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Optimal control and cost effectiveness analysis for Newcastle disease eco-epidemiological model in Tanzania

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ABSTRACT

In this paper, a deterministic compartmental eco-epidemiological model with optimal control of Newcastle disease (ND) in Tanzania is proposed and analysed. Necessary conditions of optimal control problem were rigorously analysed using Pontryagin’s maximum principle and the numerical values of model parameters were estimated using maximum likelihood estimator. Three control strategies were incorporated such as chicken vaccination (preventive), human education campaign and treatment of infected human (curative) and its’ impact were graphically observed. The incremental cost effectiveness analysis technique used to determine the most cost effectiveness strategy and we observe that combination of chicken vaccination and human education campaign strategy is the best strategy to implement in limited resources. Therefore, ND can be controlled if the farmers will apply chicken vaccination properly and well in time.

1. Introduction

Mathematical control theory is a basic principle that underlies the analysis and design of control systems. This theory is used to influence the objects behaviour so as to achieve a desired goal [24] and determine whether the species persist or extinct in natural system. It is also important for decision making regarding intervention programmes [14]. Modelling infectious diseases in species provides an important insight into disease behaviour and control measures while the epidemiological data and economic cost of controlling infectious diseases provides essential elements in evaluating the relevance of the intervention programmes. Currently, mathematical techniques are well linked with biological process of disease transmission and the epidemics of infectious diseases among humans and other animals resulting from the transmission of a pathogen either through hosts or environment [7]. The interaction between human and animals or among animals themselves may results into disease transmission which destabilize the ecosystem. The studies of [3,6,9,17,26] employed modelling techniques to analyse ecological aspect of interacting species of various animals.

CONTACT

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Tanzania poultry population is estimated to be 69 millions which comprises of traditional or family poultry and commercial poultry systems, about 90% of the poultry in Tanzania are chickens. The agricultural sector contributes 30% to the national gross domestic product (GDP) of which livestock sector contributes 18% of the agricultural GDP. Chickens only contribute 16% of livestock GDP, 3% of agricultural sector GDP and 1% of national GDP which is a significant contribution to the national economy [11]. Newcastle disease (ND) is one of the animal diseases which affect mostly domestic animals and chickens are most susceptible. It can cause a mortality rate of about 90–100% in chicken population. Incessantly loosing chickens due to ND may affect the quantity and quality of food for people on marginal diets while chickens play a vital role by providing an important source of high-quality nutrition and income at very little cost [10]. It is extremely difficult to assess the prevalence of ND at given time because in some areas the outbreaks are not reported. Moreover it extremely occur especially in rural and remote areas [2]. Vaccination provides a dormant pathogen in susceptible population which allows the vaccinated animal to produce strong antibodies against the weaker pathogen [3]. Currently, the phenomenon of prey predator ecosystem is well-studied with and without disease infection and these species in ecosystem do not exist alone [13] and the mechanisms of saving the population from extinction is biologically controlled in ecosystem [6]. The existence of ND in chickens is a big loss to human (farmers). Controlling ND threats require early preparation before the outbreak becomes overwhelming. Modelling tool plays a big role in epidemiology by providing a concrete mechanism for understanding spreads of the disease and suggesting effective control measures [8]. The intervention programmes are used in planning, implementing, evaluating, prevention, therapy and control measures [23]. The eradication of disease in the environment does not only depend on medical issues, but also on the ability of understanding the transmission dynamics of a particular disease and the application of the optimal control strategies and the implementation of logistic policies [8].

This particular study is motivated by a significant contribution of chicken 1% of GDP in national level in Tanzania [11], regardless of many obstacles such as poultry disease, poor quality feeds and inadequate technical support services. The national sample census of agriculture 2012 [5] indicates that the most dangerous poultry disease is ND which causes a very big drainage loss in many families, industries, organization and or individuals that really rely on poultry. It is against this background that this study is therefore undertaken as an attempt to apply the optimal control theory in minimizing the spread of ND and the cost of implementing control strategies. In order to achieve this goal, we use the following control parameters: chicken vaccination ($u_1$), education campaign ($u_2$) and treatment rate of infected human ($u_3$) as time dependent variables. In the next section, we derive the model that describes the dynamics of ND.

2. Model formulation

In this section, we formulate and analyse a mathematical model of ND in Tanzania. The modelled populations include chickens and human being. The epidemiological model comprises of five subclasses namely susceptible chicken $S_1(t)$, infected chicken $I_1(t)$, susceptible human $S_2(t)$, infected human $I_2(t)$ and human recovery class $R_2(t)$. The model presented under the following assumptions: The growth rate of chicken population follows a logistic function with intrinsic growth rate $r$ and carrying capacity $k$. The chicken
population gets infection when it comes into contact with other infected chicken and this contact process is assumed to follow the simple mass action kinetics with \( \beta_1 \) as the force of infection while human get infection with the force of infection \( \beta_2 \). Natural death rate of chicken \( \mu_1 \) and induced death rate due to disease \( m \) reduces the chicken population. The human population suffers loss due to the natural death rate \( \mu_2 \) and increases due to recovery rate \( \theta \) through treatment rate \( \gamma \). The predation functional response of the human towards susceptible as well as infected chicken is assumed to follow Michaelis–Menten kinetics and is modelled using a Holling type-II functional response with predation coefficients \( b_1, c_1, b_2, c_2 \) and half saturation constant \( a_1, a_2, n_1 \) and \( n_2 \). Consumed susceptible and infected chicken are converted into human with efficiency \( \alpha_1, \alpha_2, \alpha_3 \) and \( \alpha_4 \). Basing on these assumptions, we formulate the model as

\[
\begin{align*}
\frac{dS_1}{dt} &= r \left( 1 - \frac{S_1}{k} \right) S_1 - \beta_1 S_1 I_1 - \frac{b_1 S_1 S_2}{a_1 + S_1} - \frac{b_2 S_1 I_2}{a_2 + S_1}, \\
\frac{dI_1}{dt} &= \beta_1 S_1 I_1 - m I_1 - \mu_1 I_1 - \frac{c_1 I_1 S_2}{n_1 + I_1} - \frac{c_2 I_1 I_2}{n_2 + I_1}, \\
\frac{dS_2}{dt} &= \frac{\alpha_1 b_1 S_1 S_2}{a_1 + S_1} + \frac{\alpha_2 c_1 I_1 S_2}{n_1 + I_1} - \beta_2 S_2 I_1 - \mu_2 S_2 + \theta R_2, \\
\frac{dI_2}{dt} &= \beta_2 S_2 I_1 - \gamma I_2 - \mu_2 I_2 + \frac{\alpha_3 b_2 S_1 I_2}{a_2 + S_1} + \frac{\alpha_4 c_2 I_1 I_2}{n_2 + I_1}, \\
\frac{dR_2}{dt} &= \gamma I_2 - \theta R_2 - \mu_2 R_2.
\end{align*}
\]

We introduce the time dependent controls in the model (1) for the aim of controlling ND and study the strategies that curtail ND epidemic in poultry. For the optimal control problem, we consider the following model equations

\[
\begin{align*}
\frac{dS_1}{dt} &= r \left( 1 - \frac{S_1}{k} \right) S_1 - (1 - u_1) \beta_1 S_1 I_1 - \frac{b_1 S_1 S_2}{a_1 + S_1} - \frac{b_2 S_1 I_2}{a_2 + S_1}, \\
\frac{dI_1}{dt} &= (1 - u_1) \beta_1 S_1 I_1 - (m + \mu_1) I_1 - \frac{c_1 I_1 S_2}{n_1 + I_1} - \frac{c_2 I_1 I_2}{n_2 + I_1}, \\
\frac{dS_2}{dt} &= \frac{\alpha_1 b_1 S_1 S_2}{a_1 + S_1} + \frac{\alpha_2 c_1 I_1 S_2}{n_1 + I_1} - (1 - u_2) \beta_2 S_2 I_1 - \mu_2 S_2 + \theta R_2, \\
\frac{dI_2}{dt} &= (1 - u_2) \beta_2 S_2 I_1 - (u_3 + \gamma) I_2 - \mu_2 I_2 + \frac{\alpha_3 b_2 S_1 I_2}{a_2 + S_1} + \frac{\alpha_4 c_2 I_1 I_2}{n_2 + I_1}, \\
\frac{dR_2}{dt} &= (u_3 + \gamma) I_2 - \theta R_2 - \mu_2 R_2,
\end{align*}
\]

where

(i) \( u_1(t) \) the control variable based on chicken vaccination
(ii) \( u_2(t) \) the control variable based on human education campaign
(iii) \( u_3(t) \) the control variable to measure the effectiveness of treatment of infected human.

We apply control theory as a mathematical tool that is used to make decision involving complex biological situations [12]. The purpose of introducing controls in the model is to
find the optimal level of the intervention strategy preferred to reduce the spreads and cost of implementation of the control. The control variables \( u_1(t), u_2(t) \) and \( u_3(t) \) are minimized subject to the differential equations (2) and formulate the objective functional as

\[
J = \min_{u_1,u_2,u_3} \int_0^{t_f} \left( B_1 I_1 + B_2 I_2 + \frac{1}{2} A_1 u_1^2 + \frac{1}{2} A_2 u_2^2 + \frac{1}{2} A_3 u_3^2 \right) \, dt,
\]

where \( t_f \) is the final time, \( B_1 I_1, B_2 I_2 \) are the cost associated with chicken vaccination and treatment of infected human respectively while \( A_1, A_2 \) and \( A_3 \) are relative cost weight for each individual control measure. The objective function (3) involved in minimizing of the number of infected chickens as well as the cost for applying control strategies. In this paper, a quadratic function which satisfies the optimality conditions is considered for measuring the control cost as applied by [14–16,18–20,21,25]. Then the optimal controls \( u_1^*(t), u_2^*(t) \) and \( u_3^*(t) \) exists such that

\[
J(u_1^*(t), u_2^*(t), u_3^*(t)) = \min \{ J(u_1(t), u_2(t), u_3(t)) \mid u_1(t), u_2(t), u_3(t) \in \mathbb{U} \}, \quad \text{where} \quad \mathbb{U} = \{(u_1(t), u_2(t), u_3(t)) \mid a_i \leq (u_1(t), u_2(t), u_3(t)) \leq b_i, \quad i = 1, \ldots, 5 \}
\]

The optimal control must satisfy the necessary conditions that are formulated by Pontryagin’s Maximum Principle [11]. This principle converts the system of Equations (2) and (3) into a problem of minimizing point-wise a Hamiltonian \( (H) \), with respect to \( u_1(t), u_2(t), u_3(t) \) as

\[
H = B_1 I_1 + B_2 I_2 + \frac{1}{2} A_1 u_1^2 + \frac{1}{2} A_2 u_2^2 + \frac{1}{2} A_3 u_3^2
\]

\[
+ \lambda_1 \left\{ r \left( 1 - \frac{S_1}{k} \right) S_1 - (1 - u_1) \beta_1 S_1 I_1 - \frac{b_1 S_1 S_2}{a_1 + S_1} - \frac{b_2 S_1 I_2}{a_2 + S_1} \right\}
\]

\[
+ \lambda_2 \left\{ (1 - u_1) \beta_1 S_1 I_1 - (m + \mu_1) I_1 - \frac{c_1 I_1 S_2}{n_1 + I_1} - \frac{c_2 I_1 I_2}{n_2 + I_1} \right\}
\]

\[
+ \lambda_3 \left\{ \frac{\alpha_1 b_1 S_1 S_2}{a_1 + S_1} + \frac{\alpha_2 c_1 I_1 S_2}{n_1 + I_1} - (1 - u_2) \beta_2 S_2 I_1 - \mu_2 S_2 + \theta R_2 \right\}
\]

\[
+ \lambda_4 \left\{ (1 - u_2) \beta_2 S_2 I_1 - (\mu_3 + \gamma) I_2 - \mu_2 I_2 + \frac{\alpha_3 b_2 I_1 I_2}{a_2 + I_1} + \frac{\alpha_4 c_2 I_1 I_2}{n_2 + I_1} \right\}
\]

\[
+ \lambda_5 \left\{ (u_3 + \gamma) I_2 - (\theta + \mu_2) R_2 \right\},
\]

where \( \lambda_i, \ i = 1, 2, 3, 4, 5 \) are the co-state variables associated by \( S_1, I_1, S_2, I_2, R_2 \). The adjoint equations are obtained by

\[
\frac{d\lambda_i}{dt} = -\frac{\partial H}{\partial i},
\]

with transversality condition

\[
\lambda_i(t_f) = 0.
\]
From Equation (4) we obtain the following adjoint equations

\[
\frac{\partial H}{\partial S_1} = -\lambda_1 \left( \frac{r}{k} (k - 2S_1) - (1 - u_1) \beta_1 I_1 - \frac{b_1 S_2 a_1}{(a_1 + S_1)^2} - \frac{b_2 I_2 a_2}{(a_2 + S_1)^2} \right) - \lambda_2 (1 - u_1) \beta_1 I_1 - \lambda_3 \frac{\alpha_1 b_1 S_2 a_1}{(a_1 + S_1)^2} - \lambda_4 \frac{\alpha_3 b_2 I_2 a_2}{(a_2 + S_1)^2},
\]

(7)

\[
\frac{\partial H}{\partial I_1} = -B_1 + \lambda_1 (1 - u_1) \beta_1 S_1 - \lambda_2 \left( (1 - u_1) \beta_1 S_1 - m - \mu_1 - \frac{c_1 S_2 n_1}{(n_1 + l_1)^2} - \frac{c_2 I_2 n_2}{(n_2 + l_1)^2} \right) - \lambda_3 \left( \frac{\alpha_2 c_1 S_2 n_1}{(n_1 + l_1)^2} - (1 - u_2) \beta_2 S_2 \right) - \lambda_4 \left( \frac{\alpha_4 c_2 I_2 n_2}{(n_2 + l_1)^2} + (1 - u_2) \beta_2 S_2 \right),
\]

(8)

\[
\frac{\partial H}{\partial S_2} = \lambda_1 b_1 S_1 \left( \frac{1}{a_1 + S_1} + \frac{\lambda_2 c_1 I_1}{n_1 + I_1} \right) - \lambda_3 \left( \frac{\alpha_1 b_1 S_1}{a_1 + S_1} + \frac{\alpha_2 c_1 I_1}{n_1 + I_1} - (1 - u_2) \beta_2 I_1 - \mu_2 \right) - \lambda_4 (1 - u_2) \beta_2 I_1,
\]

(9)

\[
\frac{\partial H}{\partial I_2} = -B_2 + \lambda_1 \left( \frac{b_2 S_1}{a_2 + S_1} + \lambda_2 \frac{c_2 I_1}{n_2 + I_1} \right) - \lambda_4 \left( \frac{\alpha_3 b_2 S_1}{a_2 + S_1} + \frac{\alpha_4 c_2 I_1}{n_2 + I_1} - (u_3 + \gamma) - \mu_2 \right) - \lambda_5 (u_3 + \gamma),
\]

(10)

\[
\frac{\partial H}{\partial R_2} = \lambda_5 (\theta + \mu_2) - \lambda_3 \theta.
\]

(11)

The optimality of the control problem is obtained by

\[
u_i^*(t) = \frac{\partial H}{\partial u_i},
\]

(12)

where \(i = 1, 2, 3\). The solution of \(u_1^*(t), u_2^*(t)\) and \(u_3^*(t)\) are presented in compact form as

\[
u_1^*(t) = \max \left\{ 0, \min \left\{ 1, \frac{\beta_1 S_1 I_1 (\lambda_2 - \lambda_1)}{A_1} \right\} \right\},
\]

\[
u_2^* = \max \left\{ 0, \min \left\{ 1, \frac{\beta_2 S_2 I_1 (\lambda_4 - \lambda_3)}{A_2} \right\} \right\}
\]

and

\[
u_3^* = \max \left\{ 0, \min \left\{ 1, \frac{I_2 (\lambda_4 - \lambda_5)}{A_3} \right\} \right\}.
\]

3. Parameter estimation of ND model

Ordinary differential equations (ODEs) are widely used in ecology to describe the dynamical behaviour of systems of interacting populations. However, systems of ODEs rarely provide quantitative solutions that are close to real field observations or experimental data because natural systems are often subject to environmental noise and ecologists are
often uncertain about the correct parameterization [4]. Therefore, it is important to estimate model parameters for numerical simulations. In this section, we present the data of chickens death cases collected from five districts in two regions (Singida and Dodoma) in Tanzania for 2014 as summarized in Table 1. The method used to estimate parameters in this section is maximum likelihood (ML) where real data of chicken death cases from Kongwa, Chamwino, Ikungi, Singida and Mkalama districts were used.

### 3.1. The maximum likelihood estimator (MLE)

The idea of ML method is to maximize the likelihood function. In this paper, the likelihood function is the sum of squares of residual (SSR) defined as

\[
L(\theta) = \sum_{i=1}^{N} (y_i - y_i^{\text{est}})^2, \tag{13}
\]

where \(\{y_i\}_{i=1}^{N}\) is the real data and \(\{y_i^{\text{est}}\}_{i=1}^{N}\) is the solution of model equations (1) at a given parameter value. The numerical results for MLE for the ND model parameters are summarized in Table 2.

### Table 2. Estimated parameter values for ND model.

| Symbol           | Literature value | Source      | Estimate value (per month)                  |
|------------------|------------------|-------------|---------------------------------------------|
| \(a_i, i = 1, \ldots, 4\) | 0.25, 0.6, 0.8, 0.6 | [9], Estimated | 0.3093, 0.6078, 0.8939, 0.6008 |
| \(\beta_1\)     | 0.1              | [22]        | 0.1495                                      |
| \(k\)           | 500              | [17]        | 500                                         |
| \(\mu_2\)       | 0.01             | [3]         | 0.0244                                      |
| \(c_1\)         | 0.02             | Estimated   | 0.0202                                      |
| \(r\)           | 10               | [3]         | 10                                          |
| \(a_i, i = 1, 2\) | 0.25, 0.8        | Estimated   | 0.2481, 0.6306                              |
| \(n_i, i = 1, 2\) | 0.03, 0.5        | Estimated, [17] | 0.0304, 0.503                             |
| \(b_1\)         | 0.4              | [17]        | 0.4085                                      |
| \(b_2\)         | 0.6              | [9]         | 0.6019                                      |
| \(m\)           | 0.6              | Estimated   | 0.5968                                      |
| \(\mu_1\)       | 0.02             | [3]         | 0.02488                                     |
| \(\theta\)      | 0.4              | Estimated   | 0.4048                                      |
| \(\gamma\)      | 0.6              | Estimated   | 0.612                                       |
| \(\beta_2\)     | 0.012            | Estimated   | 0.0119                                      |
| \(c_2\)         | 0.05             | Estimated   | 0.4974                                      |
| \(B_1, B_2\)    | 10, 10           | Estimated   | –                                           |
| \(A_1, A_2, A_3\) | 30, 20, 10      | [3]         | –                                           |
4. Numerical results

4.1. Optimal control

In this section we study numerically the effects of optimal control strategies such as chicken vaccination, education campaign and treatment of infected human in the spread of ND. The solution of the optimal control problem was obtained by solving the optimality system of state and adjoint systems through forward–backward sweep method. The adjoint systems (7–11) were solved by fourth order Runge–Kutta scheme using the forward solution of the state equations. The optimality condition is satisfied through the convex update of the previous control values. We describe the controls in the following strategies using the parameter values in Table 2.

4.1.1. Strategy A: control with chicken vaccination \((u_1)\)

With strategy A, only chicken vaccination \(u_1\) is applied to control the system while other controls are set to zero. In Figures 1–3, the effect of chickens vaccination and its' positive impact is revealed. Figure 1(a) and 1(b) shows a significant difference in susceptible chicken population and stabilizes around the carrying capacity \(k = 500\) while infected chicken are gradually decreasing to zero. A significant difference is also observed in human population as shown in Figure 2(a) and 2(b) and the control profile suggests that the control \(u_1\) to be at the highest level for about seven months in a year before dropping to lower bound (see Figure 3). This result shows that the optimal control measure is effective in chicken and human populations and hence the community is disease free.

4.1.2. Strategy B: control with education campaign in human population \((u_2)\)

The purpose of education campaign strategy is to explore the awareness of the disease, mode of transmission, prevention and control measures in community. Figures 4–6

![Figure 1. Simulations of the model showing the effect of chicken vaccination in chicken population.](image)
Figure 2. Effect of chicken vaccination in human population.

Figure 3. Control profile for the effect of chicken vaccination.

describes the effect of implementing education campaign in human and the impact is visible in human population (see Figure 5(a) and 5(b)) while the control profile maintained at its upper bound for the interval of almost one year (see Figures 6 and 7).

4.1.3. Strategy C: control with treatment of infected human (\(u_3\))

When only control \(u_3\) is applied while others are set to zero, the significant effect occurs on the class of human populations (see Figures 8 and 9). The control profile shows high increase to the upper bound and remains effective for long before gradually decreasing to lower bound (see Figure 9(b)). This result shows that the chicken population is not free from the disease. The treatment control strategy is not effective without vaccination of susceptible chicken and hence it is not preferable to the community as the control measure for ND.
4.1.4. Strategy D: combination of education campaign in human \( (u_2) \) and treatment of infected human \( (u_3) \)

The numerical results shows that the susceptible human population increases while infected human population gradually decreases as illustrated in Figure 10. The presence of treatment and education in the community will somehow reduce the spread of disease moreover the strategy seems less effective. From Figure 11, we observed the control profile with different upper bounds and at the end both gradually decreases to lower bound.
4.1.5. **Strategy E: control with combination of chicken vaccination ($u_1$) and treatment of infected human ($u_3$)**

With this strategy, a positive impact is observed in both chicken and human populations. In Figures 12 and 13 we observe the control strategies results in decreasing the number of infected chicken and infected human while increasing the susceptible chicken and human respectively. The control profile for chicken vaccination ($u_1$) is at its optimal level for about seven months to ensure that the community is disease free (see Figure 14) while ($u_3$) maintained at upper bound for about eleven months and finally both dropped to zero.
4.1.6. Strategy F: combination of chicken vaccination ($u_1$) and education campaign in susceptible human ($u_2$)

The controls ($u_1$) and ($u_2$) are used to optimize the objective function ($f$) while ($u_3$) is set to zero. Figures 15 and 16 show a significant difference when the controls ($u_1$) and ($u_2$) are applied. This result shows that the presence of controls saves the population and enables community to benefit from chicken. The control profile suggests that the control ($u_1$) to be at the upper bound for about seven months in a year before dropping to lower bound while control ($u_2$) to be at the upper bound for about seven months and two weeks before tends to zero (see Figure 17).
Figure 10. Simulations of the model showing the effect of education campaign and treatment on the infected human (strategy D) on the dynamics of ND in human population.

Figure 11. Simulations of the model showing the effect of education campaign and treatment on the infected human (strategy D) on the dynamics of ND.

4.1.7. Strategy G: control with combination of chicken vaccination ($u_1$) and education campaign in susceptible human ($u_2$) and treatment of infected human ($u_3$)

In this strategy, the combination of three strategies ($u_1$), ($u_2$) and ($u_3$) used to optimize the objective function ($J$) and then analysed its impact in chicken and human populations. Figures 18 and 19 shows the impact of with and without control application in the model. The significant difference is observed in both chicken and human population. In Figure 20,
Figure 12. Simulations of the model showing the effect of vaccination and treatment of infected human (strategy E) in chicken population.

Figure 13. Simulations of the model showing the effect of vaccination and treatment of infected human (strategy E) in human population.

the control ($u_1$) is maintained at the upper bound until about the end of intervention, ($u_2$) to be at the upper bound for about four month before dropping to zero while ($u_3$) oscillates in between lower and upper bounds for the entire period of intervention. From the numerical simulations it is not easily to conclude the best strategy for implementation
Figure 14. Simulations of the model showing the effect of vaccination and treatment of infected human (strategy E) in control profile.

Figure 15. Simulations of the model showing the effect of chicken vaccination and education campaign in human strategy (F) in chicken population.

with limited resources. In the next section evaluates the cost effectiveness analysis (CEA) for each strategy.

5. Cost-effective analysis

In order to make decision on which intervention to choose, we evaluate the economic implications of ND control strategies using CEA technique. The CEA helps us to determine
Figure 16. Simulations of the model showing the effect of vaccination and education campaign (strategy F) in human population.

Figure 17. Simulations of the model showing the effect of vaccination and treatment of infected human (strategy F) in control profile.

and propose the most cost effective strategy to implement in limited resources. We evaluate the cost using incremental cost effectiveness ratio (ICER) which used to compare the differences between the costs and health outcomes of the two competing intervention strategies. Each intervention is compared with the next less effective alternative [14]. The infectious averted is computed by taking the difference between the total number of species individuals without control and the total number of species individuals with control. The total control costs $A_i u_i^2$, $A_2 u_2^2$ and $A_3 u_3^2$ (where $A_i$ for $i = 1, 2, 3$ are relative cost weight for each individual control measure, while $u_1$, $u_2$, $u_3$ are the chicken vaccination costs ($), costs for human education campaign ($) and costs for treatment of infected human ($) respectively) are calculated and estimated in ($) USD over the period of one year respectively. The control strategies are ranked in order of increasing infection averted as presented in Table 3.
Figure 18. Simulations of the model showing the effect of vaccination, education and education campaign (strategy G) in chicken population.

Figure 19. Simulations of the model showing the effect of vaccination, education and education campaign (strategy G) in human population.

We calculate and compare the cost effectiveness ratio (ICER) for strategy B and strategy C as follows:

| Strategies | Total infections averted | Total costs ($) | ICER  |
|------------|-------------------------|----------------|-------|
| Strategy B | 0.3021                  | 87.1431        | 288.4578 |
| Strategy C | 0.6625                  | 47.2157        | -110.786 |
The ICER is calculated as follows

\[
\text{ICER}(B) = \frac{87.1431}{0.3021} = 288.4578, \quad \text{ICER}(C) = \frac{47.2157 - 87.1431}{0.6625 - 0.3021} = -110.786.
\]

The comparison between strategies C and B shows a cost saving of $110.786 for strategy C over strategy B. The negative ICER for strategy C indicates that strategy B is strongly dominated and less effective than strategy C. Therefore, strategy B is excluded from the set of alternatives. We exclude B and compare strategy C and D, and ICER recalculated as follows

| Strategies | Total infections averted | Total costs ($) | ICER     |
|------------|-------------------------|----------------|----------|
| Strategy C | 0.6625                  | 47.2157        | 71.2689  |
| Strategy D | 0.9553                  | 131.0979       | 286.4829 |

The comparison between strategies C and D indicate that strategy D is strongly dominated and is more costly than strategy C as ICER(C) < ICER(D) then strategy D is excluded in the set of alternative hence C and G are compared.
Strategies | Total infections averted | Total costs ($) | ICER  
--- | --- | --- | ---  
Strategy C | 0.6625 | 47.2157 | 71.2689  
Strategy G | 456.5505 | 255.9165 | 0.45779  

The comparison shows that ICER(G) < ICER(C), hence strategy C is more costly and excluded in the set of alternatives. We compare strategies G and F.

| Strategies | Total infections averted | Total costs ($) | ICER  
--- | --- | --- | ---  
Strategy G | 456.5505 | 255.9165 | 0.5605  
Strategy F | 456.5515 | 147.8035 | −108113  

The negative ICER for strategy F shows that the strategy G is more costly and less effective than strategy F. Therefore, the strategy G is excluded from the set of alternatives and we compare strategies F and A as follows

| Strategies | Total infections averted | Total costs ($) | ICER  
--- | --- | --- | ---  
Strategy F | 456.5515 | 147.8035 | 0.3237  
Strategy A | 456.8543 | 148.6328 | 2.7388  

The strategy A is strongly dominated and is more costly than strategy F as then strategy A is excluded in set of alternative. Strategies F and E are compared.

| Strategies | Total infections averted | Total costs ($) | ICER  
--- | --- | --- | ---  
Strategy F | 456.5515 | 147.8035 | 0.3237  
Strategy E | 456.8662 | 191.8063 | 139.8246  

Comparison between strategies E and F shows that strategy E is more costly and less effective than strategy F as ICER(F) < ICER(E). Therefore strategy E is excluded from the set of alternatives and strategy F is cost effectiveness. Now, basing on these results we therefore conclude that strategy F (chicken vaccination and human education) is most cost effective of all strategies for ND.

6. Discussion and conclusion

In this paper, a deterministic model with optimal control for ND in Tanzania was derived and analysed to examine the best strategy for controlling ND in susceptible chicken and human in Tanzania poultry activities. The Pontryagin’s maximum principle used to derive and analyse the necessary conditions for optimal control strategies such as chicken vaccination ($u_1$), human education campaign ($u_2$) and treatment on infected human($u_3$) for minimizing the spread of ND. Numerically, the model was rigorously analysed. Graphically, strategies A, E, F, G shows a significant different in chicken populations while B, C, D, F and G its’ positive impact observed in human populations. The CEA results suggest the combination of chicken vaccination and human education campaign as the most
cost-effective strategy in case of limited resources. In 2012 the Office International des Epizooties (OIE) reported that ND can be controlled through chicken vaccination and biosecurity measures [1], this results concurred with our findings. However this conclusion should be taken with high precautions because of the uncertainties around the geographical location especially in rural and remote areas. Basing on strategy F which is sufficient to combat the ND epidemic we advise the Ministry of Livestock and Fisheries in Tanzania through regional, district, division, ward and village veterinary officers to take extra incentive in ensuring that all chickens are vaccinated properly and timely.

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Disclosure statement

No potential conflict of interest was reported by the authors.

References

[1] D.J. Alexander, Newcastle Disease. British Poultry Science, Vol. 42, 2012. Available at http://www.oie.int/fileadmin/Home/fr/Health_standards/tahm/2.03.14_NEWCASTLE_DIS.pdf.
[2] D.J. Alexander, J.G. Bell, and R.G. Alders, A technology review: Newcastle disease, J. Chem. Inf. Model. 53(9) (2013), pp. 1689–1699. doi:10.1017/CBO9781107415324.004
[3] C.S. Bornaa, O.D. Makinde, and I.Y. Seini, Eco-epidemiology model and optimal control of disease transmission between humans and animals, Commun. Math. Biol. Neurosci. 26 (2015), pp. 1–28. ISSN:2052-2541
[4] J. Cao, G.F. Fussmann, and J.O. Ramsay, Estimating a predator-prey dynamical model with the parameter cascades method, Biometrics 64(3) (2008), pp. 959–967. doi:10.1111/j.1541-0420.2007.00942.x
[5] A. Chuwaa, United Republic of Tanzania National Sample Census of Agriculture, Vol. III. National bureau of statistics III, 2012, pp. 41–44. Available at www.kilimo.go.tz/agricultural.
[6] M.F. Elettrebey and S. Aly, Optimal control of a two teams prey-predator interaction model, Miskolc Math. Notes 16(2) (2015), pp. 793–803. doi:10.18514/MMN.2015.1079
[7] N.C. Grassly and C. Fraser, Mathematical models of infectious disease transmission, Nature Rev. Microbiol. 6 (2008), pp. 477–487. doi:10.1038/nrmicro1845
[8] H.W. Hethcote, The mathematics of infectious diseases, Ind. Appl. Math. 42(4) (2007), pp. 599–653. Available at http://www.jstor.org.
[9] A. Hugo, E.S. Massawe, and O.D. Makinde, An eco-epidemiological mathematical model with treatment and disease infection in both prey and predator population, J. Ecol. Nat. Environ. 4 (2012), pp. 266–279. doi:10.5897/JENE12.013
[10] D. Knueppel, P. Coppolillo, A.O. Msago, P. Msoffe, D. Mutekanga, and C. Cardona, Improving poultry production for sustainability in the Ruaha Landscape, Tanzania, WildLife Conservation Society (2009), pp. 1–24.
[11] D. Komwihangilo, The role of chicken in the Tanzanian economy and opportunities for development. Tanzania Livestock Research Institute, Dar es Salaam, 2015, pp. 1–36. Available at http://www.slideshare.net/ILRI/acgg-tanzania-2015, accessed 19 May 2016.
[12] S. Lenhart and J.T. Workman, Optimal control applied to biological models. CRC Mathematical and Computational Biology Series, 2007.
[13] C. Liu, Q. Zhang, and J. Li, Global stability analysis and optimal control of a harvested ecoepidemiological prey predator model with vaccination and taxation, Abstr. Appl. Anal. 2013 (2013), article id 950396, 16 p. doi:10.1155/2013/950396
[14] O.D. Makinde and K.O. Okosun, Impact of chemo-therapy on optimal control of malaria disease with infected immigrants, BioSystems 104 (2011), pp. 32–41.
[15] L.N. Massawe, E.S. Massawe, and O.D. Makinde, Modelling infectiology and optimal control of dengue epidemic, Appl. Comput. Math. 4(3) (2015), pp. 181–191. doi:10.11648/j.acm.20150403.21
[16] S.C. Mpeshe, L.S. Luboobi, and Y.A.W. Nkansah-gyekye, Optimal control strategies for the dynamics of Rift Valley Fever, Commun. Optimiz. Theory 3 (2014), pp. 1–18.
[17] B. Mukhopadhyay and R. Bhattacharyya, Role of predator switching in an eco-epidemiological model with disease in the prey, Ecol. Model. 220(7) (2009), pp. 931–939. doi:10.1016/j.ecolmodel.2009.01.016
[18] K.O. Okosun and O.D. Makinde, Optimal control analysis of malaria in the presence of non-linear incidence rate, Appl. Comput. Math. 12(1) (2013), pp. 20–32.
[19] K.O. Okosun, O.D. Makinde, and T. Isaac, Analysis of recruitment and industrial human resources management for optimal productivity in the presence of the HIV/AIDS epidemic, J. Biol. Phys. 39 (2013), pp. 99–121. doi:10.1007/s10867-012-9288-2
[20] K.O. Okosun, O.D. Makinde, and I. Takaidza, Impact of optimal control on the treatment of HIV/AIDS and screening of unaware infectives, Appl. Math. Model. 37(6) (2013), pp. 3802–3820. doi:10.1016/j.apm.2012.08.004
[21] K.O. Okosun, M. Mukamuri, and O.D. Makinde, Global stability analysis and control of leptospirosis, Open Math. 14 (2016), pp. 567–585.
[22] S. Sharma and G.P. Samanta, Stability analysis and optimal control of an epidemic model with vaccination, Int. J. Biomath. 8(3) (2015). doi:10.1142/S1793524515500308
[23] O. Sharomi and T. Malik, Optimal control in epidemiology, Ann. Oper. Res. (2015), pp. 1–17. doi:10.1007/s10479-015-1834-4
[24] E. Sontag, Mathematical Control Theory, 2nd ed., Springer, New York, 1998. doi:10.1007/978-3-540-69532-5_16
[25] J.M. Tchuenche, S.A. Khamis, F.B. Agusto, and S.C. Mpeshe, Optimal control and sensitivity analysis of an influenza model with treatment and vaccination, Acta Biotheor. 59(1) (2011), pp. 1–28. doi:10.1007/s10441-010-9095-8
[26] P. Tenga, O.D. Makinde, and E.S. Massawe, An eco-epidemiological model with nonlinear incidence and infective prey treatment class, Int. J. Mod. Trends Eng. Res. 2(11) (2015), pp. 308–329.