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

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## *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).

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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.

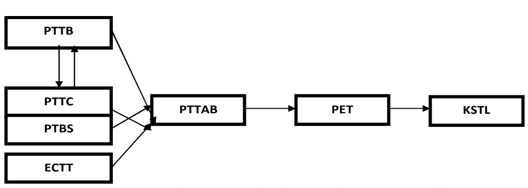


**Fig. 1:** Trust-Based Knowledge Sharing Adoption Model (TBKSAM)

### 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).

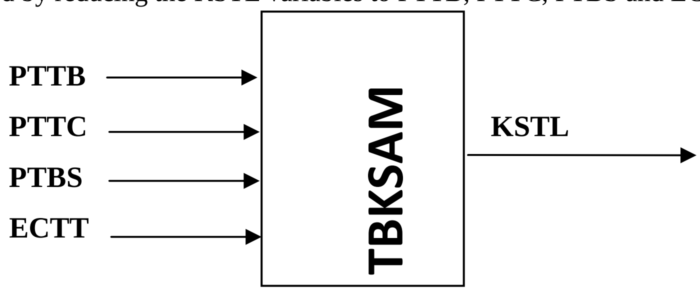


**Fig. 2:** Knowledge Sharing Trust Level Model

## 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:**

i. Determination of the relationship between KSTL variables.
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

**$H_0$:** All the four KSTL variable**s** does not lead to the adoption of TBKSAM.
**$H_1$:** 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).

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

Z = KSTL
$X_1$= PTTB
$X_2$ =PTTC
$X_3$ =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 | 0..996 | 5590.042 | 6 | 143 | 0.000 |

**Table 2:** Coefficients of KSTL model

| Model | | Unstandardized coefficients | | Standardized coefficients | | |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | T | 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. *Initializationof random valuesbetween [-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*
8. *perform crossover and mutation operation of winners of step 7*
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 > 0*
17. *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) +
(0.164*x(4))^1);
```
Where z = KSTL model (2)

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

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.

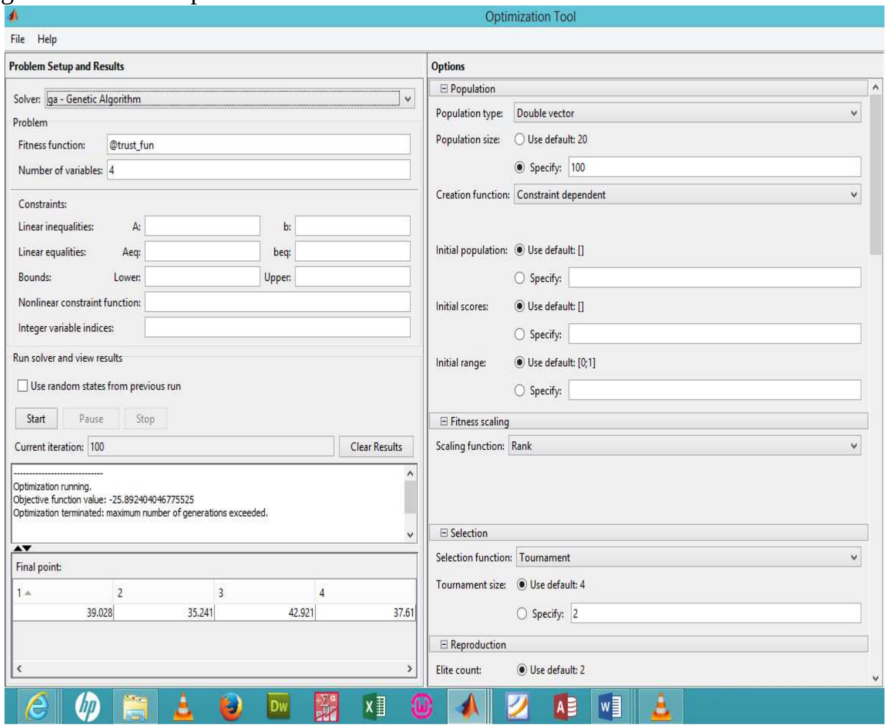


**Fig 4:** Genetic Algorithm Optimization Tool (gaobj toolbox)

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.

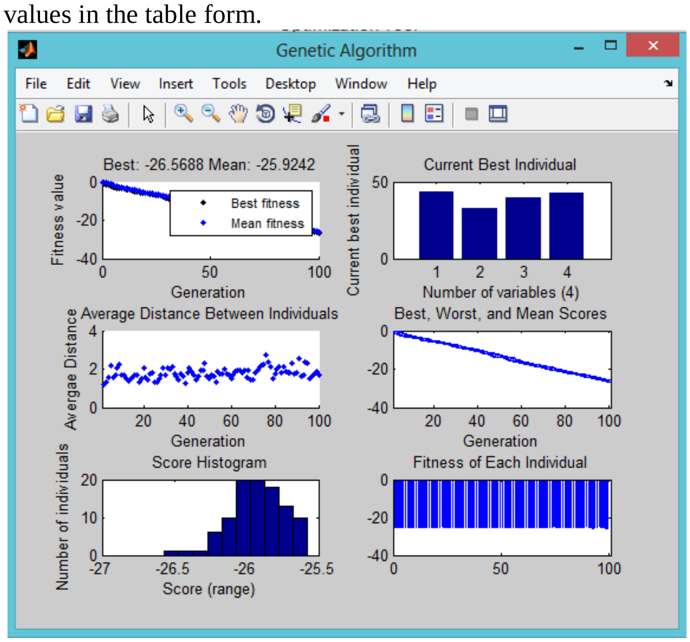


**Fig 5:** The graphical illustrations of the genetic algorithm plot function

**Table 3:** Ranked chromosomes by fitness function by Z

| 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 |

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 $X_3$representingPTTC 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.

**Table4:** Decision variables and fitness function values for each case

| RUN | $X_1$ PTTB | $X_2$ PTTC | $X_3$ PTBS | $X_4$ ECTT | Z |
|---|---|---|---|---|---|
| 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 |

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.

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