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Investigating Swine Farm Disease Spread by a Large Agent-Based Model

Gian Cercena
University of Vermont

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Abstract

Contagious swine diseases cost billions of dollars in lost profits annually, and pose dangers to other animals, including humans. These diseases can be mitigated by biosecurity measures, but the costs for these measures have collective incentives not always reflected in individual incentive structures. We design a large scale agent-based model (ABM) of the swine industry in the United States, where agent behavior is determined by their individual economic incentives, which have collective consequences in terms of disease spread. The agents in our model include swine producers (farms), feed mills, processors, and veterinarians. By simulating various scenarios under different assumptions regarding disease characteristics and network structures, the model may serve as a valuable tool for researching the impacts of disease spread on American swine supply chains. With the global demand for pork products continuing to be ever-present, ensuring the robustness of swine production networks is of vital importance. Through the exploration of disease spread dynamics and the evaluation of potential mitigation strategies, Pigs-Model contributes to the development of more effective biosecurity measures and disease management protocols, ultimately enhancing the sustainability and security of swine farming operations.

1 Introduction

The swine farming industry stands as a vital part of agriculture across the world. With the products that the industry outputs standing at the forefront of all meat consumed across the globe, accounting for 34% of all meat production [1], there is an international necessity for this production chain to be robust. The world, continuing to evolve, will demand more from food chains such as these, increasing the complexity between the many elements of the system.

This high level of workload has lead to farmers working under time constraints, with many farmers stating the time they have is "very limiting" [2]. Accordingly, there is an increase of farmers looking to streamline and simplify their processes in order to save on not only time, but money, as financial issues are also pervasive among farms [3].

One key aspect of farming is the constant clash between secure product and disease within livestock heards. With disease being one of the chief antagonists to a smoothly working supply line, many resources are needed to combat it. Over the past few decades, researchers have further investigated swine-related diseases [4], as the chance to mitigate its effects on the industry prove not only to help the farmers themselves, but the international community as a whole. A safer and more robust system could lead to lower consumer goods' prices, in turn leading to the assistance of certain areas such as potential food deserts [5]. So, it follows that with any farm, or product, disease prevention plays an essential role in the conflict between man and nature, safeguarding sustenance for communities worldwide. This collection of practices and protocols is known as biosecurity [6].

Biosecurity covers a wide variety of conventions that farms implement in order to prevent disease spread among their livestock. Examples of biosecurity on farms may include disposable footwear, extra sanitation routines, such as showers, and routine disinfection on all vehicles and tires [7]. Additionally, farms will actively monitor their livestock and isolate those which appear to be sick [8]. Biosecurity extends to all parts of the swine farm network, such as processors and feed mill producers too, who must ensure that disease is not carried back to their facilities since it could then be carried from one farm to another (see Figure 3) [9, 10, 11]. One additional aspect of biosecurity is compliance. While measures can be put into place, it is imperative that employees of a given facility actually follows these practices. In our model, we are specifically interested in the effect of producer biosecurity and the impact of incentives for producers, so for the current scope of this model, the biosecurity practices of feed mills and finishing units are assumed to generally be fixed.

An issue arises upon the realization that not all farms have equal biosecurity, which can stem from a multitude of reasons [12]. Farms can be varying sizes, and farms of different sizes can have different concerns and threats. A large proportion are farms with low swine capacity [13], which may not be large enough nor have the financial resources to have a role or shared practices dedicated to biosecurity. On the other hand, larger farms, which while a minority, produce the vast majority of goods, could be on such a scale that small oversights may not get noticed until it causes sizeable issues to render at least a part of, if not all of a farm's operations unsafe.

Specialized farms will often require specific biosecurity measures that address unique disease risks with their products. Specific to only swine producers, there is a unique process where swine are moved from one facility to another dependent on their age.

> "Livestock are often moved between facilities to reduce costs and improve productivity. There is an old adage, 'Livestock follow the grain'. Even now this aphorism seems true, as shipping animals is less expensive than shipping grains, which are required for animals to attain their slaughter weights." [14]

As the produce is moved to and from specific farm-types given their age, there are varying procedures for farms that farrow swine, farms that grow weaned swine to feeder, farms that grow feeder swine until they are brought to a finisher, or even farms that participate in all parts of this process [8, 15].

Minimizing disease within swine not only assists the industry, but will decrease the opportunity for swine-related disease to mutate and further infect other organisms, such as seen with the swine flu. The H1N1 influenza A virus, known for its high mutation rates [16], caused the deadly 1918 flu pandemic, and continues to cause issues. Resurfacing in a new form almost a century later, the virus again caused a large outbreak within the United States and Mexico [17] causing upwards of 60 million cases, 250,000 hospitalizations, and 12,000 deaths [18].

Additionally, Porcine Reproductive and Respiratory Syndrome (PRRS) stands out as a significant concern within the industry. PRRS outbreaks within swine producers can increase unmarketable swine from anywhere between 10-30%, and cause mortality in rates from 10-25% [19]. Losses from PRRS can be significant, and due to its wider variety of strains, it can be difficult to prevent transmission, shown by the fact that it can infected other herds up to 3 kilometers away [20], and persist within feed, though it varies with factors such as temperature [21].

Many strategies for controlling PRRS has been explored within the literature. Measures such as vaccinations have shown positive effects in reducing viral load [22], nursery depopulation can control for intra-producer transmission [23], and heightened biosecurity measures have such as air filtration have lowered infection rates [24].

While these practices release some of the immense strain disease has on the swine industry, it would be impossible to attempt to rectify every issue that producers face with biosecurity especially due to diminishing returns. The model described within this paper hopes to stand in place of the systems implemented across the world, to be experimented with in order to find better, more optimal practices to prevent disease spread and release part of the burden encountered by producers.

2 Agent-Based Modelling

Agent-based models (ABMs) are a modelling technique that utilizes advanced levels of compute performance in order to build and simulate complex systems comprised of many autonomously-acting agents [25, 26]. It is unique from other modelling methods which often rely on equations or data aggregated across entire systems. Whereas other methods use equations or dynamics from a top-down approach—attempting to model a behavior from a few overarching rules or prescriptions—ABMs work from the ground-up, defining rules for many agents at varying levels. Typically, many agents interact with each other, making decisions based upon rules defined within their classes, as well as based on the environment around them and the actions of other agents. The objective is to simulate these systems typically starting at a low level, to observe emergent phenomena that would occur in real-life.

Due to the large scale of many ABMs, the micro-level patterns and behaviors observed by the individual agents eventually lead to the emergence of macro-level patterns and observations. These observations can be the focused output of a given model, though the actions of the individual agents can very well be of interest to. In recent years, ABMs have seen a rise in popularity, owing to their flexibility and increases in available computing power [27].

ABMs have found success across many disciplines since they can be adapted to model vastly different environments. Pharmaceuticals [28], marketing [29], environmental planning [30], and psychology [31] are just a sample of fields where ABMs have been utilized to great effect [27]. Specifically related to disease modelling in livestock, supply chains [32], economics [33], and epidemiology [34] have all also had success with ABMs, lending confidence to this model and future works.

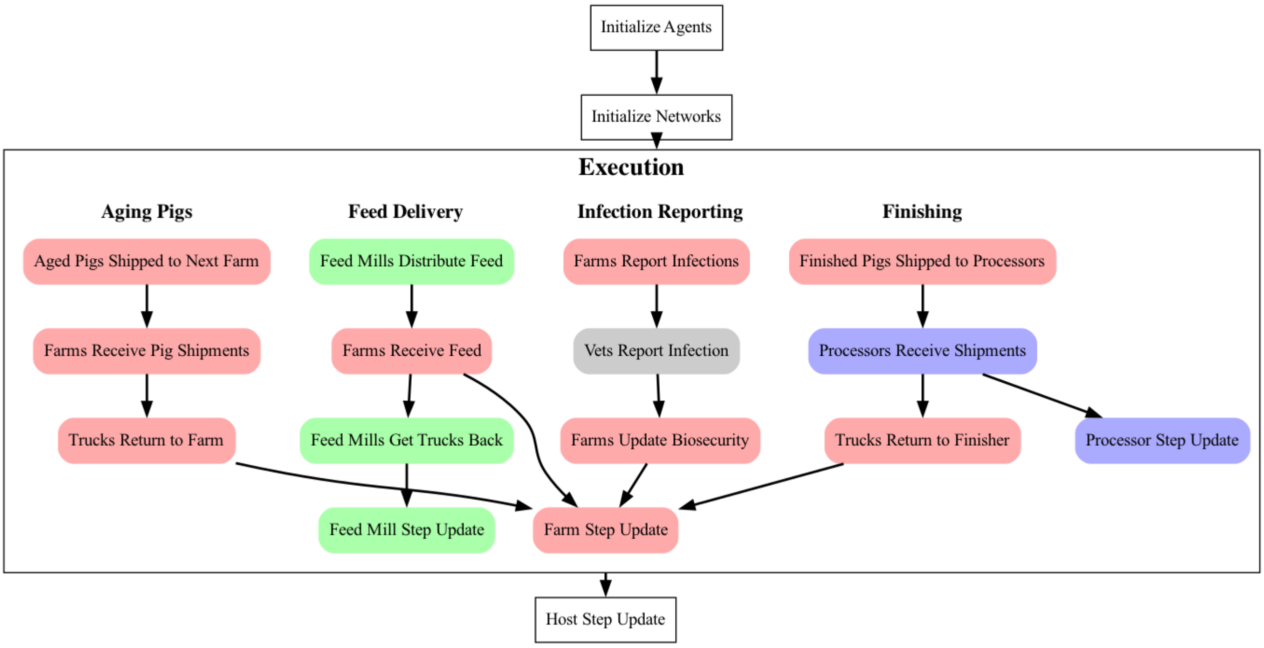

Figure 1: *Pigs-Model process chains. Red processes are for producers, green are for feed mills, grey are for veterinarians, and blue are for processors.*

2.1 FLAMEGPU

The building and fine-tuning of an agent-based model (ABM) was the bulk of the work within this paper. The creation of this ABM was largely based off of a pre-existing model [35, 36, 37], but recreated and built upon within the FLAMEGPU framework [38]. FLAMEGPU is an agent based modelling framework, built to be domain-independent, and efficient. FLAMEGPU is useful in modelling computationally expensive large scale simulations with massive parameter spaces such as this one due to the computationally expensive nature of ABMs. Using graphics processing units (GPUs) in order to speed up the simulation by parallelizing the large amount of computations that happen within simulations.

Central processing units (CPUs) serve as the computational core of a computer, tasked with speedily reacting to real-time input making them latency-focused. In contrast, graphics processing units (GPUs) are optimized for handling large amounts of parallel computations, focusing on high throughput of data. This is due to inherent differences of the architecture within CPUs and GPUs. CPUs feature a smaller selection of high performance cores, each able to perform complex sequential tasks at high speeds. On the other hand, GPUs have a many smaller cores able to execute simpler tasks in parallel, which allows them to handle many more operations simultaneously [38, 39]. Furthermore, the better cost-effectiveness per parallel process inherent to GPUs increases their value to those interested in modelling computationally intensive tasks, making them more suitable for simulating large models.

This gives massive speed gains for complex simulations such as *Pigs-Model*, allowing it to handle multiple independent process chains at once as seen in Figure 1 where the chains labeled Aging Pigs, Feed Delivery, Infection Reporting, and Finishing are able to run simultaneously. There is an exception due to the fact that processes relating to the same agent type (color) within the figure belong to the same agents, meaning they cannot be parallelized.

3 *Pigs-Model*

3.1 Description and Purpose

Pigs-Model is a comprehensive agent-based model designed to simulate the intricate dynamics of specifically socioeconomically important diseases and their spread within swine farm networks. The model aims to capture the complex interactions among different agents, including producers, processors, feed mills, and veterinarians, as well as pseudo-agents like swine batches and markets. The model incorporates various agent interactions, each playing a crucial role in disease transmission within the system. The intent is for it to be used as a tool to research the impacts of disease spread through American swine supply chain under varying assumptions concerning disease characteristics and production chain network

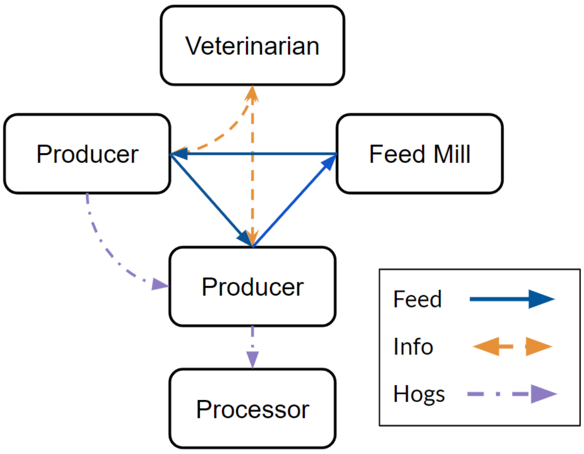

Figure 2: *The agents within Pigs-Model and their connections.*

structure.

3.2 Temporal Scale

The temporal scale of the model refers to the time frame of the simulation and how time is represented within it. In the case of the *Pigs-Model*, each time step is discrete, representing a single day in real life. Choosing a day as the time unit is significant for several reasons. First, it is evident that with a more granular time step, such as hours, the computational requirements would increase significantly. While finer detail could be captured with hourly time steps, the simulation runtime would become considerably longer, and managing the resulting data output would become challenging.

Days are chosen because many activities on swine farms occur on a daily basis. Additionally, data regarding disease transmission in swine farming is typically recorded and analyzed on a daily basis, as tracking it on an hourly basis would be impractical. Given this context, modeling based on days aligns the simulation with the typical rhythm of events occurring within swine producers.

3.3 Agents

In *Pigs-Model*, there are four categories of agents: producers (swine farms), processors (slaughter plants), feed mills, and veterinarians, along with two pseudo-agents: swine batches, and markets (see Figure 2). Again, much of the following has been adapted from or used previous works as a reference [35, 36, 37].

3.3.1 Producers

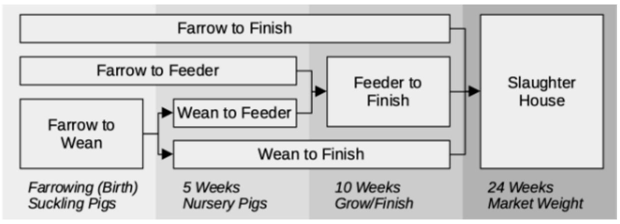

Figure 3: *Types of Producers. Note that not all types will necessarily be in a given network.*

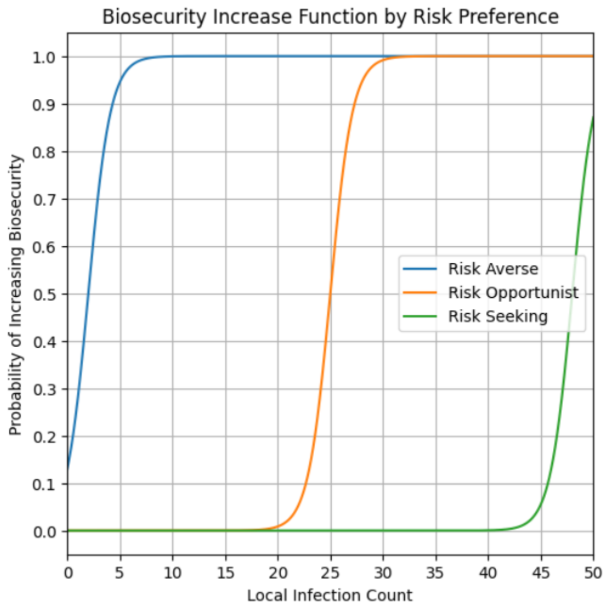

Figure 4: *The percent chance to increase biosecurity based on the producer risk preference.*

Producers are defined as the actual swine farms within the model. They have the largest and most involved action space, and each timestep they control a multitude of values such as increasing or decreasing biosecurity, shipping batches of swine to other farms or processors, requesting and receiving batches of swine from other farms, and potentially farrowing new batches of swine.

First, understanding how biosecurity affects the dynamics of disease spread within a system of swine producers is vital, so each producer is assigned a risk preference. They can be within one of three groups, risk averse, risk opportunist, and risk tolerant. Depending on their category, producers follow one of three sigmoid functions (see Figure 4) which gives them a probability of updating their biosecurity level each time they interact with their veterinarian based on the amount of other infections within their local network (the other producers associated with the veterinarian). Note that the maximum amount of producers within any veterinarian network is 50 which was worked out to be a suitable number given the quantity of producers within the system. Within

Pigs-Model, biosecurity modifies the values used to determine the probability that a farm will acquire a disease given an interaction with a disease actor for a given farm, so higher biosecurity levels reduce the probability of infection.

As for the swine themselves, each producer has "batches" of swine, where each batch contains the swine of the same age (detailed later in *Swine Batches*). Producers can have up to 20 unique batches, each acting independently from each other. Producers only hold on to batches that exist within a defined age range based upon its type (see Figure 3). There are four defined categories, farrow, wean, feeder, and finish. Farrowing producers are unique in the fact that they are at the start of the swine network, as they have the capability of farrowing (giving birth) to piglets. The amount of farrowing batches at a given time is determined by the amount of sows uniquely available within the producer. Dependent on the amount of sows, farrowing producers can have anywhere between 1 and 4 sow batches, each with their own cooldowns on how often they can farrow a new batch. These cooldowns can be thought of as a gestation period, though for a proper inflow of batches into the system, this period may be adjusted to lengths that could be unrealistic in real-life, but would account for out-of-system farrowed swine entering.

These batches are a fix to an issue that arises within large agent based models due to the potentially large count of individual agents. Representative agents such as the batches of swine allow the simulation to model more individuals in a collective way than normally would be able to be simulated independently given the computational capacity available. Representative agents can be dynamic, rescaling populations in real-time [40, 41], or can be done from the start as within *Pigs-Model*.

3.3.2 Processors

Processors would be the agents representing the processor plants (slaughterhouses). They are one of the two final destinations for all swine within the model, with the other being the markets (see Section 3.3.5.2). They serve as a representation of the slaughtering of the swine, and provide the producer with monetary compensation for the sold swine. Additionally, they act as another point of disease spread within the system. As swine remain within processing plants, due to the fact that they can arrive from various producers, they can serve as a nexus point for disease spread. This is of particular importance since the trucks that deposit swine at processing plants will return to their producer potentially transmitting a disease that they picked up at the processor.

3.3.3 Feed Mills

Feed mill agents are what supply the producers the feed required for the consumption by swine. Each feed mill has a local network of producers that is determined based on proximity upon agent initialization. Feed mills generate $D \sim \text{Poisson}(\lambda = 2)$ delivery routes that each deliver to a maximum of 15 producers within their local network, with the individual producers being chosen uniformly until either all have been selected or the maximum route limit is hit.

3.3.4 Veterinarians

Veterinarians, as briefly described earlier, exist as an agent to give producers a way to determine if they are infected, and to spread information regarding local infection counts. Producers have regularly scheduled veterinary visits, they will potentially call the veterinarian based on their biosecurity level (with a higher level increasing the likelihood) if they have symptomatic pigs, and they will call the veterinarian if they were previously told they were sick and would like an update on whether or not they still are. Additionally, veterinarians play a crucial role in enabling producers to determine whether to enhance biosecurity measures based on their risk preference as briefly described in Section 3.3.1 and elaborated later within Section 3.4.4.

3.3.5 Pseudo-Agents

Below are pseudo-agents due to the fact that while they can act as agent in some aspects, they tend to be associated with specific agents, or exist entirely within functions of other agents, and are noted here for clarity.

3.3.5.1 *Swine Batches*

While modelling at such a low level where individual swine were agents could be deemed preferable, certain simplifications were made to save on memory and computational power. Instead of managing each swine independently, swine of the same age and same infection status within the same producer are grouped into batches, which follows real-life industry practices [8, 11]. This means each batch has the same disease status, so if the batch is exposed to an infection event and catches it, the entire batch would become infected.

A batch is categorized as either "susceptible", "exposed", "infected", or "recovered". A batch is susceptible if it has not been infected yet, exposed if it has been infected, but not showing symptoms, infected once it starts showing symptoms, and recovered after the disease has left the batch after a given amount of time, or if the entire batch dies from the disease. Additionally, batches on the farm can infect each other, leading to intra-farm disease dynamics. Each batch can be thought of as a pen of swine that share the values noted above, age and disease status.

The size and age of each batch is randomly initialized during the start of a simulation, where the size is based upon the total capacity of the producer, and the age is uniformly selected from the age range the producer type allows it to have (see Figure 3). This is a meso-scale metapopulation model of disease spread on a farm, with each batch representing a small subpopulation within a larger metapopulation.

3.3.5.2 *Markets*

Mentioned earlier, a market is an alternative way for swine to exit the system. After swine batch reaches a certain age (21 days after initially being able to be sold), they are sold to secondary-level markets. The key aspect of this is to ensure that there is no blockage of swine that fills a producer that cannot sell, in order to keep the system properly functioning. These types of markets exist in reality, there are dealers who act as intermediaries who buy swine from producers and sell to processors or other dealers within the market. They benefit producers who can occasionally sell swine to hedge against price fluctuations in the market, as well as processors to ensure a steady inward supply of swine. While these exact phenomena are not modeled within *Pigs-Model*, the alternative exit of swine through these markets is in order to maintain the movement of swine throughout the system.

3.4 Agent Interactions

There are many agent interactions to aid *Pigs-Model* in being a comprehensive model that covers many aspects of the real-life swine industry.

3.4.1 Producer-Producer Interactions

When swine are for example weaned (at 5 weeks of age within *Pigs-Model*), depending on the producer type, they can either be bought or sold. Sales and purchases of batches typically involve transferring the entirety of a single batch from one producer to another. However, in rare cases where no neighboring producer can accept the entirety of the batch, only the portion that can be accepted will be sold, while the remainder will remain with the original producer. It is important to note that the selling period for each farm type is an additional 3 weeks past the specification of age for the swine type, meaning that weaned swine can start to be bought at an age of 35 days, but can continue to be sold until the batch is 56 days old. A similar process occurs for feeder swine as they can be bought within an age range of 70 to 91 days.

3.4.2 Producer-Processor Interactions

If a producer has the capability of carrying swine to market weight age (168 days), instead of selling to another producer upon reaching its sale age, the producer sends the batch to the processor they were initialized with a connection to. As processors do not have a capacity, and within the model instantly process the swine, there is no complications such as overloading a processor that can occur. Additionally, the processor will monetarily compensate the producer for the batch sent.

3.4.3 Producer-Feed Mill Interactions

The significance of feed mills within the model isn't necessarily to actually supply feed to the producers, as that has been abstracted away from this model, but instead to simulate the potential disease spread through feed trucks from one producer to another. Depending on the combination of the current producer's and feed mill's biosecurity levels, disease can either be carried away from a producer if it is infected or carried to a producer from a previously visited producer that passed the disease to the feed mill truck.

3.4.4 Producer-Veterinarian Interactions

Veterinarians inform how producers adjust their biosecurity level. When a veterinarian visit occurs the veterinarian alerts the producer to how many other infected producers there are within the local veterinarian network. Since the veterinarian network is generated based on proximity, this information is crucial for producers to know, as the higher that value tends, the greater likelihood there is for that producer to become infected due to various transmission pathways.

Seen in Figure 4, each producer is assigned a risk preference level which determines their attitude to biosecurity. This is intended to represent attitudes found in real-life producers where some practice higher levels of biosecurity than others, either due to the preference of the personnel within the producer, or the company that owns the farm or the swine. The more producers within the same veterinarian network that are infected, the more likely it is that a producer increases their biosecurity level. Additionally, if a producer finds themselves infected, an extra weight is placed upon them (by artificially increasing the local infection count) incentivizing them to

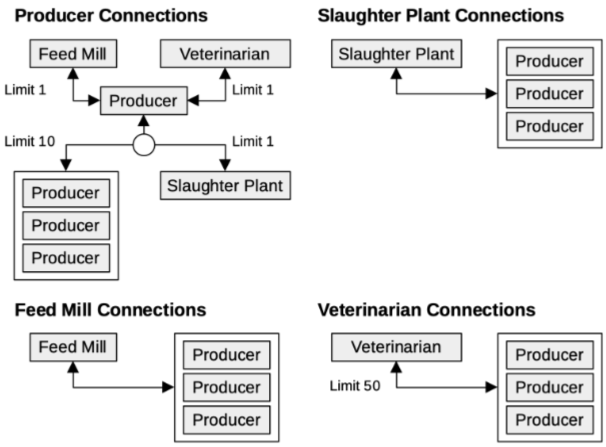

Figure 5: *The connections available to each agent.*

increase biosecurity more often.

When producers have swine that become symptomatic, they can call in a veterinarian to determine whether or not there is a disease present within their batches. This is implemented to simulate the common practice of a pooled oral fluid collection test [42], with the probability of false negative and false positive probabilistically dependent on fraction of batches in a farm which are infected. If a producer finds they are infected, they will summarily not decrease their biosecurity during the duration, regardless of their risk preference, though increasing it is still determined on their risk preferences against the local infection count and whether or not they are infected.

3.4.5 Producer-Market Interactions

If a producer has a batch of swine that is not able to be sold for 21 days after it has reached its sale age (e.g. each farm it can sell has been at capacity), the batch then gets bought by a market, defined above. These external markets are not individual agents, nor are they tied to specific producers. Instead, their functionality gets utilized by producers who have batches that reach past their selling age.

3.5 Agent networks

Each agent type is connected to other agents of its type and other types through several overlaid network structures (see Figure 5), which define the potential list of interactions between agents. Producers interact with other producers directly through the swine shipment network. Feed mills, processing plants, and veterinarians interact directly with producer agents through the feed mill routing network, the processing plant network, and the veterinarian network, respectively. While these are the only direct interactions, disease or information may be spread between agents who do not have a direct interaction through multiple steps on the same network or through a collection of interactions over multiple networks. In our model, these networks are defined by two aspects: the information, parameters and constraints, which go into the construction of the list of directly interacting agents, and the nature and directionality of these interactions. In this section we will focus on the network parameterization and construction.

The swine shipment network is a hierarchical, directed, modular network. It is directed in that for each pair of connected agents, one a selling agent and one is a buying agent for that connection depending on farm type. It is hierarchical in that there is a directional flow of the shipments from farms which raise younger pigs to farms that raise older pigs resulting in no cycles in the shipment network. The shipment network is modular in that producers tend to be connected to other producers affiliated with the same company.

The producer network structure is constructed through the following steps. First, we initialize or read in the farm-type, company affiliation, and the number of customers for each producer. Then, we use a degree-corrected stochastic block model [43] to create a network of buyer-seller pairs. In this network, each producer exclusively ships to other producers with the same company affiliation. Moreover, each producer, on average, serves the specified number of customers, and exclusively sells to corresponding producer types. For instance, farrow-to-wean producers exclusively sell to wean-to-feeder or wean-to-finish producers (see Figure 3).

The processing plant networks are similar to the swine shipment networks, in that the swine move in one direction from finishing farms to processing plants. However, the processing plant that a given producer ships to is determined only by distance, with company affiliation not playing a role.

The networks used in this model for the feed mills are an abstraction of the true routing procedure for how grain is taken to farms in the system. Farms are serviced by the nearest feed mill, and as trucks typically dump all feed and refill and clean at the mill between each customer, the order of customers for a given day has no effect on disease dynamics. For other diseases which can survive in feed, these abstractions would likely cause more discrepancies, however, for PRRS, research suggests this is not a major factor [44], and the major vector is thought to be the drivers. The construction of the feed mill networks consists of each farm being serviced by its closest feed mill, and each feed mill has multiple trucks which each service a random set of customers per day in a random order.

For the veterinarian, the producer too joins with the nearest veterinarian, but each veterinarian is capped at 50 total producers, so if the nearest has reached its capacity, the producer searches for the next-nearest veterinarian with less than 50 producers. Note that this currently means feed mills and slaughterhouses can have variable connection counts to producers based on their location.

The current producer data being utilized is from the Farm Location and Agricultural Production Simulator (FLAPS) [13]. Since there is no publicly available collection of national data regarding swine populations across farms within the US, FLAPS was utilized to impute values for farms within each state, giving researchers a better source of data for various applications while keeping a level of company confidentiality. This synthetic data has been constructed to accurately simulate the 2012 Census of Agriculture data. FLAPS had an absolute percent difference of less than a tenth of a percent at the state-to-national and individual farm-to-county levels. Within the FLAPS data, the state of North Carolina has been of initial focus within *Pigs-Model* due to its higher density of swine population.

3.6 Infections/Disease

The infection enters the simulation at a specified date, rather than at the model's outset. This approach is useful for evaluating the infection onset separate from any potential influence a burn-in period might have on the system. A burn-in period denotes the duration, from the model's initial step, until the simulation reaches a behavior that is expected. Given that the initialization of producers and their swine batches is user-controlled, the decisions made regarding how they are initialized at the beginning of the simulation may not resemble their appearance at a later timestep within the same simulation.

Burn-in is difficult to account for, and while marginal gains can be made towards reaching a smaller burn-in period through more concentrated efforts, it can potentially lead to isolated instances where the system behaves anomalously due to unrealistic initial conditions. By introducing the infection at a specified later date rather than at the start, we allow the simulation to reach a certain level of stability first, yielding more reliable and realistic results when the disease is initiated.

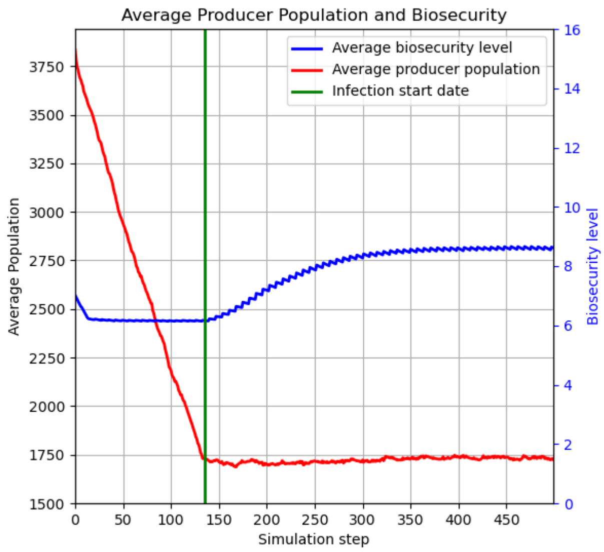

Figure 6: *An example of population burn-in and an infection-caused biosecurity response within Pigs-Model.*

Seen in Figure 6, for the parameters in this given run, the burn-in period for biosecurity lasts until timestep 13, whereas the burn-in period for the average producer population ends at timestep 132. This is determined by looking at the average producer population across the system and noting when it reaches a stable figure. The infection is then introduced at timestep 135 after the effects of burn-in have ended. When the infection enters the system, an fraction of producers (and other agent types too if desired) are infected at random according to the initial infection rate input variable. Also note that an infection has a certain infectious length, meaning that after a certain amount of timesteps of being infected, the batch will gain immunity from it. Immunity can also be calibrated for a certain length, but this is not considered for this model as the timescale of immunity is less than the length of a typical life of a pig in this industry.

There are two chief ways to transfer an infection agent-to-agent, either through direct infection transfer, or contact infection transfer. Direct infection transfer occurs when an infected producer sells to another agent, be it either another producer or processor. When an infected producer sells an infected batch of swine to a susceptible producer, and the batch is accepted, the receiving producer becomes infected. Alternatively, if an infected producer sells a batch of swine to a processor the processor becomes infected as a result from receiving the batch.

Second is contact infection transfer which covers scenarios which an agent interacts with another agent

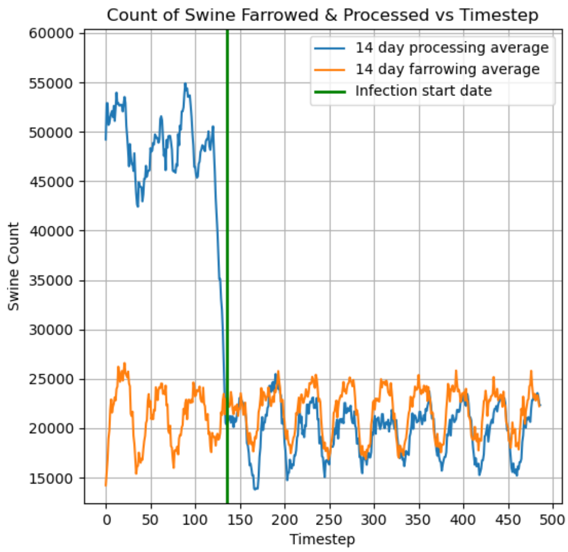

Figure 7: *14 day averages for farrowed and processed swine. The infection start is at timestep 135.*

that recently was in contact with infected swine. Each of the following occur through the result of a truck carrying disease from one agent to another. Infected feed mill trucks can deliver disease to susceptible producers, non-infected feed mill trucks can pick up a disease from an infected producer, an infected feed mill truck can bring a disease back to its feed mill, and if an infected processor picks up sold market weight swine from a susceptible producer, an infection can be transferred to that producer.

4 Results

The results for *Pigs-Model* will generally be in the form of model validation, this paper aims to serve as a foundation to stimulate future research questions on the basis of this ABM. Note that the results listed here may not completely represent true values within the American swine system as of now. The purpose of these results are to show the proper functionality of the model. Additional parameter tuning will eventually lead to results that fall more in line with reality.

4.1 System-Wide

As mentioned within Section 3.6, burn-in is an issue when it comes to models where parameter initialization is complex. The challenge apparent in the behavior within Figure 7 for the beginning of the simulation. For the first 130 timesteps, there is a large difference in the the number of swine being processed (leaving the system) per timestep and those being farrowed (entering the system). This difference arises due to the initialization of producer capacity and distribution of batch ages not accurately reflecting the more complex distributions of these variables at model equilibrium. Since swine batches are assigned ages uniformly within their producers given age range, this causes an anomalous amount of swine that are processed until a full market weight age cycle of 168 days passes. As time progresses and the maximum age of a swine batch (168 days) is reached, the processing rates fall to align themselves roughly with the farrowing rates, exiting the burn-in period. Note that the cycles, when grouped in sizes of 4, roughly reflect the 168 day life cycle of swine within the system. This also exemplifies the up to 4 sow batches per farm mentioned in Section 3.3.1.

Once the processing values fall in line with the farrowing values, comparing the two also shows us that there is a lower amount of swine being processed than farrowed which confirms that during their life cycle, the amount of total swine is decreasing over time due to the infection.

4.2 Producer-Specific

As *Pigs-Model* has a primary focus on the spread of an infection throughout a system, it is vital to ensure that it is properly spreading throughout a the given system. After the burn-in period, at timestep 135, an infection is introduced to the system, as seen in Figure 8. For the specific simulation shown in this figure, an initial infection rate of 5% was chosen, meaning that randomly, 5% of all producers have a batch that receives an infection. An initial spike is seen following this infection, which then sharply retreats, and then trails off after time.

Farrow-to-finish producers can be seen to have a slight burn-in period and afterwards their population percentages rise to an average of about 80%. Interestingly, for their infection rates, there is a large decline at about timestep 200. This is due to multiple factors within *Pigs-Model*. First, farrow-to-finish producers carry the same batches throughout their entire life cycle. They are unique to other producers in this aspect which benefits them by giving them a lower likelihood of being introduced to disease via the buying and selling mechanic. This can be noted in the later infection values for these producers, as it tends towards 0. Additionally, a batch only remains infectious for a certain length, 60 in this specific simulation, which explains the sudden drop at timestep 200, at it is about 60 steps after the initial infection.

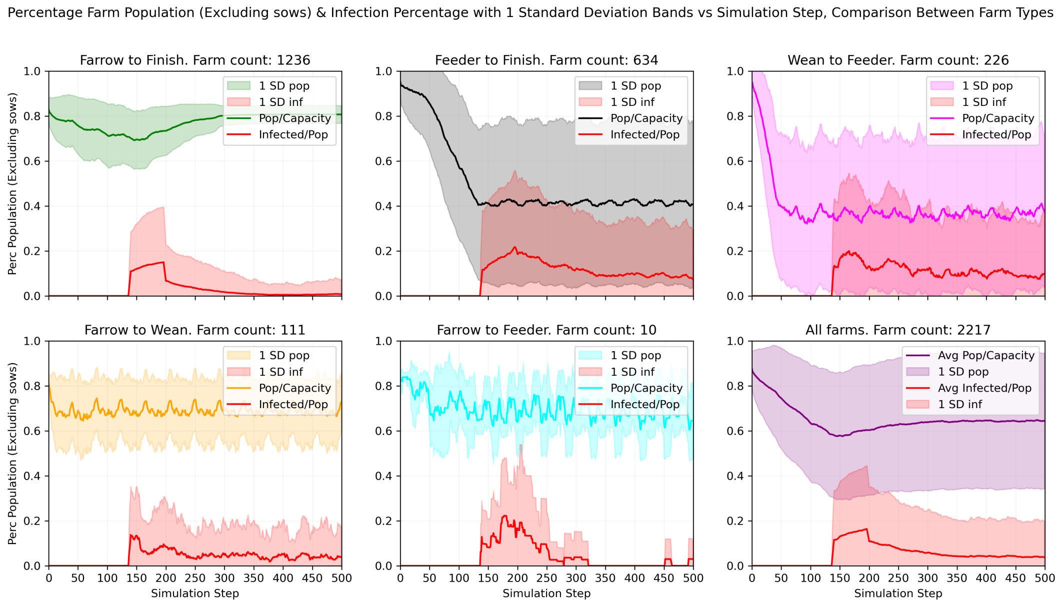

Figure 8: *Average population and infections for each farm type and aggregated across all, as well as a 1 standard deviation band for each measure from an example simulation.*

Moving to feeder-to-finish and wean-to-feeder producers, we observe similar trends. Again, there is an initial burn-in period with wean to feeder producers taking approximately 35 timesteps, corresponding to the length of time that swine remain in that specific producer. Similarly feeder-to-finish producers have a similar burn-in period to farrow-to-finish. The values these producer types tend to over time are lower than farrow-to-finish's 80.74%, as they sit at around 41.47% and 36.86% averaged across the mean values for the last 100 timesteps respectively. Since they cannot introduce their own swine into the system, they have to rely on previous producers and have competition between producers of their own type when trying to purchase new batches. Some producers, due to their initialized connections, may experience more or less competition, as seen by the larger standard deviation band around the average population percentage values for these producers. Additionally, the infection rates differ from farrow-to-finish, with feeder-to-finish and wean-to-feeder stages exhibiting much higher rates. The mean of their average values across the last 100 timesteps being 9.02% and 9.52% respectively. During the initial infection period, some farms experienced even higher rates. Feeder-to-finish had 52.05% of farms reach over 50% of their swine infected for at least one timestep while wean-to-feeder had an even higher value of 60.62%. This is clearly attributed to the increased truck and swine batch activity, as these farms are visited more frequently, thereby increasing the chances of infection.

Farrow-to-wean and farrow-to-feeder producers each are seen to have very small burn-in periods. Additionally, their swine population values are prone to act in a cyclic behavior. Since these two producer types farrow their own swine, as they sell batches of swine to feeder or finish producers, they repopulate based upon their sow batch cooldowns. Once their burn-in period has ended, they evidently enter a cycle relating to these cooldowns. In addition, the standard deviations for these producers at any given point post burn-in is much smaller than the producers that do not farrow, which follows due to the fact that they do not rely on any producer previous to them to give them product.

4.3 Biosecurity

The average level of biosecurity across a given simulation will be correlated with the prevalence of the infection within the system. As the amount of uniquely infected producers increase, the average producer will have a higher likelihood of increasing biosecurity. This can be clearly seen within Figure 6 as after the initial infection date, biosecurity is seen responding in turn, increasing at first rapidly, then leveling out as this infection becomes endemic and each producer reaches a stable individual biosecurity level. This is seen to notable effectiveness as infection levels within Figure 8 tend downwards as the simulation continues.

5 Future Work

Pigs-Model leaves many areas open for future exploration of disease dynamics and supply chain management within the American swine industry. The models size and complexity, as well as its versatility and adaptability lends itself well for utilization in future works. Below are future plans for work within the model and potential avenues for future research.

5.1 Model-Specific Work

At present, Pigs-Model remains incomplete. Though it lies near the threshold of a viable product, several modifications are needed to improve its utility.

5.1.1 Model Calibration

Pigs-Model does not model a specific disease, instead it can—dependent on initialization and creation of parameters—model a variety of infections such as porcine reproductive and respiratory syndrome (PRRS), porcine epidemic diarrhea virus (PEDV), or even the initial onset of African Swine Fever. There are many such variables that then need to be determined in order to run a simulation faithful to real-life disease dynamics and characteristics. These variables may include transmission or mortality rates, incubation or immunity periods, and other parameters specific to the disease being modeled.

A resource that will be invaluable in this process will be the Morrison Swine Health Monitoring Project (MSHMP) [45]. MSHMP collects data across the United States and reports values of infectious diseases (PRRS, PEDV, and senecavirus A) within swine. It is voluntary and joined by most of the larger swine producers within the US, giving vital insights to the actual incidence of infections that will be used for future calibration within *Pigs-Model*.

5.1.2 Simulating Novel Disease Outbreaks

One of the primary uses of *Pigs-Model* could be to simulate the spread and impact of novel diseases on the American swine industry. Given varying initialization parameters, the effects of different disease can be analyzed. One important disease of note is African Swine Fever (ASF). Due to the fact that its presence has not made its way into mainland North or South America yet, (though it has found its way into nearby island nations of the Dominican Republic and Haiti [46]) it is of interest to analyze its potential effects on the American swine network. Through simulating series of ASF infections within *Pigs-Model*, areas of improvement can be noted in order to devise policies that can help better protect against the initial onset of such an outbreak.

By leveraging model data coupled with machine learning techniques, producer agents can dynamically adjust their biosecurity measures and operational practices to either ramp up defenses in response to heightened risks or scale them down when the threat level decreases. Such adaptive strategies serve as a mechanism for calibrating the model to new system attributes. Before introducing ASF into the simulation, the model is first calibrated using data pertaining to PRRS. It is then equilibrated to incorporate preemptive system-wide biosecurity measures. This preparatory step allows us to observe how the system's adaptations to these preemptive changes influence the United States' capacity to combat ASF, should it ever breach biosecurity barriers.

Additionally, endemic diseases that already exist within the swine network can be analyzed in order to find ways of stifling their growths. PRRS is one example of a common disease that has found its way into most parts of the world [47]. Though it has entrenched itself within the system for decades, there is hope that a model such as this could help find policies to continue to limit its impact.

5.1.3 Biosecurity Updates

As biosecurity plays a vital role within this model, updating it to be more indicative of real-life practices can enhance the accuracy of this model. Biosecurity could be broken down into two separate categories, one for biosecurity-related infrastructure (such as air filtration) that could be a one-time investment, and the other for daily biosecurity practices (such as the likelihood of calling a vet) that could be dependent on producer types, or the company the producer belongs to. Other key points such as outdated biosecurity tables, simplified risk assessment methods, and compliance of biosecurity practices by employees within producers are issues that remain to be explored.

Relating to this, an additional mechanic where producers could potentially reject swine batches upon finding out that they are sick, or quarantining them if the producer has a requisite biosecurity level could be implemented to more closely follow with real-life scenarios.

5.1.4 Nationwide Model

Eventually, a transition to a national network would be in place as that is the end goal for *Pigs-Model*. In order to properly understand the disease dynamics of the swine industry across American, it will be vital to simulate diseases across the entire country. There are issues that too arise when focusing in on specific states (such as North Carolina) due to the fact that many states can have a net positive or negative inflow of swine of specific ages. This can cause issues within the supply chain for specific states, so being able to simulate the entire US will help get the model to act more realistically.

5.1.5 Objective Functions

Objective Functions play a crucial role in understanding the effectiveness any attempted enhancements or optimizations within complex agent based models such as *Pigs-Model*. These functions serve as a way to quantify the "goodness" of any given mode's outcome. By utilizing these metrics and comparing them against previous or future iterations of *Pigs-Model*, it will be easier understood what to adapt in subsequent versions of the model.

Several metrics can serve as useful objective functions within *Pigs-Model*, each highlighting a varying part of the model that might be an area of interest in a given undertaking. First could be infection count. This would total the amount of individual infected swine (though the amount of infected batches could also be of interest) as this would track with the extent of the infection throughout the system or even the count of infected agents can also be utilized. Along these lines, the count of swine and their deaths are another useful point for an objective function.

What would likely need further development would be more involved values that could be used as objective functions such as a producer's budget, or currently available money. If swine infection rates weren't of interest, and maximizing profits were in a hypothetical paper focusing in on greedy producer strategies, proper monetary values for all such parts of the model would have to be accurate and well understood.

Also, metrics used to define the performance of the supply chain could be developed. Ideas could include throughput, efficiency, and resilience.

5.2 Network Optimizations

One such way of limiting disease spread could be through the optimization of the swine network itself. This meaning the rewiring of inter-producer, producer-to-feed mill, or producer-to-processor connections [48]. There has been much research done into the robustness of networks and they have been seen to great effect [49, 50, 51, 52].

Many measures to define robustness exist, both based on the adjacency and Laplacian matrices [53, 48]. Two example adjacency spectrum measures are spectral radius and spectral gap [50, 54]. These utilize the eigenvalues of the adjacency matrix in order to define robustness, each unique in their application. Specifically, as an example, spectral radius is used to determine the rate of spread of a process among a network, defined as the largest, or principal eigenvalue. These processes could be a disease in the case of *Pigs-Model*, and if one were to want to minimize its spread, a strategy would have to be defined to minimize the value of the principal eigenvalue of the network. Accordingly, since spectral gap is based upon the difference between the first and second largest eigenvalue, it also is used to determine the speed of the spread of a process on a network. Optimizing for a smaller spectral gap could also assist in the suppressing of disease spread.

Considering the vast space of possible viable shipment networks and the challenges in traversing them, innovative approaches are necessary. One approach is designing a heuristic that traverses the space of all possible networks, utilizing parameters derived from user-defined data, as well as information regarding the input network. An example of such value could be the preference for having a company affiliation or remaining unaffiliated. Alongside this, spectrum measures including spectral radius or spectral gap, mean shortest path length, and component size are used to minimize an output objective function such as lowered mortality rates. By iteratively rewiring the network within the space defined by these metrics, the space needed to traverse is manageable, enabling machine learning techniques to be of use. This approach steps around the computational inefficiencies inherent in a large ABM, as the time needed to run all simulations could be unwieldy.

It is vital to recognize the trade-offs inherent in optimizing network structures to mitigate disease spread. While reducing spectral gap or mean shortest path length may seemingly enhance resilience against outbreaks, such optimizations could unintentionally compromise other aspects of network robustness, potentially disrupting the efficiency of trade within the swine supply chain. Thus, any optimization strategy must strike a delicate balance between disease containment and network resilience, a consideration that warrants further investigation for informing policy recommendations.

6 Conclusion

In conclusion, the development and analysis of *Pigs-Model* has provided, and will continue to provide, valuable insights into the dynamics of disease spread within the American swine industry. It highlights the important interactions within the network, as producers respond to diseases that permeate the system. Through running *Pigs-Model* in various scenarios, this model will contribute a platform for understanding the effects diseases have on the swine supply chain, and inform potential policies for mitigating the spread of such diseases.

Overall, the results obtained by *Pigs-Model* demonstrate the complex nature of the swine industry in cases where infections are present. Despite issues such as burn-in, and model calibration, the model clearly indicates its future usefulness, able to efficiently examine the effects of disease within the system. Moving forward, there are many avenues for future research and model refinement, indicating the potential of this model. More closely utilizing real-world data to simulate the effects of novel outbreaks such as ASF can prove to be vital for the continual building of safer supply chains. By combining empirical data with machine learning techniques, robust network optimizations, and epidemiological explorations, this model will serve as a valuable tool for informing policy decisions aimed at defending the American swine industry against disease.

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