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TABU-GENETIC ALGORITHM-BASED MODEL FOR POULTRY FEED FORMULATION

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ABSTRACT

Poultry feed cost represents a significant part of operational cost of poultry production. Consequently, efficient feed formulation practice is required for a sustainable poultry production. Many poultry farmers, employ inefficient methods like rule of thumb and intuition to handle feed formulation problem. This paper presents the report of the development of a feed formulation model which can be used to harness the potentials of locally available feed stuffs toward producing a balanced poultry feed. To achieve this aim, a hybrid Tabu-Genetic Algorithm Model ((TAM) was developed for layers mash feed formulation as case study. Thirteen (13) decision variables and eight (8) constraints were identified and used in the research. Secondary data were collected from the recommended nutrient requirements schedule made available by both the Ondo State Ministry of Agriculture and the Freedom Feed Mill (a local feed miller) in Akure, South-West Nigeria. Based on this data, the optimal solution of the TAM developed for the layers mash produced a balanced feed at reduced cost.

Contribution/Originality: This study uses a hybrid of tabu search (TS) and genetic algorithms (GA) to formulate poultry feed. GA being a global search algorithm is usually slow. The introduction of TS helps to reduce the time taken to arrive at the optimal solution.

1. INTRODUCTION

One of the veritable means of realizing the full potentials of livestock is improved nutrition. Formulation of livestock feed that contains the right proportion of nutrients at minimum cost is an important goal of animal nutrition specialists. Also, in a developing country, there is increased clarion call to source livestock feed from local ingredients (feed stuffs) so as to conserve foreign exchange. Some previous studies reveal that livestock products contribute between 17% kilocalorie and 33% protein consumption globally with a wide gap between developed and developing countries. Livestock production and demand in developed countries, though at higher rate, is already stagnating while the demand in developing countries is on the increase. This scenario presents an opportunity for livestock farmers in developing countries to increase their production capacity. Poultry is one of the alternative sources of animal protein. It could be raised for meat or egg or both. Compared to other livestock, it has a short gestation period, thus making it to have quick turnover. This constitute a major source of attraction to investors. The cost of feeding constitutes between 65% and 70% of operation cost (Steinfeld *et al.*, 2006).

Consequently, there is the need to produce a balanced feed at least cost in order to maximize profit. Formulation of a balanced feed is multi-objective and multi-constraint. It has to be in the right quantity and quality.

Owing to scarce foreign exchange in most developing countries, there has been efforts to source poultry feed from local feed stuffs. However, the need to get optimum feed mix that will serve the nutritional needs of poultry at minimum cost remains paramount.

A search through the literature reveals that there is no universally acceptable method of poultry feed formulation. Development of satisfactory diet requires an understanding of the quantity and quality of nutrients in feed stuffs. The process include feed stuff selection and the determination of the nutrient level in each feed stuff. In order to produce a balanced feed, a combination of feed stuffs are required. Also, proper knowledge of the feed stuffs, nutrients contained, the type and age (stage of growth) of the livestock to be fed are also required. Apart from essential nutrients, the feed should be acceptable to the animal being fed and should have little or no environmental impact (Chappell, 1974). It should also be devoid of anti-nutritional factors and toxins.

2. A REVIEW OF LIVESTOCK DIET FORMULATION TECHNIQUES

Quite a number of methods have been proposed for solving the problem of formulating a balanced feed that satisfies one or more constraints. In Roush and Cravener (2002) pearson Square Method which shows the proportion of two feed stuffs to be mixed together in order to obtain the percentage of particular nutrients was proposed. The method was used to balance crude protein to meet specific requirements. It does not consider other nutritional requirements such as energy, vitamins, minerals; and so on. Hence, the method could not be used to handle complex feed mix problem. The Simultaneous Algebraic Equation Method (SAEM) was introduced to address the limitations of the Pearson Square Method (Gillespie and Flanders, 2009). With SAEM, more than two feed stuffs could be combined to balance more than one nutrients. However, as the nutrient requirements increases, the system of equations also increases thus making it more complex to solve (Omidiora *et al.*, 2013).

Trial and Error Method has been applied to formulate rations for pigs and poultry (Forsyth, 1995; Adejoro, 2004). It is either done manually or with the use of computer spreadsheet such as Excel, Quatro Pro and Lotus 123 [6]. Different combination of feed stuff are tried until a feed mix that satisfies the nutritional requirements is discovered. This method is commonly used in most developing countries. The method is cumbersome and time consuming when many feed stuffs and nutritional requirements are involved.

Linear Programming (LP) is a one of the quantitative approaches that has gained wide application due to the advent of personal computers. LP is able to handle many constraints while satisfying the objective function such as getting the optimal feed mix at least cost. LP requires basic information such as available feed stuffs and their nutrient composition, ration (feed) specification and production information. Modern versions of LP software could handle additional concepts such as total amino acids, profit maximization, digestible formulation, precision feeding, ideal proteins and so on. LP method is predicated on a number of assumptions such as linearity, additivity, certainty, divisibility, non-negativity, finiteness and proportionality (Al-Deseit, 2009). The major flaw of the LP method is the assumption of linearity of relationship between the decision variables. The reality is that not all feed formulation problems are linear in nature. Other limitations of the LP method are reported in Munford (1996); Mitani and Nakayama (1997); Pesti and Seila (1999); Render *et al.* (2006). However, despite the limitations of LP it however, has obvious advantages over some other methods (Onwurah, 2005).

Non-linear Programming techniques have also being employed to address the shortcomings of Linear Programming in the formulation of livestock feed (Guevara, 2004). This is because real life situations shows that some objectives and constraints of producing efficient feed mix are non-linear. Multiple Objective Programming (MOP) technique which is a more flexible option to the LP has also been employed in formulating livestock feed. MOP seeks to minimize nutrients variance and minimize cost. It introduces deviation variables which could be used to provide acceptable (compromise) solutions for conflicting objectives instead of seeking to obtain optimal solution (Guevara, 2004). MOP is capable of handling several conflicting objectives. It allows decision makers to make trade-offs between minimum cost and nutrient variation. In fact, there could be trade-off between multiple, conflicting feed formulation objectives. The most efficient solution is Pareto optimal, that is, that which cannot be improved upon without sacrificing at least one of the objectives. Unlike LP, MOP could also handle non-linear problems. Satisfying Trade-off Method (STOM) to improve on MOP to solve nutritional imbalance in feed mix has also been employed (Mitani and Nakayama, 1997).

The concept of goal programming (GP) was introduced by Anderson and Earle (Saxena and Chandra, 2011). GP could be used to determine (i) required resources to achieve a desired set of objectives, (ii) degree of attainment of the goals with available resources or (iii) provide the best satisfying solution under varying amount of resources and priority of goals. A major weakness of GP is that the solution may be sometimes Pareto inefficient, that is, satisfaction of certain goal may make the attainment of at least one other goal infeasible. However, attempts have been made by some researchers to address this deficiency (Anderson and Earle, 1983; Lara and Romero, 1994).

Genetic Algorithm (GA) which is premised on the theory of evolution is a powerful optimization technique which has been employed in solving complex real life problems. It could handle multiple objectives with multiple constraints which may be linear, non-linear or both. It is capable of searching the entire solution space in multiple directions without being trapped in local optimum. With its powerful operators namely selection, crossover and mutation, it is capable of producing an optimal solution after several generations of reproduction achieved by mating chromosomes. Each chromosome represents a potential feasible solution to the problem. GA have been used to solve feed mix problems. The major drawback of GA is that it is slow in attaining the optimal solution. Hence, attempts have been made to hybridize it with some local heuristic algorithms so as to speed up the process of convergence and produce a more efficient solution. Tabu Search (TS) proposed by Glover and Laguna (1997) is a very powerful search algorithm which has been used to solve complex search problems. TS generates a Tabu list where previous solutions are stored during iteration. In this manner, previous solutions are kept away from being considered in subsequent iterations. The best neighbor of the current solution that is not in the tabu list is selected until the stopping criteria is satisfied (Glover and Laguna, 1997).

In this study, a hybrid Tabu-Genetic Algorithm Model (TAM) for poultry feed formulation is proposed as a means of achieving an efficient feed mix in poultry production.

3. THE PROPOSED SYSTEM

a. Tabu-genetic Algorithm Model

GA can be combined with TS to create combinational heuristics. For example, The Tabu-genetic Algorithm Model is a combination of the GA and TS techniques. In general, TAM follows procedures similar to the GA. However, for the selection process, TAM uses the Tabu search procedure. In GA, an initial population consisting of a set of solution is chosen and then the solutions are evaluated. Relatively more effective solutions are selected to have more offspring which are, in some way, related to the original solutions. If the genetic operator is chosen properly, the final population will have better solutions. GA improves the whole population. TS aims at producing one best solution. For the TS, we require several good initial solutions to ensure the required number of good initial solutions are obtained.

b. System Architecture

The proposed system is based on a 2-tier architecture. This architecture is divided into two layers namely: user interface-logic layer, and the data layer. The user interface and logic layer is the layer that the user interacts with. It consists of application form interface and it is where the operation and functionality of the application lies. This layer is the heart of the application where the genetic algorithm and tabu search are hybridized for optimization. The data storage layer is the layer where the application dataset resides. The dataset is a single file with several rows and columns, where information needed by the user interface and logic layer are pooled together.

The system architecture proposed here is made up of eight components. These components include; the Data Loader, Gene Identifier, Constraint Function (CF), Chromosomes Builder (CB), Population Generator, Gene Swapper, TS Optimizer, and Fitness Function Picker (FFP). The Data Loader is the component responsible for the loading and formatting of data into the system. It takes the poultry feed information and other relevant data, parameterize and render them as input for the system. The output of the Data loader is then fed into the Gene Identifier as input. The gene identifier then sieves the required parameters which are then coded as gene. The coded genes are then forwarded to the CF which ensures that the total weight of the genes does not exceed the target weight. Besides, the CF also moderates the CB such that, the chromosomes it builds are those with valid gene weight.

The CB helps to build prospective solutions by combining distinct genes already validated by the CF. The outcome of this component serves as input to the population generator. The Population generator helps to generate population of chromosomes by bonding several output of CB to produce a single generation. Next is the TS Optimizer, which makes use of Tabu search algorithm to produce optimized numbers of best crossover parent, offspring and mutation (parent or offspring) to yield best fit chromosomes. Furthermore, it helps the Gene Swapper to make the best move during gene swapping process within the chromosomes. The Gene Swapper helps to achieve the process of crossover and also produce the right choice of coded gene weight which will swap or replace existing gene with a chromosome validated by the CF. Lastly, the FFP is designed to select best fit chromosomes during population generation and production of final solution. The FFP depends on the TS-optimizer for accurate and best output. The proposed system architecture and flowchart are shown in Figures 1 and Figures 2 respectively.

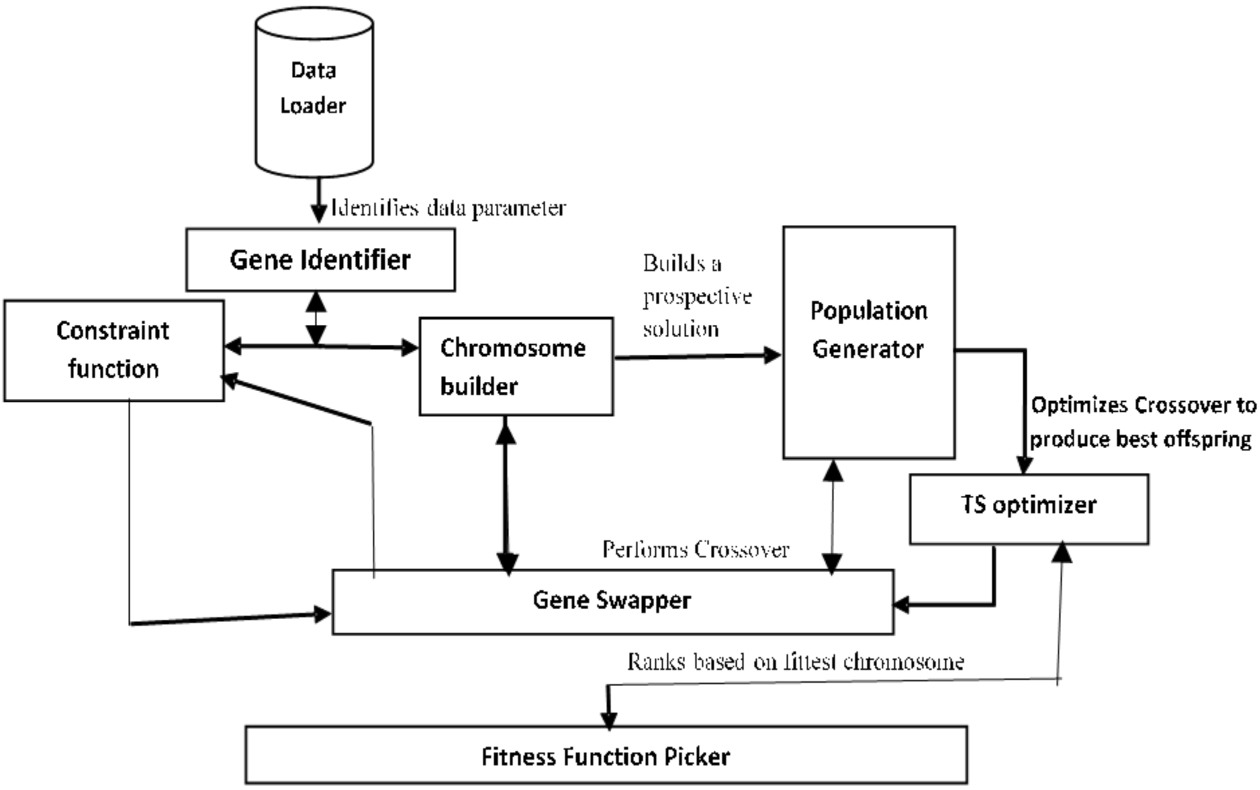

Figure-1. Proposed system architecture.

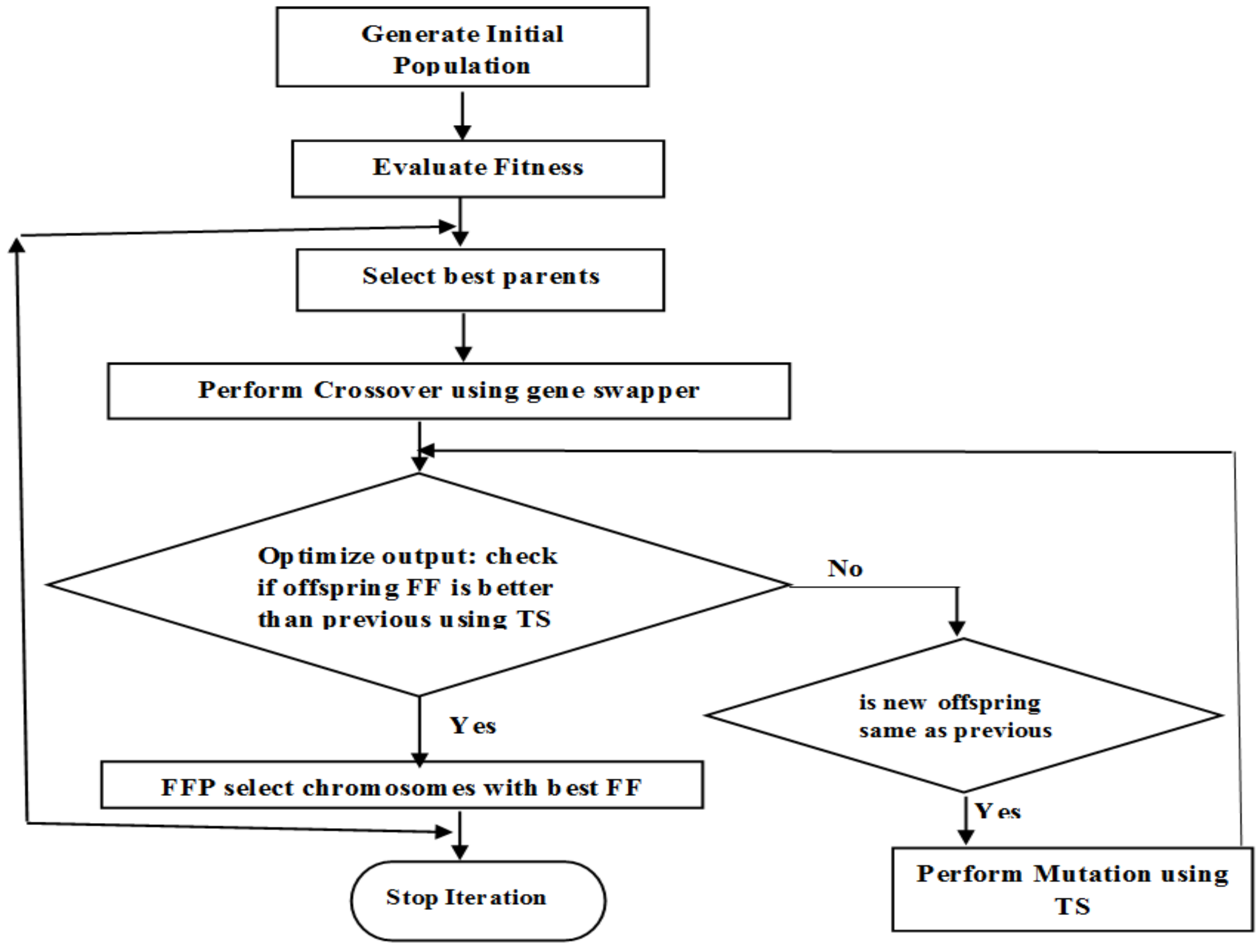

Figure-2. The TAM Flowchart.

4. PHASES INVOLVED IN FEED FORMULATION

Feed formulation can be broken into phases as follows

4.1. Information Gathering

This involves the collection of relevant information about production of poultry feeds. The information are grouped into three categories namely poultry feed formulation ingredient data, basic nutrient requirement, cost implication and nutrient levels of feed ingredients. The poultry feed formulation ingredient data was acquired from Moreson Nigeria Ltd (1998) and Freedom Feed Mill Onyearugbulem Market, Akure, Ondo State, Nigeria. It consists of 13 columns and 46 rows. The rows include the weight of the following: Maize (yellow), sorghum offals, soyabean meal, groundnut cake, palm kernel meal, rice bran, bone meal, oyster shell, salt, lysine, methionine, premix and enzyme. The target weight was 50kg.

Table-1. First 8 rows of a typical poultry feed formulation data with varying ingredient weights.

SN	Maize	Sorghum	Soya Bean Meal	Groundnut Cake	Palm Kernel Meal	Rice Bran	Bone Meal	Oyester Shell	Salt	Lysine	Methi onine	Premix	Enzyme
1	8	7	6	5	4	3	2	1	2	4	5	1	2
2	7	6	6	4	3	2	1	2	4	5	5	2	3
3	16	10	3.5	4	1.5	4	0.05	0.05	0.15	0.75	3	2	5
4	14	5.5	4	5	1.6	5	0.02	0.03	0.75	0.6	6	3	4.5
5	15	10	4.5	6	1.7	6	0.05	0.04	0.66	0.05	3	2	1
6	12	11	4	7	1.8	3.5	0.06	0.05	0.05	0.04	1	6	3.5
7	10	9.5	5	6	1.9	8	0.04	0.06	0.45	0.05	3	4	2
8	8	6	10	11	2	4	0.1	0.65	0.125	0.125	5	2	1

Source: Freedom Feed Mill, Akure, Ondo State, Nigeria.

Table-2. Poultry feed nutrient requirements.

	Protein Min %	Fat Min %	Fibre Min %	Calcium exact	Phosphorous available	Lysine Min %	Methionine Min %	M. E Kcal/kg
Chicks mash	20.0	3.5	5.0	1.0	0.45	1.0	0.40	2640
Growers mash	16.0	3.5	7.5	1.0	0.35	0.80	0.27	2475
Layers mash	16.5	3.7	6.5	3.5	0.45	0.70	0.27	2530
Broiler starter	23.0	4.0	3.5	1.0	0.45	1.12	0.45	2860
Broiler finisher	19.5	3.5	3.5	0.9	0.40	1.10	0.40	3080
Broiler breeder	16.0	3.0	5.0	3.0	0.45	0.70	0.30	2420

Source: Oladokun and Johnson (2012) as adopted from MNL (1998).

Table-3. Cost implication and nutrient levels of feed ingredients (Naira).

Ingredient	Maize	Sorghum	Soya Bean Meal	Groundnut Cake	Palm Kernel Meal	Rice Bran	Bone Meal	Oyester Shell	Salt	Lysin	Methionine	Premix	Enzyme
Price(N/kg)	54	50	78	61	13	12	33	12	40	420	1140	980	3000
CrudeProtein	10.0	9.0	45.0	45.0	18.0	12.0	0	0	0	95.0	58.0	0	0
Energy ME	3434	3300	2700	2640	2175	2860	0	0	0	0	0	0	0
EtherExtract	4.00	5.00	2.00	6.00	6.00	12.5	0	0	0	0	0	0	0
CrudeFibre	2.00	6.0	6.50	5.00	12.0	12.5	0	0	0	0	0	0	0
Lysine	0.25	0.25	2.80	1.60	0.64	0.50	0	0	0	1.0	0	0	0
Methionine	0.18	0.18	0.59	0.48	0.39	0.24	0	0	0	0	1.0	0	0
Calcium	0.01	0.10	0.20	0.20	0.21	0.04	37.0	38.0	0	0	0	0	
Phospho	0.09	0.09	0.60	0.20	0.16	0.46	1.5	0	0	0	0	0	

Source: Oladokun and Johnson (2012).

The basic nutrient requirement and cost implications was adopted from Oladokun and Johnson (2012) as it fit well with the research data. Details are shown in Tables 2 and Tables 3.

4.2. Parameter Initialization Phase

In this phase, poultry feed formulation data with varying ingredient weights from Table 1 are parameterized to construct the assignment stage for the research model.

Let N represents the set of feed ingredient, W represents the corresponding weight in kg, G represents the set of required nutrient from distinct ingredients, P denotes corresponding price per kg for set of ingredients, and T denotes the target weight such that;

$$N = \{ n_1, n_2, n_3, \dots, n_k \}$$

$$W = \{ w_1, w_2, w_3, \dots, w_y \}$$

$$G = \{ g_1, g_2, g_3, \dots, g_z \}$$

$$P = \{ p_1, p_2, p_3, \dots, p_x \}$$

$$T = 50kg \ where \ k, x, y, z = \{1,2,,3,..,13\}$$

Let $\chi_t, \psi_t, \omega, \beta$ represent total cumulative price value of any instance of ingredient, nutrient, weight and weight generated during mutation respectively, such that:

$$\chi_t = \sum_{i=0}^{k} N_i(W_i P_i) \qquad 1$$

$$\psi_t = \sum_{i=0}^{k} N_i(\frac{W_i}{T} G_i) \qquad 2$$

$$\beta = \sum_{i=0}^{k} N_i(W_i) \qquad 3$$

$$\Upsilon = W_i \pm \omega \qquad 4$$

where Υ is the weight obtained during mutation process within chromosomes.

4.3. GA Population Generation Phase

This phase deals with the formation of sets of chromosomes to make an initial population for the genetic algorithm. First, the parameters are identified. These are used to represent genes that constitute chromosomes in the population. The genes are made up of thirteen (13) parameters namely Maize (yellow), sorghum offals, soyabean meal, groundnut cake, palm kernel meal, rice bran, bone meal, oyster shell, salt, lysine, methionine, premix and enzymes. Their corresponding weights are captured from Table 1 and modeled as gene. Typical example is shown in Table 4.

Table-4. Feed ingredient weight extract from Table 1 as gene representation.

SN	Maize	Sorghum	Soya Bean Meal	Groundnut Cake	Palm Kernel Meal	Rice Bran	Bone Meal	Oyester Shell	Salt	Lysine	Methionine	Premix	Enzyme
1	8	7	6	5	4	3	2	1	2	4	5	1	2
2	7	6	6	4	3	2	1	2	4	5	5	2	3
3	16	10	3.5	4	1.5	4	0.05	0.05	0.15	0.75	3	2	5

Table-5. Population formation.

SN	Gene Formation of chromosomes	Population family
1	Maize(8kg)==>Sorghum(7kg)==>SoyaBeanMeal(6kg)==>GroundnutCake(5kg)==> PalmKernelMeal(4kg)==>RiceBran(3kg)==>BoneMeal(2kg)==>OyesterShell(1kg)==> Salt(2kg)==> Lysine(4kg)==> Methionine(5kg)==> Premix(1kg)==> Enzyme(2kg)	**Chromosomes1**
2	Maize(7kg)==> Sorghum(6kg)==> SoyaBeanMeal(6kg)==> GroundnutCake(4kg)==> PalmKernelMeal(3kg)==>RiceBran(2kg)==>BoneMeal(1kg)==>OyesterShell(2kg)==> Salt(4kg)==> Lysine(5kg)==> Methionine(5kg)==> Premix(2kg)==> Enzyme(3kg)	**Chromosomes2**
3	Maize(16kg)==>Sorghum(10kg)==>SoyaBeanMeal(3.5kg)==>GroundnutCake(4kg)==> PalmKernelMeal(1.5kg)==>RiceBran(4kg)==>BoneMeal(0.05kg)==>OyesterShell(0.05kg)==> Salt(0.15kg)==> Lysine(0.75kg)==> Methionine(3kg)==> Premix(2kg)==> Enzyme(5kg)	**Chromosmes3**

Table 5 shows a typical chromosomes formation pattern for a first generation level through the combination of genes. This is later used for crossover and produce new offsprings and potential parents for the next generation.

4.4. GA Constraints Initialization

The genetic algorithm constraint initialization phase is the phase where all constraint required for the modeling of the proposed system is initialized. More so, the phase encompasses set of minimum nutrient required in the combination of ingredients used to form the target feed and target weight. Let F_j represents any instance of feed type in Table 2, R be the set of corresponding required nutrient of F_j and w denotes the weight, such that:

$r_m \in R_w$ and $R \subseteq N, where\, m = [1{:}8]$

Therefore,

$$\psi_m \geq r_m : \forall r_m \in R_w \qquad 5$$

$$\beta = T : T > 0 \qquad 6$$

$$\exists \rho \in m : \rho \leq m \bigwedge \rho > 0$$

$$\Upsilon > 0 \qquad 7$$

$where\ \rho\ is\ the\ maximum\ swap\ moves$

4.5. GA Chromosomes Crossover Phase

Crossover is a process in genetic algorithm where two best fit parents reproduce by donating their genes to give birth to an offspring. In this research, chromosomes are potential parents that reproduce an offspring through the use of Gene Swapper. Hence, the crossover process takes place between the chromosomes through the help of the gene swapper which swaps genes' positions between the chromosomes by several moves. This process is optimized to give the best output with the aid of Tabu Search optimizer that look ahead to the nearest neighbour of the initial swapped genes and quickly compute the fitness function and then match with previous if fitter. TS reduces the number of moves the gene swapper makes by performing permutation of best possible gene swap arrangement and picking the least cost price. It also conserves time spent during the crossover. Several swapping moves are made until the fittest offspring is produced. One of such swapping move is depicted in Figure 3.

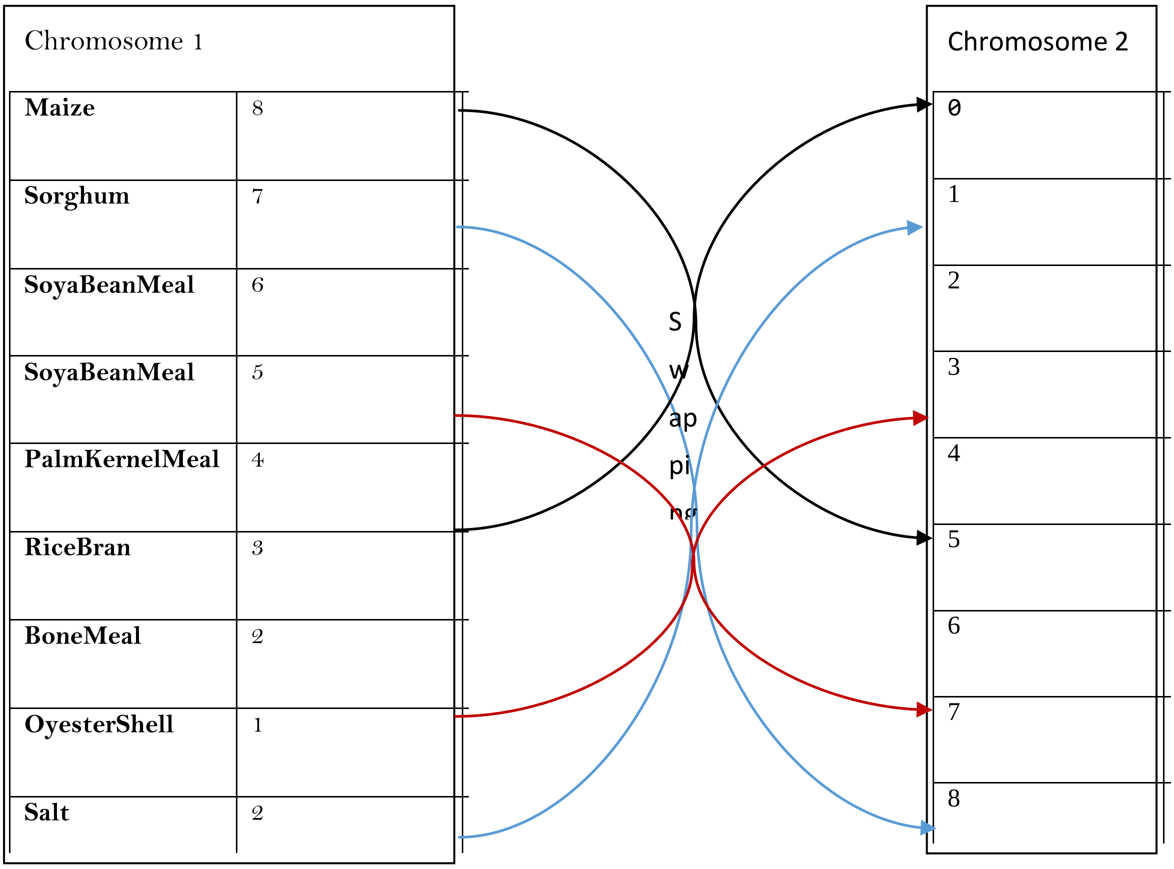

Figure-3. A typical crossover operations swapping moves.

The result of the crossover operation produced by the several crossover swapping moves is presented in Table 6.

Table-6. Result of crossover.

Maize	Sorghum	Soya Bean Meal	Groundnut Cake	Palm Kernel Meal	Rice Bran	Bone Meal	Oyester Shell	Salt	Lysine	Methionine	Premix	Enzyme
1	7	2	5	4	3	2	8	2	4	3	1	6

4.6. Tabu Search Based Mutation Phase

The mutation phase is the phase where genes within the chromosomes are altered. In this research model, the mutation process solely depends on the TS-optimizer enhanced by plus $(+)$ and minus $(-)$ operators. The operators work simultaneously i.e. whenever there is plus (addition) operation there exist a subtract operation and vice versa. TS-optimizer initialize a starting point (index), then picks another point (index) randomly and generate a weight greater than the weight in the point but within the range of the gene weight in the considered chromosomes. The initial point is then altered by performing an addition operation using the plus $(+)$ operator and also alter the second point, subtracting the generated weight from it using the minus $(-)$ operator.

Table-7. Table showing mutation operation on Table 7.

Index1:BoneMeal (W_i)	Index2:Enzyme (W_i)	Generated weight (ω)	Plus operator (Υ)	Subtract operator (Υ)
2	6	5.5	$2(+)5.5 = 7.7$	$6(-)5.5 = 1.5$

The mutation points are at the locations which corresponds to BoneMeal and Enzyme. Based on the calculations in Table 7, the values at these points changes to 7.7 and 1.5 respectively. The result is presented in Table 8.

Table-8. Result of mutation.

Maize	Sorghum	Soya Bean Meal	Groundnut Cake	Palm Kernel Meal	Rice Bran	BoneMeal	Oyester Shell	Salt	Lysine	Methionine	Premix	Enzyme
1	7	2	5	4	5	7.7	8	2	4	3	1	1.5

4.7. GA Fitness Function Picker (FFP)

The fitness function picker helps in the process of selecting the best fit chromosomes. In this research, the aim of the GA process is to give the best feed formulation with the least price. Hence, the fitness function picker search through the chromosomes based on set constraints and picks the chromosomes with the minimum cost price attribute. This is achieved through object sorting action of a population

$$f = FFP\left(p_{best\_fit} < p_{best_{fit}+1} < p_{best_{fit}+2} < \cdots < p_{best_{fit}+n-1}\right) \qquad 8$$

$$where\ f\ is\ the\ function\ that\ returned\ best\ fit\ at\ index\ zero$$

5. EXPERIMENTAL RESULTS

The data for the research was captured, tuned and normalized to fit into the Tabu-Search based genetic algorithm driven application. The result obtained from the application were captured and recorded and also compared at every stage of the generated result. A total of forty-seven chromosomes were generated by the application and the feed type was based on Layers Mash. Table 9 shows the selected minimum of the required nutrients.

Table-9. Showing Selected Minimum Required Nutrient.

Feed Type	Protein	Fat	Fibre	Calcium	Phosphorous	Lysine	Methionine	Energy
Layers mash	16.5	3.7	6.5	3.5	0.45	0.70	0.27	2530

6. PERFORMANCE EVALUATION OF THE PROPOSED TAM FEED FORMULATION MODEL

In order to evaluate the proposed hybridized TAM feed formulation model, its performance on the feed formulation procedure was compared with the performances of the ordinary GA model and the Linear Programming (LP) based model. The comparison of the performances of these models was carried out based on three (3) standard metrics; first, the value of the major nutrients contained in the sample of layers mash formulated using the three models/algorithms. Secondly, comparison was also done in terms of total cost of 50kg produced using the optimum mix of nutrients obtained from the three algorithms. Thirdly, comparison was carried out in terms of number of iterations and runtime of the three algorithms/models in generating the optimal solution

Results presented in Table 10 revealed that the nutrient content for layers mash formulated with TAM model is higher than the recommended minimum value and is higher than those formulated with LP and GA models except that the GA model's ether extract content was slightly higher than that of TAM. The value for TAM is 5.395 while that of GA is 5.612. This difference however, may not have significant impact on the animals since the value for TAM is higher than the recommended minimum value. The results are further illustrated in Figures 4 to 10.

Table-10. Nutrient content in formulated layers' mash.

Nutrient/Total Cost	Minimum	TAM	LP	GA
Crude Protein	16.5	20.677	17.64	20.012
Energy	2530	2544.76	1967	22024
Ether Extract	3.7	5.395	4.062	5.612
Crude Fibre	6.5	6.645	5.943	6.473
Lysine	0.70	0.777	0.701	0.742
Methionine	0.27	0.27932	0.234	0.2621
Calcium	3.5	8.70612	7.238	8.7051
Phosphorus	0.45	0.53848	0.490	0.599
Total Cost		2314.4	24572	2399

Table-11. Comparative analysis of the algorithms based on number of iterations/runtime

	TAM	LP	GA
Number of Iterations	36	34	42
Runtime (seconds)	67	60	78

The results presented in Table 11 also reveals that the number of iterations and runtime for generating the optimal solution for TAM was lower than that of GA and but higher for LP. Usually, the smaller the number of iterations and the runtime the more efficient is the algorithm. The major motivation for hybridizing GA with Tabu Search to produce TAM in this paper was to enhance the speed of the GA algorithm. The result in Table 11 clearly shows that introducing a local search algorithm (Tabu search) has succeeded in increasing the speed of generating the optimal solution of producing a balanced feed at the least cost. The result is also presented in a graphical form in Figure 9.

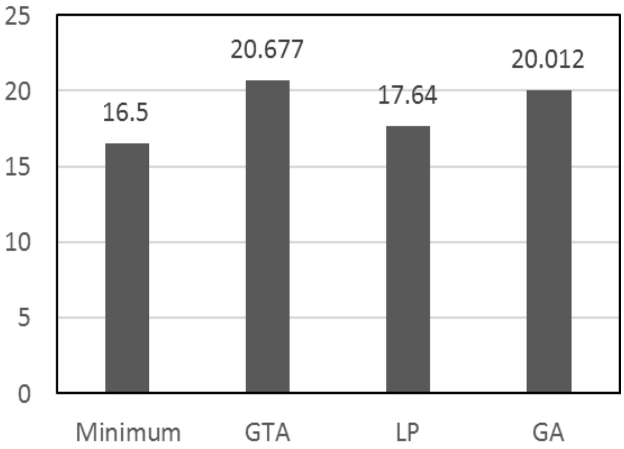

Figure-4. Comparison based on Crude Protein of Formulated Feed

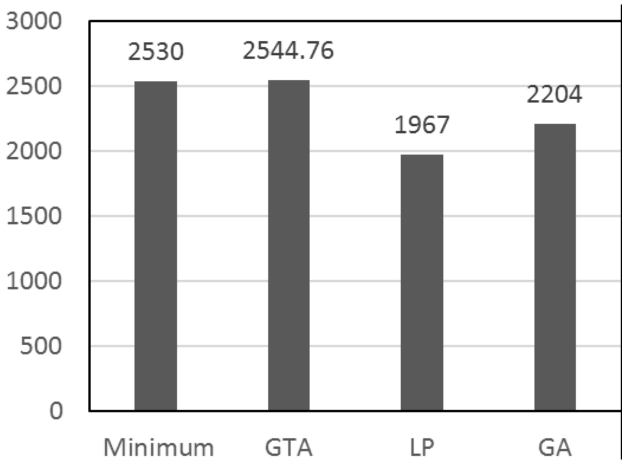

Figure-5 Comparison based on Energy Content of Formulated Feed

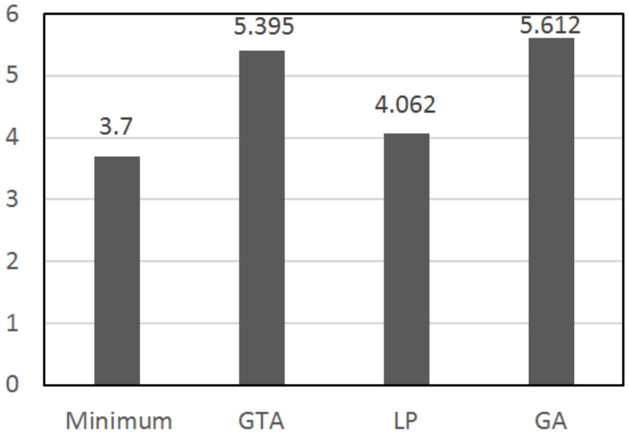

Figure-6. Comparison based on Ether Extract of Formulated Feed

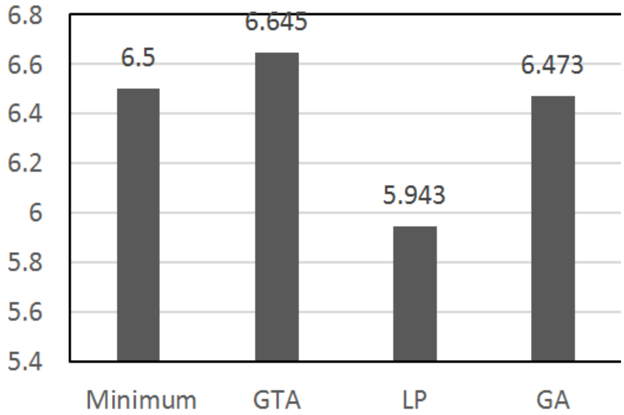

Figure-7. Comparison based on Crude Fiber Content of Formulated Feed

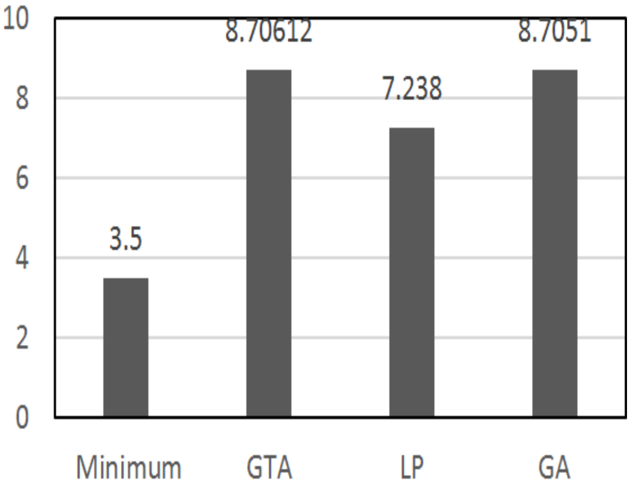

Figure-8. Comparison based on Calcium Content of Formulated Feed.

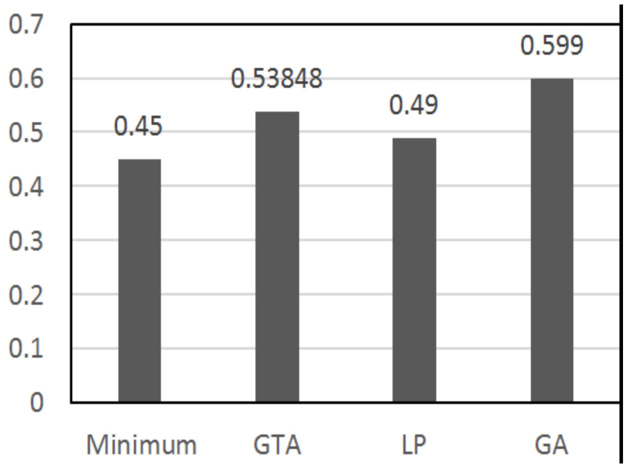

Figure-9. Comparison based on Phosphorus Content of Formulated Feed.

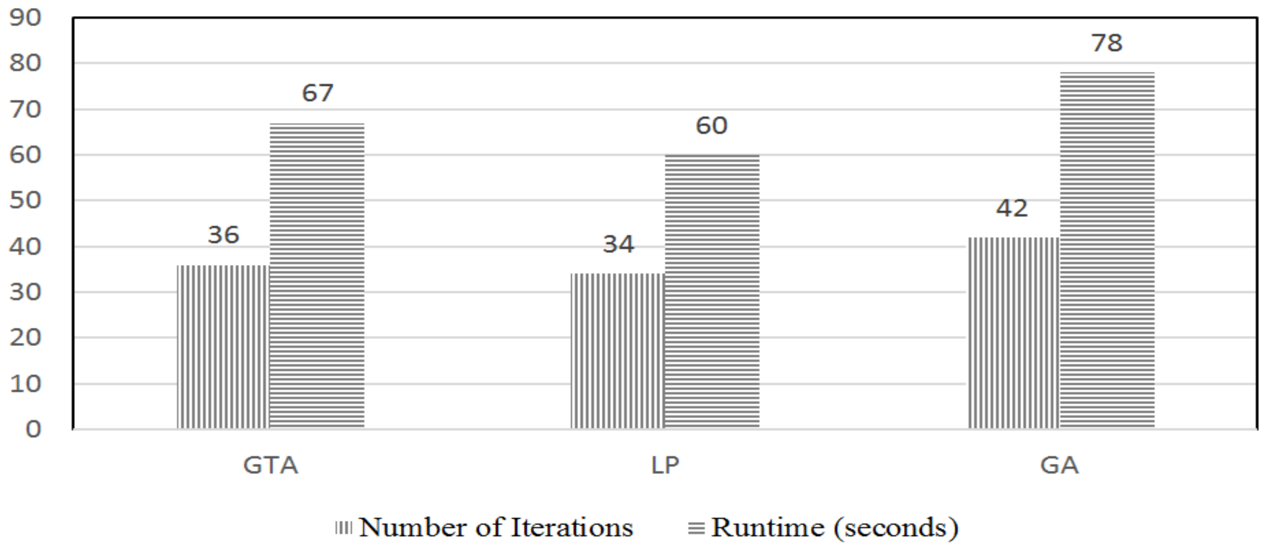

Figure-10. Comparison based on Number of iterations and runtime.

7. CONCLUSION

In this research, a hybrid tabu search and genetic algorithm model for solving the problem of poultry feed formulation at least cost was developed. The model was used to formulate layers feed at the lowest price possible and still contain the needed nutrients in the right proportion. Comparison of the hybrid TAM model developed with the existing LP and ordinary GA shows improved performance especially in terms of nutrient content, cost reduction and runtime reduction. Since feed plays an important role in poultry production, this model can be used to formulate poultry feeds in other to get optimum result at least cost thereby improving the profit margin for poultry farmers. This research work considered poultry feed formulation. Future works can consider formulation of feed for other livestock.

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