


A system dynamics model for disease management in poultry production

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ABSTRACT The objective of this article was to provide the nonmodeler reader of *Poultry Science*, an overview of the system dynamics modeling method (SDM) through development of a broiler house disease management simulator (BHDMS). System dynamics modeling uses feedback theory and computer-aided simulation to help elucidate relationships between factors in complex systems, which may be circular or interrupted with long delays. Materials used to build the simulator include data from literature and industry indices. The methods used were the steps in SDM, namely: 1) Identify the problem and boundaries; 2) develop a dynamic hypothesis explaining cause of the problem; 3) build the causal loop diagram (CLD); 4) develop the stock and flow model; 5) conduct model simulations; and 6) model validation. Results presented here are the CLD and stock and flow model of the simulator, results of scenario simulations, and model validity tests. The simulator consists of the

main model, the disease submodel, and the antimicrobial use submodel. The main model represents a cycle of production in the broiler house of a specified length of time, which repeats after a specified down time. The disease submodel shows population dynamics in the broiler house in terms of changes over time in number of susceptible, infected, recovered, and dead birds. Production parameters that could be modified in the model include delivery size, grow-out period, down time, and efficacy of antimicrobials. Disease mortality levels, above the set threshold, trigger antimicrobial use in the model. The model showed the effect of antimicrobial use intervention on the population dynamics, namely, on the proportion of the susceptible, infected, recovered, and dead birds in the population. Thus, the BHDMS was able to simulate the effect of the intervention on population dynamics and would facilitate evaluating management interventions such as antimicrobial use.

Key words: broiler house disease management simulator, poultry production system, system dynamics modeling, Vensim

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INTRODUCTION

Broiler chicken production in the United States is a vertically integrated system from breeder/hatchery to grow-out to processing and then to the consumer (Vukina, 2001). Poultry production is a complex system which involves management factors, host factors, disease agent factors, and environment factors. The poultry industry faces complicated disease challenges, which have high economic cost to the industry, such as necrotic enteritis, coccidiosis (Immerseel et al., 2009), avian

influenza (Poultry World, 2018), and infectious bronchitis (Cook et al., 2012). In 2016, the USDA implemented new standards for prevalence monitoring of *Salmonella* and *Campylobacter* in poultry (USDA-FSIS, 2016), placing even more demands on the industry to control these organisms. In addition to being very costly, disease challenges are complex because of their multifactorial etiology (Al-sheikhly and Al-saieg, 1980; Arakawa et al., 1992; Bailey et al., 2001; Williams, 2005) including variation in pathogen virulence and pathogenicity, pathogen interactions, environmental factors, litter management, production practices, host immune status, vaccine efficacy, and host nutritional plane. The breadth of factors and their potential interaction make control of diseases difficult.

According to Jay Forrester, the human mind is quite capable of understanding the components and structure of a complex system but is not well equipped to predict

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system behavior in response to interactions of its various parts (Forrester, 1973). System dynamics modeling (SDM) seeks to study, understand, and analyze complex systems as they change over time (Forrester, 1961, 1971; Ford, 2010). Modeling has been used in poultry production for many years in the form of feed and growth models, risk factor modeling for introduction and maintenance of disease on a farm, and modeling effect of disease on production parameters (Emmans, 1981; Senties-Cué et al., 2010; Volkova et al., 2010) and economic models (Williams, 1999). Pathogens have been studied using various models including kinetic, statistical, and predictive modeling techniques (Dodge and Peters, 1960; Vukina et al., 1998; Yang et al., 2001, 2002; Oscar, 2004; Singer et al., 2007). These models were designed to study linear relationships between identified factors and incidence of disease. Linear models are useful and informative; however, system dynamics models are able to address the complexity of a dynamic production system and incorporate inherent feedback loops and delays of the system (Sterman 2000; Homer and Hirsch 2006). Forrester originally developed the SDM approach to help industrial corporate management apply feedback control theory into their problem-solving capability (Forrester, 1961). A simple example of feedback loops and delays in broiler production is the cooling system in a house. A higher temperature in the house triggers turning on ventilation fans. Following a delay during which air is brought into the house through cooling cells, feedback of lowering the temperature results in turning off fans. A constant buildup of heat in the house because of increased ambient temperature and heat production by broilers results in increased temperature, triggering the cooling cycle to occur again. However, if the ambient temperature is cold, fans might be minimally used with increased delays in cycling fans resulting in increased ammonia levels in the house, which after longer term delays can result in health consequences. System dynamics modeling has the ability to work with circular relationships and delays which are common in complex systems (Forrester and Senge, 1980; Richardson, 1991). We believe that SDM is an excellent tool for dealing with the complex dynamics of disease in the broiler production system.

This article aims to introduce the methodology of SDM to the field of poultry production and management through development of a broiler house disease management simulator (BHDMS). A simulation modeling platform that is simple to understand and modify would be a useful tool for veterinarians, producers, and production managers to meet challenges facing the poultry industry through better understanding the dynamics of diseases on the farm and the effects of interventions on the system. Management “flight simulators” have been developed for managers in other fields, just as the original flight simulators were for pilots (Sterman, 1988, 1994). There is no currently available review of system dynamics in veterinary medicine or poultry science; however, an in-depth analysis of the importance of systems thinking and SDM in dealing with impediments to learning in complex systems can be found in Sterman

(2006). In addition, Homer and Hirsch (2006) discussed applications of SDM in public health and cited examples of models in that field. A literature review of application of system dynamics in transportation has also been published (Shepherd, 2014) as well as a scoping review on application of the approach in environmental health (Currie et al., 2018). A BHDMS, a computer simulation of the broiler grow-out house, could facilitate decision-making regarding disease prevention and control and by evaluating multiple possible solutions simultaneously, thereby avoiding potential costs incurred by having to test these options in the field. In this article, we will explore the basics of SDM and demonstrate its broad utility in understanding the dynamics of broiler production, including disease introductions and efficacy of interventions such as antimicrobial use.

The objective of this article is to introduce SDM as a method that could be applied in the field of poultry science and production. Although this article is limited in scope to the disease management aspects of the method, it could also be used on evaluating productivity and profitability of the poultry production enterprise. To demonstrate the functionality of the model, 3 separate disease scenarios were developed and simulated to explore the performance of the model. The grow-out period was set at 42 d, and downtime was set at 14 d for all 3 scenarios. Scenario 1 shows the model for 1 cycle without antimicrobial use, whereas Scenario 2 was run with antimicrobial use, and Scenario 3 shows disease dynamics in the system for 3 production cycles.

MATERIALS AND METHODS

Causal Loop Diagram

One of the advantages of SDM over other types of modeling is its ability to accommodate feedback loops that are inherent in complex systems, and these loops can either be positive (reinforcing) or negative (balancing) feedback loops (Sterman, 2000). Reinforcing loops are causal (cause and effect) loops in the model, wherein a change in 1 variable causes a change in another variable in the same direction. On the other hand, balancing loops are those wherein a change in one variable causes a change in other variables so that the collective effect is in the opposite direction. Causal loop diagrams (CLD) can be used to illustrate the concept of closed loop thinking. For example, in Figure 1, beginning with the variable Disease Prevalence, it is positively correlated with Mortality so that an increase in Disease Prevalence results in an increase in Mortality. Mortality is negatively correlated with Farmer's Profit so that as mortality increases, Farmer's Profit decreases. As Farmer's Profit decreases, it is assumed Disease Prevention increases, resulting in decreased Disease Prevalence. Collectively, these relationships have a balancing effect on the system that results in decreased prevalence. This CLD is an example of a negative feedback loop (Figure 1), which can be

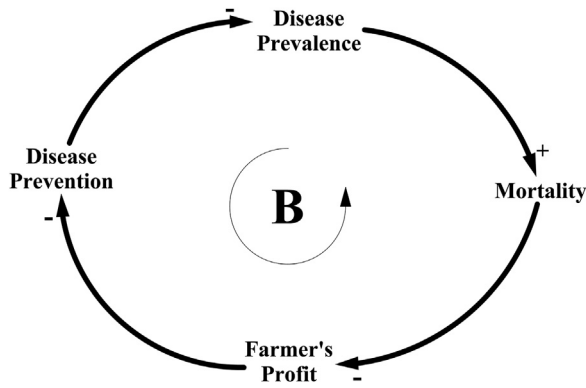


Figure 1. Causal loop diagram example. Arrow indicates causal relationship. + sign = indicates positive correlation; - sign = indicates negative correlation; B = indicates balancing loop (negative feedback).

ascertained by noting there is an odd number of negative correlations between variables within the loop.

Stock and Flow Models

System dynamics modeling makes use of computer-aided simulation whose building blocks are stocks, flows, delays, and feedback loops (Forrester, 1973; Sterman, 2000; Richardson, 2001; Homer and Hirsch, 2006). Stocks are defined as levels or accumulations of materials (e.g., susceptible, infected, recovered, and dead chickens) and are depicted as boxes or rectangles in SDM. Flows are the rates of processes and are symbolized by the valve icon in SDM. Flows can be inflows to or outflows from a stock. An example of a stock and flow is shown in Figure 2.

Time delays are inherent in complex systems. When delay between cause and effect is short, it is easier to see the connection between cause and effect, but when delay is protracted, SDM helps facilitate our understanding of a more complicated cause and effect relationship (Forrester, 1961; Sterman, 2000).

Variables (also known as converters) contain information that transform variables, modify flows, change units, and perform algebraic operations. These can be constants or formulas. Arrows (also known as connectors) connect variables to flows or to other variables passing on information about stocks, flows, or variables to a flow or variable (Richmond, 2001).

Model Development and Methodology

Data from literature and industry performance standards were used to build the model (Reyna et al., 1983; Lasley et al., 1988; Reid, 1989; Macklin et al., 2008;

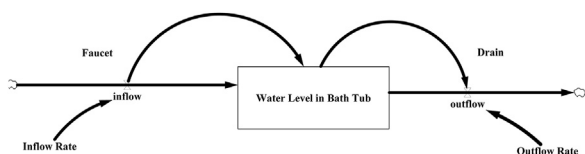


Figure 2. Stock and flow model example (bathtub).

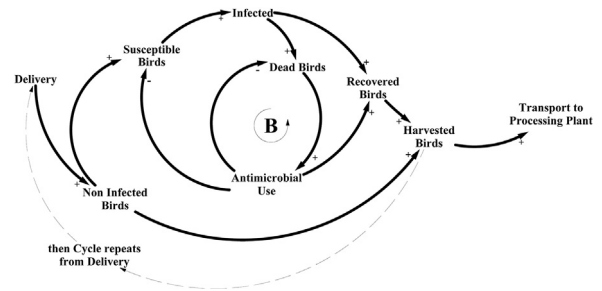


Figure 3. Causal loop diagram of broiler grow-out production system. Arrows indicate causal relationship. + sign indicates positive correlation; - sign indicates negative correlation. B indicates balancing loop (negative feedback).

Cobb-Vantress, 2018; Aviagen, 2018, 2019). The following steps, adapted from the classic SDM process, were used to develop the model (Sterman, 2000):

Identify the Problem and Boundaries The problem identified was the challenge of effectively controlling disease through appropriate interventions in a broiler grow-out house. The BHDMS was developed to demonstrate how SDM could help meet this challenge by allowing the user to evaluate an intervention (e.g., antimicrobial use) for disease management in a broiler production system. The scope of the BHDMS model was limited to the broiler grow-out production segment of the poultry production continuum and a hypothetical disease. The model was designed to start with the delivery of chicks on day 1 of the cycle, continued through harvesting and down time, and repeated over multiple cycles.

Develop a Dynamic Hypothesis Explaining the Cause of the Problem Our hypothesis is that the broiler grow-out system, being a complex system, contains factors, delays, feedback, and circular causal loops and that a better understanding of these interactions would facilitate better decision-making regarding interventions. The dynamic interaction between these factors make it so that any intervention could have not only the expected results but also unintended impacts.

Build the Causal Loop Diagram Beginning with a mental model based on a conceptual framework about the system of the broiler grow-out house, we developed a CLD of the causes and effects in the broiler production system (Figure 3). The CLD was developed based on relevant literature and from personal knowledge and experience of the authors (Reyna et al., 1983; Lasley et al., 1988; Reid, 1989; Macklin et al., 2008; Cobb-Vantress, 2018; Aviagen, 2018, 2019). The CLD that was developed (Figure 3) shows the production structure and major feedback loops involved in disease dynamics within the broiler house system. The causal loop structure captured the all-in, all-out scheme of populating the broiler house (Aviagen, 2018; Cobb-Vantress, 2018). The chicks are delivered all at once at the start, and broilers are transported to the processing plant all at once at end of the growth period. The end of the grow-out is followed by a down time during which the house is cleaned and prepared (Cobb-Vantress, 2018). The CLD does not have equations built into it and therefore

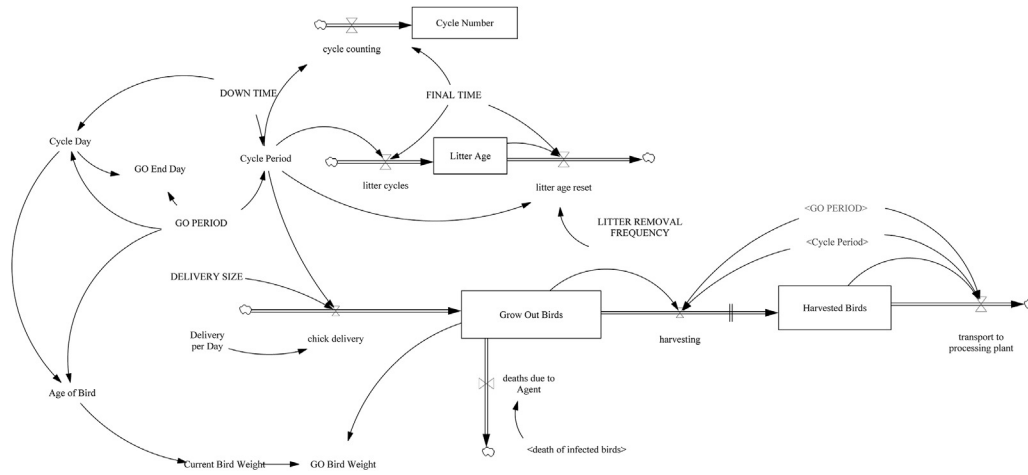


Figure 4. Main model of the broiler house disease management simulator.

cannot be used for computer simulations. Diagramming causal relationships in the system is a helpful first step in understanding the system. The modeling software Vensim Professional for Windows, Version 7.0 (Ventana Systems, Inc., Harvard, MA) was used to develop the CLD.

Develop the Stock and Flow Model Vensim Professional for Windows, Version 7.0 (Ventana Systems, Inc., Harvard, MA) was also used for building the stock and flow model. The stock and flow model was developed

based on the CLD, following the method previously described (Repenning et al., 2010). The stock-and-flow model makes use of equations and formulas, whereas the CLD is mainly a relationship model giving direction of flow or influence and suggesting where feedback is occurring. To build the stock and flow model, relevant literature as well as personal knowledge and experiences were gathered, and each component and stage of the relationship in the model structure was based on this information (Reyna et al., 1983; Lasley et al., 1988;

Table 1. Modifiable parameters, calculated parameters, stocks, and flows of the main model and their definitions.

Modifiable parameters	Definitions	Source
Delivery size	Number of chicks delivered on day 1	This Article
Grow-out period	Duration of rearing the chicks until they are transported to the processing plant	Authors, Cobb-Vantress, 2018
Down time	Time between when broilers are hauled out at the end of grow-out until the next delivery	Cobb-Vantress, 2018
Litter removal frequency	Number of grow-out cycles before litter is removed	Reyna et al., 1983; Reid, 1989; Macklin et al., 2008
Calculated parameters		
Cycle period	Sum of Grow-Out Period and Down Time in days	
Age of bird	Age of bird in days	
Current bird weight	Average individual bird weight based on age	Aviagen, 2019
Grow-out bird weight	Product of current bird weight and total number of birds at a point in time	
Stocks	Definition	
Grow-out birds	Number of birds in the broiler house	
Harvested birds	Number of birds harvested/collected at end of growth period and transported to the processing plant	
Litter age	Number of cycles that litter has been in use in the broiler house	
Cycle number	Number of cycles of production.	
Flows		
Chick delivery	Inflow to Grow-Out Birds stock; also, number of chicks delivered to the house on day 1 of production	
Harvesting	Flow from Grow-Out Birds stock to Harvested Birds stock, with delay of Grow-Out Period and repeated every Cycle Period (sum of Grow-Out Period and Down Time in days)	
Deaths due to agent	Outflow from Grow-Out Birds stock; number of birds that died	
Transport to processing plant	Outflow from Harvested Birds stock	
Litter cycles and cycle counting	Used to keep track of the number of grow-out cycles and total house cleanout of litter	

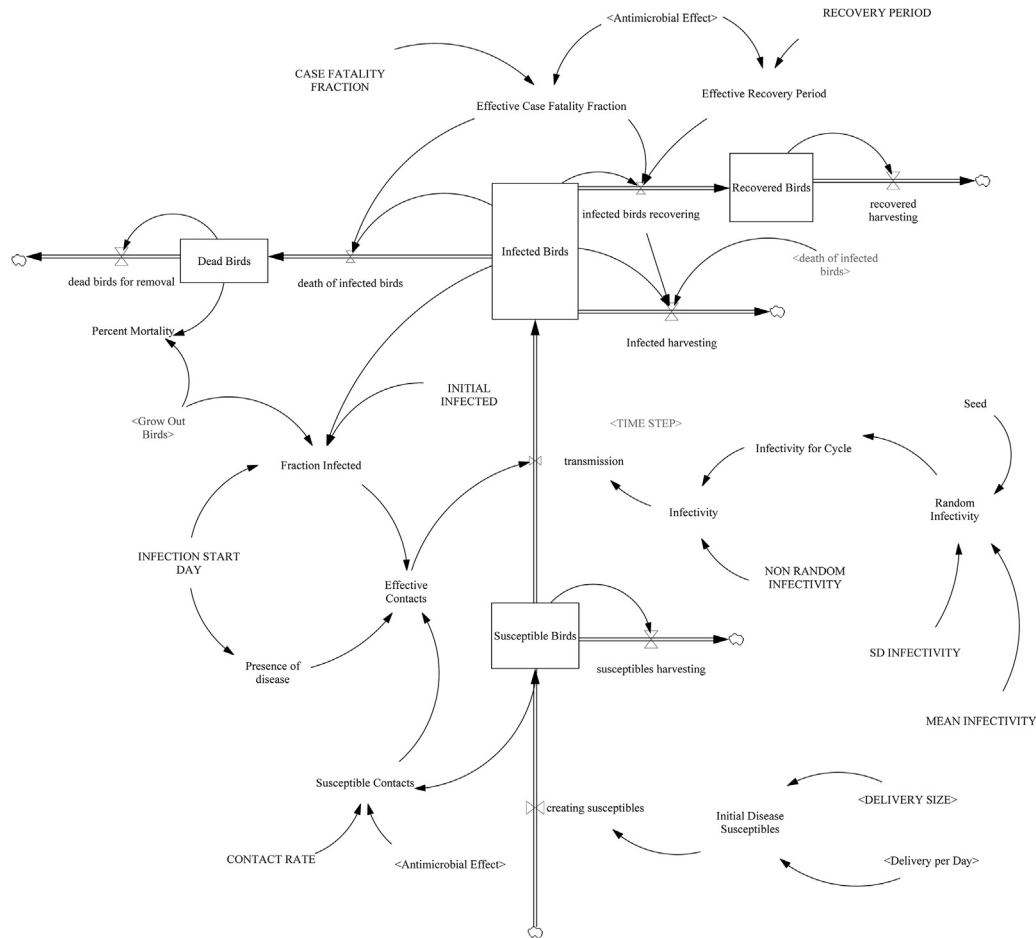


Figure 5. Susceptible–infected–recovered submodel.

Reid, 1989; Macklin et al., 2008; Aviagen, 2018, 2019; Cobb-Vantress, 2018). For the purpose of this article, we have limited the factors associated with 1 hypothetical bacterial disease that would respond favorably to antimicrobial therapy. The values used for the parameters in the model were based on known industry values when available, but some values, especially for disease parameters, were assigned for demonstration purposes. The stock and flow model of the BHDMS was made up of the main model and 2 submodels.

The main model structure (Figure 4) is a representation of a 42-d broiler production process starting from chick delivery and ending with transport to the processing plant, with the delay of the grow-out period (42 d) and downtime (14 d). Modifiable parameters, calculated parameters, important stocks, and flows in the main model are listed and defined in Table 1. It is noted that litter age and cycle number keep track of these components so that factors, which can be transferred to subsequent flocks such as accumulation of pathogens or antimicrobial resistance, can be followed over time.

The dynamics of an outbreak or epidemic of an infectious disease can be characterized by models in which individual subjects can transition from a susceptible state to an infected state followed by a state of recovery, if they survive the disease. These models of disease dynamics are known as susceptible–infected–recovered

(SIR) models (Halloran, 1998). Within the stock and flow model, an SIR model was used as the basis of a submodel, SIR submodel, to accommodate the dynamics of the disease outbreak (Figure 5). Modifiable parameters, calculated parameters, important stocks, and flows in the SIR submodel are listed and defined in Table 2.

The antimicrobial use submodel (Figure 6) incorporates the decision tree for antimicrobial intervention in response to disease mortality. In summary, there are threshold levels of mortality for the agent which, if exceeded, trigger the use of antimicrobials. Modifiable parameters, calculated parameters, important stocks, and flows in the antimicrobial use submodel are listed and defined in Table 3.

Conduct Model Simulations After the model was parameterized, the next step was to run simulations. In SDM, we were able to run “what-if scenarios”, or hypothetical situations setting different levels of variables to see what would happen if those situations were to occur and how the system would be affected (Sweeney and Serman, 2007). Three separate disease scenarios were developed and simulated to explore the function of the model (Table 4). The grow-out period was set at 42 d, and downtime was set at 14 d for all 3 scenarios. Scenario 1 was designed to show 1 production cycle without antimicrobial use, whereas Scenario 2 was designed to show changes because of antimicrobial use,

Table 2. Modifiable parameters, calculated parameters, stocks, and flows of the susceptible, infected, and recovered model and their definitions.

Modifiable parameters	Definitions	Source
Infection start day	Cycle day at which infection with disease starts	This Article
Initial infected	Number of birds initially infected with disease	This Article
Contact rate	Number of times per day a bird interacts with another bird in a way that could result in transmission of disease if the other bird was infectious	This Article
Case fatality fraction	Proportion of infected birds that die	This Article, Aviagen, 2018
Recovery period	Number of days that bird infected with disease takes to recover	This Article
Mean infectivity	Average ability of the disease to infect birds and can range from 0 to 1, used in randomly calculating Infectivity	This Article
SD infectivity	SD associated with mean infectivity, used in randomly calculating Infectivity (see below)	This Article
Nonrandom infectivity	Allows a fixed value for infectivity to be selected	This Article
Calculated parameters		
Susceptible contacts	Number of birds that have come in contact with other birds and are susceptible to infection. Susceptibility can be modified by antimicrobial effect (Table 3)	
Effective contacts	Number of Susceptible Contacts that have come in contact with an infected bird	
Infectivity	Probability of infection of a susceptible bird following contact with an infected bird (ranges from 0 to 1)	
Effective case fatality fraction	Case Fatality Fraction modified by the Antimicrobial Effect (Table 3)	
Effective recovery period	Recovery Period modified by the Antimicrobial Effect (Table 3)	
Stocks		
Susceptible birds	Refers to the number of birds that have not been infected but are susceptible to the disease	
Infected birds	Refers to the number of birds that have been infected by the disease	
Recovered birds	Refers to the number of birds that have been infected and recovered from the disease	
Dead birds	Refers to the number of birds that have been infected and subsequently died from the disease	
Flows		
Creating susceptibles	Periodic inflow of delivered chicks into the susceptible birds stock	
Susceptibles harvesting	Harvesting of susceptible birds that were never infected	
Transmission	Transmission of disease from effective contacts	
Infected harvesting	Harvesting of infected birds while still infected with disease	
Infected birds recovering	Recovery of infected birds to become recovered birds	
Recovered harvesting	Harvesting of recovered birds	
Death of infected birds	Death of infected birds to become dead birds	
Dead birds for removal	Removal of dead birds	

and Scenario 3 was intended to show disease dynamics in the system for 3 production cycles. The withdrawal period for antimicrobial use was set at 7 d before harvest, the start day of infection for the pathogens was set at 5 d, and infectivity for pathogens, defined as the rate of transmission occurring per contact between an infected and a susceptible bird, was set at 0.1.

Model Validation We used structure assessment test, utility test, and sensitivity analysis to validate the model (Forrester and Senge, 1980; Barlas, 1996; Sterman, 2000). Structure assessment determines how consistent the model is with the knowledge of the real system with respect to the particular purpose. As a model of the broiler grow-out production system in the United States, the model structure was designed to capture current knowledge of this system from delivery of chicks on day 1 to the end of the down time period (14 d after transport for harvest). The model structure gives the model the ability to behave as the real system would, with

parameters such as infectivity, contact rate, and case mortality fraction. Utility test entails the process of establishing confidence in the usefulness of the model, based on whether the objective of the model has been achieved (Sterman, 2000). Utility test has to do with whether the model is useful for its purpose, which, in this case, was to serve as a tool for evaluating a disease intervention (use of antimicrobials) for managing disease in the complex broiler production system. The BHDMS simulator allows simulation of the population dynamics (susceptible, infected, recovered, and dead) as well as the effect of the intervention on these through scenario simulations. Sensitivity analyses were conducted to determine the robustness of the model on the number of infected birds and cumulative number of dead birds when infectivity, contact rate, and antimicrobial efficacy were individually varied. Starting parameter values were infectivity set at 0.1, contact rate set at 10, case mortality fraction set at 0.10, mortality trigger percentage

Table 4. Summary of the differences in the parameters in Scenarios 1, 2, and 3 of broiler flocks raised to 42 d with a downtime of 14 d.

Parameters	Scenario 1 Without antimicrobial use	Scenario 2 With antimicrobial use	Scenario 3 Random infectivity
Simulation time	56 d	56 d	168 d
Time step	0.0625 d	0.0625 d	0.0625 d
Mortality percentage trigger	100%	2%	2%
Infectivity	0.1	0.1	Random Mean = 0.25 SD = 0.25
Case fatality fraction	0.1	0.1	0.1
Withdrawal period of antimicrobial use (days before harvest)	7 d	7 d	7 d
Start day	5	5	5
Efficacy of antimicrobial	-	0.7	0.7
Contact rate (birds/d)	10	10	10

Simulation time (time in days of simulation); Time step (unit of time per step in simulation); Mortality percentage trigger (percent mortality at which the use of antimicrobials is triggered in the model); Infectivity (the rate by which the pathogen infects the population e.g., infectivity of 0.10, the pathogen infects 10% of the population); Case Fatality Fraction (proportion of the infected that died); Withdrawal period of antimicrobial use in days before harvest (number of days before harvest that the use of antimicrobials is discontinued); Start Day (day of production cycle at which the infection starts); Efficacy of antimicrobial (level of effectiveness of antimicrobial in reducing infection); Contact rate (number of birds an individual infected bird contacts per day).

(represented by the gray line) was triggered at day 14 as expected in the face of increased mortality and stopped after 7 d as prescribed in the model but was triggered again at day 34. This resurgence of disease occurred because the infection had not been completely eliminated and once again triggered antimicrobial use, which stopped on day 35 because of the withdrawal period. The model behaved appropriately according to the settings in the model which limits the use of antimicrobials to 7 d duration and until 7 d before harvest (withdrawal period of antimicrobial) as is required for food safety and public health. Scenario 3 shows the dynamics of infection over 3 cycles (Figure 9) with infectivity changing randomly for each cycle. The simulation showed the varying levels of infected birds in 3 cycles and how this affected disease dynamics. In the first grow-out period (Days 0–42), a high infectivity value resulted in a rapid rise in infected birds, triggering early antimicrobial use followed by a rapid drop in infected birds as recovered birds increased. Even with high infectivity, mortality was controlled. The randomly selected infectivity in the second grow-out period (Days 56–98) was so low that an outbreak did not occur. In the third grow-out (Days 112–154), the level of infectivity was relatively low in contrast to the first grow-out; however, this resulted in somewhat unexpected dynamics. It resulted in a more protracted outbreak, as might be expected, but with 2 courses of antimicrobial use and mortality levels similar to the first grow-out even though there were more susceptible birds remaining at the end of grow-out.

Model Validation/Testing

Model testing was done through structure assessment, sensitivity, analysis and utility test. The problem identified in the broiler production system was the challenge of effectively controlling disease through appropriate interventions in a broiler grow-out house. The BHDMS was developed with the objective of meeting the challenge of

disease management in the complex broiler production system. Structure assessment tested the resulting model's composition and how organization of the model was able to represent the broiler grow out production system from start to harvest. The structure and organization of the model was presented at conferences to evaluate the potential acceptability of the model to researchers and scientists in the field. The software's built-in model reality check as well as the dimensional/unit consistency check in the software were also used in the structure assessment test. With the built-in trigger for antimicrobial use, the simulator was also able to apply an intervention that is antimicrobial use. Beyond the simple decision tree of whether antimicrobials were used, the model enabled evaluation of the impact of the intervention (antimicrobial use) on the population dynamics. The model system behaved as the real system was expected to behave when the parameters of infectivity and antimicrobial use were modified as in the scenario analyses (Figures 7–9). Thus, based on the behavior of the model in the scenarios, the model had achieved its objective of disease management simulation.

The sensitivity analysis showed major changes in number of infected birds and cumulative number of dead birds in response to minor changes in infectivity, contact rate, and efficacy of the antimicrobial (Figures 10–12). The sensitivity analyses provided insight into the dynamics of disease and confirmed the utility and effectiveness of the model. An infectivity of 0.15 (Figure 10A) results in the earliest signs of infected birds followed by an infectivity of 0.10 and then 0.05. Infectivity of 0.10 and 0.15 both result in 2 peaks in the number of infected birds because of triggering of antimicrobial use which temporarily decreases the number of infected birds followed by a resurgence when antimicrobial use is discontinued. Interestingly, an infectivity of 0.15 results in fewer cumulative dead birds (Figure 10B) than 0.10. The higher infectivity results in earlier transmission but also earlier treatment of the disease, whereas an infectivity of 0.10 results in a later onset of disease with a high number of

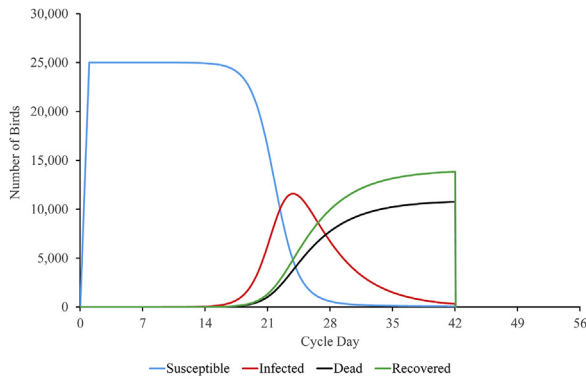


Figure 7. Scenario 1 results demonstrating disease dynamics without antimicrobial use and contact rate set at 10, case mortality fraction set at 0.10, mortality trigger percentage set at 100%, antimicrobial effect on pathogen set at 0.7, antimicrobial use duration set at 7 d, and antimicrobial withdrawal period set at 7 d.

infected and therefore dead birds in the last part of the grow-out period because antimicrobials are withdrawn in time for harvest.

A similar pattern of disease dynamics occurs for changes in contact rate (Figures 11A, 11B). The rate of transition from susceptible to infected birds is denoted by the transmission flow (Figure 5) which is the product of number of effective contacts and infectivity; consequently, changes in either parameter result in similar responses proportional to the magnitude of the change.

An antimicrobial efficacy of 1.0 results in an immediate decline in the number of infected birds (Figure 12A) that is maintained until withdrawal before harvest. The cumulative number of dead birds rises sharply at the onset of disease but remains flat until antimicrobial withdrawal. A lower efficacy of 0.7 results in a slower decline in infection that is followed by a second increase sustained until harvest, as seen in the analyses for infectivity and contact rate. The slower initial decline and the second sustained increase in infected birds results in a sustained increase in the number of cumulative dead birds (Figure 12B). As might be expected the lowest efficacy modeled, 0.4, results in a more sustained

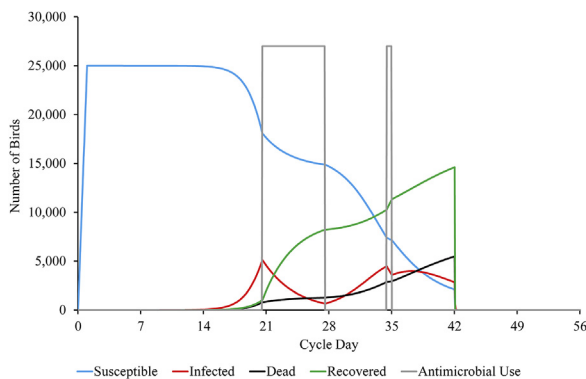


Figure 8. Scenario 2 results demonstrating disease dynamics with antimicrobial use and contact rate set at 10, case mortality fraction set at 0.10, mortality trigger percentage set at 2%, antimicrobial effect on pathogen set at 0.7, antimicrobial use duration set at 7 d, and antimicrobial withdrawal period set at 7 d.

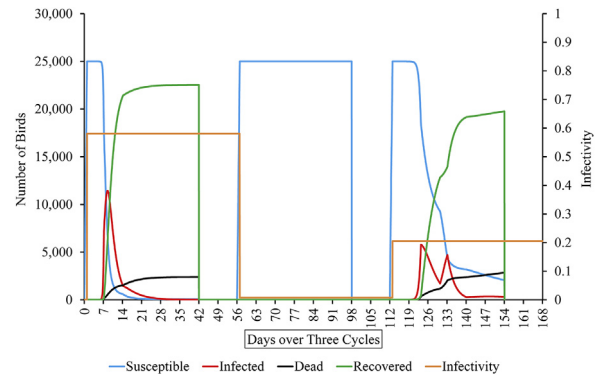


Figure 9. Scenario 3 results demonstrating disease dynamics over 3 grow-out cycles with randomly changing infectivity of disease agent (Mean infectivity of 0.25 with an SD of 0.25). Other parameters included antimicrobial use and contact rate set at 10, case mortality fraction set at 0.10, mortality trigger percentage set at 2%, antimicrobial effect on pathogen set at 0.7, antimicrobial use duration set at 7 d, and antimicrobial withdrawal period set at 7 d.

and higher increase in the number of infected birds (Figure 12A) with a resulting sustained increase in the cumulative number of dead birds that slightly exceeds that seen with an efficacy of 0.7.

DISCUSSION

We have built a BHDMS to simulate the grow-out stage of broiler production and to demonstrate SDM as a tool for disease management in the broiler poultry production system. System dynamics modeling can be a great tool for the poultry industry because poultry production is a complex system which has circular feedback loops and disease dynamics. In contrast to other modeling approaches, a system dynamics model accommodates the feedback or consequences of the decision (e.g., antimicrobial use) such as effect on susceptible, infected and recovered birds, as well as incorporates the importance of the antimicrobial withdrawal period.

The BHDMS can be used to study the interrelationships between production flow, management practices, disease dynamics, and the impact of interventions, such as antimicrobial use, on the susceptibility, infectivity, recovery, and death of broilers in the broiler production house. In the simulator, the hypothetical disease agent is a bacterial pathogen. A bacterial disease example was used for the purpose of modeling the effects of using antibiotics as an intervention. If the disease is viral, then antimicrobial (antibiotics) use may not be effective and hence, not recommended. On the other hand, this model may also be modified such that the disease agent is a protozoan, which may be controlled by antimicrobials or biologicals (vaccination); and managed by tweaking environmental factors such as litter moisture.

The dynamics of infection were compared between Scenario 1 “without antimicrobial use” (Figure 7) and Scenario 2 “with antimicrobial use” (Figure 8). The model was able to show that without antimicrobial use there was a more rapid onset and higher prevalence of infection in birds. With antimicrobial use, the levels of the infected

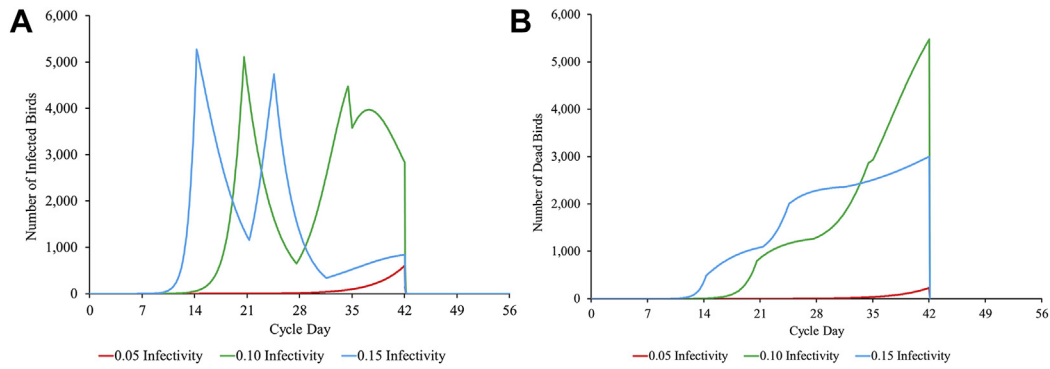


Figure 10. Sensitivity analysis of the number of infected birds (A) and cumulative number of dead birds (B) over time in response to changing the infectivity of the pathogen from 0.05, 0.10, and 0.15 with contact rate set at 10, case mortality fraction set at 0.10, mortality trigger percentage set at 2%, antimicrobial effect on pathogen set at 0.7, antimicrobial use duration set at 7 d, and antimicrobial withdrawal period set at 7 d.

and dead birds were reduced compared with their levels without antimicrobial use. The level of infected birds peaked later and lower, and this could be because of the prophylactic effect of antimicrobial use by reducing the number of susceptible contacts that become effective contacts, leading to a smaller number of infected birds, which in return results in fewer recovered birds. There was also an antimicrobial effect on the effective case fatality fraction resulting in fewer deaths of infected birds while increasing number of recovered birds. The model behaved correctly or functionally because once the threshold level (mortality percentage trigger) was reached, the antimicrobial intervention was implemented in Scenario 2 but was not initiated in Scenario 1. In addition, the antimicrobial use ended according to the settings in the model, which stopped the use of antimicrobials after 7 d. However, immediately after antimicrobial use ended, there was an abrupt increase in infected and recovered. In fact, in the simulation, the trigger for antimicrobial use was reached a second time at day 34 but stopped the next day to meet the 7-d withdrawal period. Although it is unlikely that antimicrobials would have been used in this manner in the field, the model demonstrated possible repercussions of antimicrobial treatment not eliminating the disease. It is also interesting to note that the model captures the possibility that there might be some infected

birds at the time of harvest that are brought to the processing plant. When high levels of disease are present at the time of harvest, the veterinarian and producer may decide to either keep the flock longer for treatment and necessary antimicrobial withdrawal period, but the model does not currently accommodate this type of decision.

In the sensitivity analyses, changing the values for infectivity resulted in unanticipated dynamics. Although the higher infectivity value of 0.15 resulted in earlier onset and higher number of infected birds as expected, the infectivity value of 0.10 resulted in higher number of dead birds. This unanticipated consequence resulted from the interaction of transmission onset and magnitude, timing of antimicrobial use, and antimicrobial withdrawal period. It is likely that antimicrobials would be continued as needed to reduce the deaths because of disease, but the analysis demonstrates the unexpected dynamics that might occur.

As noted earlier, the transmission flow between susceptible and infected birds is the product of the number of effective contacts and infectivity; consequently, changes in contact rate result in a similar pattern of disease dynamics as seen with changes in infectivity. Once again, the results do not necessarily reflect management or treatment decisions that would be followed in the face of a disease outbreak, but the model allows one to see

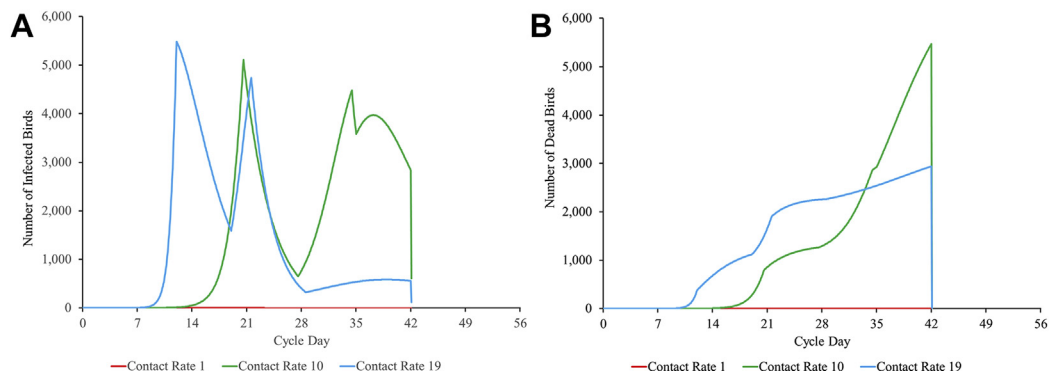


Figure 11. Sensitivity analysis of the number of infected birds (A) and cumulative number of dead birds (B) over time in response to changing the contact rate from 1, 10, and 19 with infectivity set at 0.10, case mortality fraction set at 0.10, mortality trigger percentage set at 2%, antimicrobial effect on pathogen set at 0.7, antimicrobial use duration set at 7 d, and antimicrobial withdrawal period set at 7 d.

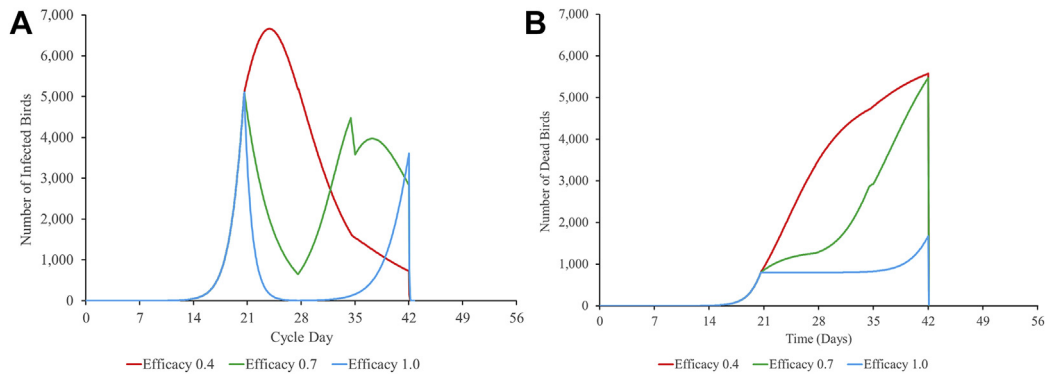


Figure 12. Sensitivity analysis of the number of infected birds (A) and cumulative number of dead birds (B) over time in response to changing the efficacy of the antimicrobial from 0.0, 0.7, and 1.0 with infectivity set at 0.10, contact rate set at 10, case mortality fraction set at 0.10, mortality trigger percentage set at 2%, antimicrobial use duration set at 7 d, and antimicrobial withdrawal period set at 7 d.

how the disease dynamics might unfold over time. The model could also be altered so that duration of treatment would be continued until a decreased level of morbidity or mortality was reached rather than for a set duration (7 d) as used in the current demonstrations.

In this prototype simulator, we have included the component of infection with only 1 disease agent for the purpose of simplifying the introduction of the methodology. In the real world, there could be multiple infectious agents that are simultaneously occurring in the flock. In the future, this basic model will be expanded to include the complexities of such co-infections. The simulator does not end with the decision to use antimicrobials but is able to show the impact of the intervention on the susceptible, infected, recovered, and dead birds through feedback loops, while taking into consideration the required antimicrobial duration and withdrawal periods.

One of the limitations of this study is the use of relatively few variables. For the purpose of introducing the SDM approach to poultry production, we have opted to use a relatively simple model form and have purposely limited the number of variables to the bare minimum and still be able to effectively demonstrate the potential usefulness of the methodology. Even with the limitations we imposed on the model, the model exposed unexpected patterns within relationships between susceptible, infected, recovered, and dead birds after implementation of antimicrobials in response to mortality reaching a threshold level. The model showed that infected and dead birds could potentially increase rapidly once again if the antimicrobial treatment was not effective enough to eliminate disease transmission. Another interesting finding was the greater peak of recovered birds with antimicrobial use compared with no treatment, likely due to antimicrobial use thereby allowing infected birds to recover rather than die.

The purpose of this one disease model is to provide the nonmodeler reader an overview of the methodology of SDM. The model developed can be modified structurally and to include other variables and relationships to focus on the dynamics of other diseases or production challenges. The simulator can be used as a teaching tool

for growers, veterinarians, researchers and students to learn the dynamics of disease in the broiler house. The simulator could be used to evaluate interventions (their efficacy and the costs) which could promote better decision-making and management of disease. In addition, future expansions of this model could include or focus on other stages of the poultry production continuum such as breeder farms, hatcheries, and processing plants which could help facilitate decision-making on interventions for those areas of production.

The use of antimicrobials in broiler production leads to the development of antimicrobial resistance, but estimating the effects of antimicrobial usage practices on antimicrobial resistance is very difficult and would benefit from the use of modeling. The model currently does not address antimicrobial resistance as an effect of antimicrobial use but is one of the future directions of this research.

The BHDMS could serve as a platform to facilitate decision-making by veterinarians, researchers, producers, and production managers for better informed disease control strategies through scenario testing. Various scenarios could be simulated using different values of model parameters to study the impact of these changes on the dynamics of disease and production. The simulator can be expanded and adapted to accommodate other pathogens and other interventions, for example, vaccination, litter management, ventilation, and nutrition. The model could also be modified to incorporate other broiler house conditions that impact disease dynamics such as food and water consumption, watering system, brooding management, and stocking density. The current model used contact rate among birds to determine effective contacts but broiler stocking density, calculated through broiler house size and number of chicks placed, could be used instead to better simulate modes of transmission other than direct contact. Future work will include modifying the model for specific disease agents and specific antimicrobials as well as modeling the development of antimicrobial resistance in the poultry production system. Other modifications include adjusting the model so that the infectivity is not stochastic but as a feedback loop based on the past prevalence of

infection in the broiler house or status of infection of the preceding flock. Another future application of the simulator would be evaluating the effects of disease management measures on production parameters such as weight gain and feed efficiency.

A well-known quote is that “All models are wrong, but some are useful” (Box, 1976). Although all models are simplifications of reality and as such they are flawed, there are some aspects of models that are useful. It is anticipated that the BHDMS can serve as a useful tool for understanding the dynamics of specific disease agents and specific antimicrobials as well as other disease intervention measures toward improved disease management in poultry production systems.

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