: Uppe Nonlinear constraint function: Initial population: Uite andows states from previous run Specify: Stat Population Stat Population: Constraints: Uite andows states from previous run Stat Population: Optimation running: Clear Results Optimation running: Specify: Optimation running: Specify: Optimation running: Specify: Optimation running: Generation: Optimation running: Specify: Optimation</th>	Problem Setup and Results Options Solver ge- Genetic Algorithm Population Problem Fitness function: @trust fun Number of variables 4 Population type Constraints: bit @population size Linear equalities: Ac bit Bounds Lower: Uppe Nonlinear constraint function: Initial population: Uite andows states from previous run Specify: Stat Population Stat Population: Constraints: Uite andows states from previous run Stat Population: Optimation running: Clear Results Optimation running: Specify: Optimation running: Specify: Optimation running: Specify: Optimation running: Generation: Optimation running: Specify: Optimation
Solve: ge: Genetic Algorithm Problem Filness function: Etrust fun Number of variables 4 Constraints: Linear inequalities: Acg: beq: Unear equalities: Acg: beq: Unear inequalities: Acg: beq: Unear equalities: Acg: beq: Unear equalities: Acg: beq: Unear equalities: Acg: beq: Unear equalities: Acg: beq: Uppe: Unear equalities: Acg: beq: Uppe: Uppe: Intial point: 1A 2 1A 2 33b.28 35.241 42.921 35.41 42.921 35.41 42.921	icher: g: Genetic Algorithm robler: g: Genetic Algorithm robler: @ Population type Population type Double vector Population state: A	Solver ge: Genetic Algorithm Problem Filness function: Etrust fun Number of variables 4 Constraints: Linear inequalities: Acq: beq: Initial population: Bounds: Lower: Upper: Integr variable indices: Save only even usuals Use random states from previous run Start Start Start Paule Stop Current iteration: 100 Clear Result: Specify: Start Star
Norte: gar venich stugentim robben Fines function @trust fun Number of variables 4 Constraints: Linear equalities: Acq beq Bounds: Lower: Upper: <	North: general: robbin Probletion Primes function: @trust_fun Number of variables 4 Constraints: Linear nequalities: Acg: beg: Initial population size: Upper: Nonlinear constraint function: Integer variable indices: Start Pauce Start Pauce Start Pauce Start Pauce Start Pauce Start Pauce Start Pauce Start Pauce Start Pauce Start Pauce Start Start	Nore: ger version: Augument Population type:
Protection Fitness function: Brunds function: Constraints: Linear equalities: Acq. beq: beq: Bounds: Lower: Upper: Intial population size: Upper: Intial population: Use default: Dome: Upper: Intial population: Use random states from previous run Star: Pause: Star: Star: Pause: Star: Star: Star: Star: Star: </td <td>Population size Fitness function: @thust.fun Number of variables: 4 Constraints: Linear requalities: Aeq: beq: Bonds: Lover: Upper: Nonlinear constraint function: Integr variable indices: Unsolver and view results: Use random states from previous run Start Pause: Stop: Integr variable: Start Pause: Stop: Traination: Integr variable: Start Pause: Stop: Traination: Start Pause: Start Pau</td> <td>Protection Fitness function: Brust_fun Number of variables 4 Constraints: Linear inequalities: A eq: beq: Initial population size Use default: Initial population: Use random states from previous run Star Pause Stop Current feation: Initial range: Use default: Princes scaling Scaling function: Star Pause: Stop</td>	Population size Fitness function: @thust.fun Number of variables: 4 Constraints: Linear requalities: Aeq: beq: Bonds: Lover: Upper: Nonlinear constraint function: Integr variable indices: Unsolver and view results: Use random states from previous run Start Pause: Stop: Integr variable: Start Pause: Stop: Traination: Integr variable: Start Pause: Stop: Traination: Start Pause: Start Pau	Protection Fitness function: Brust_fun Number of variables 4 Constraints: Linear inequalities: A eq: beq: Initial population size Use default: Initial population: Use random states from previous run Star Pause Stop Current feation: Initial range: Use default: Princes scaling Scaling function: Star Pause: Stop
Number of variables Number of variables Constraints: Linear requalities: Aeq beq Initial population: Ourstraint dependent Initial population: O Specify: Initial scores: O Use default: I Initial range: O Use default: O Specify: O Speci	Hindes of vailables Aumber of vailables Constraints: Linear equalities: Acq beq Bounds: Lower: Upper Unifierer constraint function: Initial population: Use random states from previous run Stat: Pause: Stop Initial range: Use random states from previous run Stat: Pause: Stop Initial range: Use default [0] Stat: Pause: Stop Initial range: Use default [0] Initial range: Use default [0] Stat: Pause: Stat: <td>Number of variables Number of variables Constraints: Linear equalities: Aeq: beq: Initial population: Bounds: Lowers: Upper: Initial population: Use andom states from previous run Start Pause Stop Current fleation: 100 Clear Results Start phinteson runnip_ phinteson runnip_ phinteson runnip_ phinteson runnip_ phinteson runnip_ phinteson runnip_ Start Pause Start Pause <</td>	Number of variables Number of variables Constraints: Linear equalities: Aeq: beq: Initial population: Bounds: Lowers: Upper: Initial population: Use andom states from previous run Start Pause Stop Current fleation: 100 Clear Results Start phinteson runnip_ phinteson runnip_ phinteson runnip_ phinteson runnip_ phinteson runnip_ phinteson runnip_ Start Pause Start Pause <
Number of variables 4 Constraints Constraints Linear requalities: Aeg: beg: Initial population: Outree: Upper: Integer variable indices: un solver and view results Ube random states from previous run Start Pouse Stop Start primation timinated: timination: inal point: Inal point: Inal 2 30.028 35.241 42.921 37.61	Number of variables: 4 Constraints Constra	Number of variables 4 Constraints Constraints Linear requalities: Acq: beq: Initial population: Constraint dependent Initial population: Constraint function: Initial population: Upper: Upper: </td
Constraints: Linear requalities: Acg: beq: Initial population: Use default: Intial population: Use default: Intial scores: Use default: Intial range: Start: Start: Intial point: A 2 30.028 35.241 4 Specify: 2 35.241 4 Specify: 2 35.241 4 Specify: 2 <	Creation function: Constraint dependent Creation function: Creation fu	Constraints: Linear inequalities: A: b: hit is poulation: Constraint dependent ininger qualities: Aeg beg hit is poulation: Use default: [] Initial population: Use default: [] Initial scores: Us
Linear inequalities: A _ be; be; Initial population: @ Use default [] Seconds: Lower: Upper. Specify: Initial scores: @ Use default [] Initial scores: @ Use default	Linear inequalifies: Ac beq beq beq beq beq binitial population: @ Use default [] binitial population: @ Use default [] binitial scores: @ Use default [01] binitial score	Linear inequalities: A: beq beq here a constraint function: Upper beg here a constraint function: Upper begins functio
Linear equalities: Aeg beg here here for the source of the	Linear equalities: Aeq: beq: hinital population: @ Use default [] hinital population: @ Use default [] Specify: [] hinital scores: @ Use default [] hinital scores: @	Linear equalities: Aeq: beq: Bounds: Lower: Upper: Nonlinear constraint function: Specify: Initial scores: © Use default: [] Initial range: Specify:
Bounds: Lower Nonlinear constraint function: Integer variable indices: un solver and view results: Use random states from previous run Start Pause Stop urrent iterator: (Do Clear Results: primazion running: primazion running: petive function value: 2 3 4 39.028 35.241 42.23 34.4 39.028	Bounds: Lower: Upper: Nonlinear constraint function:	Bounds: Lower: Upper: Specify: Nonlinear constraint function: Initial scores: Use default: Initial scores: Integer variable indices: Initial scores: Use default: Initial scores: Use default: Initial range: Isser andom states from previous run Specify: Initial range: Use default: Initial range: Use default: Initial range: Specify: Initial range: Specinfy: <td< td=""></td<>
Nonlinear constraint function integer variable indices integer variable indices into volver and view results index and one states from previous run Start Pause Stop integer variable indices intege	Nonlinear constraint function: Integer variable indices: Integer variable	Nonlinear constraint function: Initial scores: Use default [] Integer variable indices: Specify: Initial range: Use default [0,1] Use random states from previous run Specify: Initial range: Use default [0,1] Start Pause: Stop Specify: Initial range: Specify: urrent heaton: 100 Clear Results Selection Selection primazion running: Specify: State Specify: Selection stat Specify: Selection Selection Selection stat Selection inction: Tournament Selection Selection
Integer variable indices: un solver and view results Use random states from previous run Start Pouse Stop turrent freation: 100 Clear Results primation running, primation running,	Integr variable indices: un solver and view results Use random states from previous run Start Pause Stop Urrent iteration: 100 Clear Results promotion running promotion running	Integer variable indices: un solver and view results Use random states from previous run Start Pause Stop turrent freation: 100 Clear Results primasion running. primasion running. Sedemail (1) Selection Selection Selection Selection
start view results un solver and view results un solver and view results Use random states from previous run Start Pouse Stop urrent fereation: 100 Clear Results Scaling function: Rank Scaling function: Ran	unsolver and view results unsolver and view results Use random states from previous run Start Pause Stop urrent teators: 100 Clear Results primation running. primation running. p	sover and view results instant manual in solver and view re
un solver and view results Use random states from previous run Start Pause Stop Uurrent iteration: 100 Clear Results primazion running. primazion running. primazion running. primazion running. primazion running. primazion running. primazion running. Salard 44 Salard 44 S	un solve ir drule view results User andom states from previous run Stat Pauce Stop User andom states from previous run Stat Pauce Stop Use default Stat Stat Pauce Stop Use default Stat Stat Stat Stat Stat Stat Stat St	un solver and view results Use random states from previous run Start Pause Stop Uurrent iteration: 100 Clear Results persons running. persons
Use random states from previous run State from previous run State Pause Stop Current iteration: 100 Clear Results Dybinization running: Scaling function: Rank Dybinization running: Solution Scaling function: Rank Dybinization running: Solution Scaling function: Rank System function value: 2.892;40:40:4775:25 Solution Solution: Final point: Selection function: Tournament 1 ^ 2 3 4 Specify: 2 30;028 35;241 42;521 37;61 Subse default 4 Specify: 2	Use random states from previous sun Stat Pause Stop Stat Pause Stop Current iteration: 100 Clear Results Splittization running. Splittization running. Selection Specify: Image: Splittize of the splittize o	Use random states from previous run O Specify: Start Pause Start Pause <
Start Paure Stop Current iteration: 100 Clear Results Dotimization reministed: maximum number of generations exceeded. Scaling function: Results Selection function: Terministed: Selection function: Terministed: Selection function: 1 ^ 2 3 4 4 Start 4 2.521 390,028 35.241 42.521 37.64	Start Pause Stop Current fleation: 100 Clear Results Definization: Clear Results Section: Section: Section: Section: Tournament size: Use default: 4 Section: Section: Section: Section: Conserver: Section:	Start Pause Stop Current iteration: ID Clear Results System 6 Enclorin value: 25.8924042677525
Current iteration: 100 Clear Results Construction: 200 Clear Results Construction: Rank C	Current iteration: 100 Clear Results Scaling function: Rank Domination running. bytensident eministed: Scaling function: Rank Domination running. bytensident eministed: Scaling function: Rank Selection Scaling function: Tournament 1 A 2 3 4 39.028 35.241 42.821 37.611 C Sperioduction Sperioduction Ellie court: © Use default: 4 Seproduction Sperioduction	Current iteration: 100 Clear Results Saling function: Rank Scaling f
Specific direction Configuration Texting direction Specific direction Specific direction Specific direction	Constructions from Constructions	Selection Control Control Contro Control Control Cont
Specific function value: 25.89249496775525 Image: 25.89249496775525 Specific function: Image: 25.89249496775525 Specific function: Image: 25.89249496775525 Specific function: Image: 25.89249696775525 Specific function: Image: 25.892496775525 Specific function: Image: 25.892496775525 Specific function: Image: 25.8924977575757575757575757575757575757575757	polinization running Image: 25.8924046/752525 Specific function value: -25.8924046/752525 Image: 25.8924046/752525 Specific function value: -25.8924046/752525 Image: 25.8924046/752525 Final point: Image: 25.8924046/752525 1 m 2 3 39.028 35.241 42.921 37.61 Image: 25.8924046/75255 Image: 25.8924046/75255 Specify: 2 Image: 25.8924046/75255 Image: 25.8924046/75255 Image: 25.8924046/75255 Specify: 2 Image: 25.8924046/75255 Image: 25.8924046/75255 Image: 25.8924046/75255 Specify: 2 Image: 25.8924046/75255 Image: 25.8924046/75255 Image: 25.8924046/75255 Image: 25.8924046/7	Spetimization running. Image: 25.89240-49:77525 Specime Enrimoted: maximum number of generations exceeded. Image: Specime Enrimoted: maximum number of generations exceeded. Image: Specime Enrimoted: maximum number of generations exceeded. Image: Specime Enrimoted: Specime Enrimated: Specimeted: Specime Enrimoted: Specime Enrimated: Specime:
Specific function value: 25.89240-046775525 Specific function: Selection Final point: Selection function: Tournament 1 ^ 2 3 4 39.028 35.241 42.921 37.61	bjective function value: 23.8924049775325 pointicator terminated: maximum rumber of generations exceeded. Final point: 1 ^ 2 3 4 39.028 35.241 42.921 37.61 C	Uptotice function value: 25.8924949675535 Image: 25.8924949675535 V Image: Selection V Image: Selection Final point: Selection function:
Selection Selection Selection function: Tournament size 1 * 2 3 4 39.028 35.241 42.521 37.61	Image: second	v v Selection Selection Selection Tournament
Image Image <th< td=""><td>V Selection function: Tournament size: O Use default: 4 39.028 35.241 42.921 37.61 c V V V V</td><td>inal point: Selection function: Tournament</td></th<>	V Selection function: Tournament size: O Use default: 4 39.028 35.241 42.921 37.61 c V V V V	inal point: Selection function: Tournament
inal point: a 2 3 4 39.028 35.241 42.921 37.61	inal point: 2 3 4 39.028 35.241 42.921 37.61 c > > Specify: 2 Elite count: Ibite default: 2	inal point:
a 2 3 4 39.028 35.241 42.921 37.61 O Specify: 2	1 2 3 4 39.028 35.241 42.921 37.61 c > Breproduction	Tournament size: Use default: 4
39/1/28 53:241 42:321 37.01 Specify 2	39/020 32/41 42/3/21 3/.01	
	c → Use default: 2	39/1/28 33.241 42.321 37.01 Specify 2
□ Reproduction	< ►> Elite count:	
Elite count: I Use default 2		<

Fig 4: Genetic Algorithm Optimization Tool (gaobj toolbox)

The Fig. 5 shows the graphical view of the optimization process of the genetic algorithm with a visual representation of the fitness value, current best individual, average distance between individuals, and the scores of individuals in population. This visual view is important for better understanding of how genetic algorithm operates and as an alternative to the final ranking values in the table form.



Fig 5: The graphical illustrations of the genetic algorithm plot function

RUNS	X ₁ PTTB	X ₂ PTTC	X ₃ PTBS	X ₄ ECTT	Z KSTL
1	39.028	35.241	42.921	37.61	25.892
2	36.302	39.21	39.906	42.258	26.335
3	39.889	34.298	40.465	35.162	25.074
4	37.907	38.604	36.325	36.102	24.905
5	39.12	38.675	33.294	35.584	24.535
6	43.706	32.97	39.404	42.665	26.569
7	33.901	38.652	39.704	39.049	25.267
8	41.625	37.312	37.082	35.62	25.382
9	35.584	41.56	41.132	35.879	24.303
10	38.336	41.56	41.132	35.879	26.233

Table 3: Ranked chromosomes by fitness function by Z

From Table3, it revealed that hypothesis H_1 can be accepted, since most of the (trials) runs in gaobj shows that variable X_1 which represent PTTB is most likely to lead to the adoption of KSTL. Similarly, variable X_2 and X_3 representing PTTC and PTBS respectively follows X_1 in the fitness ranking based on the overall average score of each variable from the ten (10) runs as shown in Table 3. Therefore, PTTB is the most optimal of the KSTL trust variables leading to the adoption of KSTL and variable X_4 representing ECTT can be removed since it is the least in the fitness ranking of Table3.

4.1 Sensitivity Analysis:

Sensitivity analysis studies the effects of discrete changes of one or more variables in the fitness function. This study evaluated the GA using the sensitivity analysis method by varying some of the coefficient of the variables at each instance to verify changes at the point of final solution. The coefficient of X_1 is changed from 0.173 to 0.180 resulting to the final value of Z to be 26.166 which is a little higher than the value produced by the GA . Similarly, coefficients of X_2 , X_3 and X_4 in case 2, case 3 and case 4 respectively was changed to 0.195, 0.197 and 0.174 producing Z values of 27.511, 26.288 and 25.228 respectively. Table4shows the changes due to coefficient adjustments in knowledge and the fitness function values for the first four (4) runs.

RUN	X ₁	\mathbf{X}_2	X ₃	X_4	Ζ
	PTTB	PTTC	PTBS	ECTT	
1	39.028	35.241	42.921	37.61	26.166
2	36.302	39.21	39.906	42.258	27.511
3	39.889	34.298	40.465	35.162	26.288
4	37.907	38.604	36.325	36.102	25.228

Table4: Decision variables and fitness function values for each case

It is clear that the GA is not affected by changes in the coefficient of the variables as the aggregation method. Therefore, the GA is efficient and does not need any changes to any of the variables coefficient in advance of each of the optimization problem.

5.0 Conclusion

This study has been able to show that the relationship between the KSTL variables is significant thus leading to the rejection of the null hypothesis H_0 . It is also evident that knowledge variable X_1 (PTTB) on (Table3) is the best in optimality leading to the adoption of KSTL. GAoptimization method has been shown to be more robust and stable in dealing with real life situation than the aggregation method. The proposed knowledge sharing trust level measurement adoption model based on genetic algorithm optimization has shown an optimal solution due to the nature of genetic algorithm. Therefore, GA is a better method for organization to make decision on the adoption of KSTL compared to the aggregation method with coefficient adjustment.

References

- [1] Folorunso, O. (2015). Knowledge Sharing Trust level Measurement Adoption Model basedon Fuzzy Expert System. Computer and Information science vol. 8, No.2, pp. 89-101.
- [2] Zadjabbari, B., Mohseni, S. and Wongthongtham, P. (2009). Fuzzy logic based model to measure knowledge sharing. In *Digital Ecosystems and Technologies*, *DEST'09. 3rd IEEE International Conference* http://espace.library.curtin.edu.au/cgi-bin/espace.pdf?file=/2010/03/12/file_1/132702 (accessed 02-07-2013)
- [3] Zadjabbari, B., Wongthongtham, P. and Hussain, F. K. (2010). Ontology based Approach in Knowledge Sharing Measurement. *J. UCS*, Vol. *16. No.*6, pp. 956-982.

- [4] Rupesh Kumar Tiwari (2013) Multi objective Optimization of Drilling Process Variables Using Genetic algorithm for precision drilling operation. International journal of Engineering Research and Development, Vol. 6, Issue 12, pp. 43-59.
- [5] Esmaeili, R. and Dashtbayazi, M. R. (2014). Modeling and optimization for microstructural properties of Al/SiC nanocomposite by artificial neural network and genetic algorithm. *Expert Systems with Applications*, Vol. 41. No.13, pp. 5817-5831.
- [6] Chayanika Sharma, Sangeeta Sabharwaland Ritu Sibal (2013). A Survey on Software Testing Techniques using Genetic Algorithm. International Journal of Computer Science issues, Vol. 10, issue 1, No 1, pp. 1694-0814.
- [7] Chen, Z., Mi, C. C., Xiong, R., Xu, J. and You, C. (2014). Energy management of a power-split plug-in hybrid electric vehicle based on genetic algorithm and quadratic programming. *Journal of Power Sources*, Vol. 248, pp. 416-426.
- [8] Seyed Mahdi Homayouni, Sai Hong Tang and Omid Motlagh (2014). *A genetic algorithm for optimization of integrated scheduling of cranes, vehicles, and storage platforms at automated container terminals. Journal of Computational and Applied Mathematics Vol. 270, pp. 545–556.*
- [9] Sadra Ahmadi Chung-Hsing Yeh, Rodney Martin and Elpiniki Papageorgiou: (2015) *Optimizing ERP readiness improvements under budgetary constraints.* Int. J. Production Economics Vol. 161, pp. 105–115.
- [10] Castro, C. F., António, C. C. and Sousa, L. C. (2010). Pareto-based multi-objective hot forging optimization using a genetic algorithm. In 2nd International Conference on Engineering and Optimizationhttp://www1.dem.ist.utl.pt/engopt2010/Book_and_CD/Papers_CD_Final_Version/pdf/01/01075-01.pdf (accessed 7-10-2014)
- [11] Grosan, C., Abraham, A. and Helvik, B. (2007). Multiobjective evolutionary algorithms for scheduling jobs on computational grids. In *International Conference on Applied Computing* http://m.2002.softcomputing.net/ac2007 2.pdf(accessed 7-10-2014)
- [12] Md. Saddam Hossain Mukta, T.M. Rezwanul Islam and Sadat Maruf Hasnayen (2012): "Multiobjective Optimization Using Genetic Algorithm" an international journal of emerging trends and technology in computer science.http://ijettcs.org/Volume1Issue3/IJETTCS-2012-10-25-098.pdf (accessed 7-10-2014)
- [13] Maashi, M., Kendall, G. and Özcan, E. (2015). Choice function based hyper-heuristics for multi-objective optimization. *Applied Soft Computing*, Vol. 28, pp. 312-326.
- [14] Davies, F.D. (1989). "Perceived Usefulness, Perceived Ease of Use and User Acceptance of Information Technology." *MIS Quarterly* Vol. 13. No.3: pp. 319-340.
- [15] Taylor, S.and Todd, P. A. (1995). UnderstandingInformation Technology Usage: A Test of CompetingModels. *Information Systems Research*, Vol. 6. No.2, pp. 144–176.
- [16] Venkatesh, V and Davis, F.O (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Sciences*; Vol. 46. No.2, pp. 186-204.
- [17] Huang, J. (2010). Remote Health Monitoring AdoptionModel Based on Artificial Neural Networks.*Expert Systems with Applications*, Vol. *37*, pp. 307–314.
- [18] Connelly C.E. and Kelloway E.K., (2003). Predictors of employees' perceptions of knowledge sharing cultures. *Leadership & Organization Development Journal*, Vol. 24. No (5/6), pp. 294–301.
- [19] Pavlou, P.A. and Dimoka, A. (2006). The Nature and Role of Feedback Text Comments inOnlineMarketplaces: Implications for Trust Building, Price Premiums, and SellerDifferentiation. *Information Systems Research Vol.* 17. pp. 392-414.
- [20] Rosenstock, I.M.(1966). "Why People Use Health Belief Model: Milbank Memorial Fund Quarterly, Vol. 44. pp. 94-124
- [21] Rosenstock, I.M.(1974): Historical Origins of the Health Belief Model". *Health Education Monographs*, Vol.2, pp. 1-8.
- [22] Strecher, V. J. and Rosenstock, I. M. (1997). The health belief model. *Cambridge handbook of psychology, health and medicine*, pp. 113-117.
- [23] Rahul Malhotra, Narinder Singh and Yaduvir Singh (2011).Genetic Algorithms: Concepts, Design for Optimization of Process Controllers. Computer and Information Science Vol. 4, No. 2; pp. 39-54.