Proceedings of the 2022 Winter Simulation Conference
B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C.G. Corlu, L.H. Lee, E.P. Chew, T. Roeder, and P. Lendermann, eds.

DATA-DRIVEN ECONOMIC ANALYSIS OF POULTRY DATA USED IN COMPLEX LONG-TERM EGG PRODUCTION SYSTEMS COMBINING SIMULATION AND MACHINE LEARNING

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ABSTRACT

A hybrid modeling approach was proposed and developed as a tool for the economic analysis of poultry breeds used in complex long-term egg production systems. The factors considered included both the stored and collected internal operational data that related to the within-breed historical life-cycle reliability and the related economic data that influenced egg prices and poultry life spans in a poultry farm. In the designed simulation models, the forecasted egg sales prices from a designed machine learning algorithm were incorporated to evaluate the economic analysis of specific poultry breeds. Our analysis results demonstrated that simulations could be combined with machine learning to serve as a powerful large-scale data analysis tool for the poultry breeds used in complex long-term egg production systems.

1 INTRODUCTION

Producing quality egg products or meeting customer requirements using reliable long-term egg production systems is crucial for today's poultry industry. The public marketing channel of egg supply chains enables real-time trade information concerning poultry supply and historical sales prices for the agroecological management of livestock production systems. In this context, managers of poultry production operations constantly face the challenge to implement best practices that ensure the optimal functioning of complex long-term egg production systems.

Innovations in breeding strategies are adapted to different species to improve the egg-laying intensity, poultry viability, and so on. Phocas et al. (2016) discussed sustainable breeding strategies for agroecology, especially the method of preserving breed diversity and maintaining multiple adaptation options for a variety of production environments and contexts. Although many technologies have focused on improving growth performance, certain poultry farms have attempted to improve the precision of the egg production estimates using daily operational data and related external economic data; egg production estimates have a major influence on egg prices and poultry life spans. For instance, internal operational data relating to the within-breed historical life-cycle reliability could include the egg-laying intensity, poultry viability, fodder consumption, and proportions of egg sizes; these data are stored and collected during daily egg production. The related external economic data have a major influence on egg prices and poultry life spans, which influence the egg sales prices of poultry farms and egg dealers, the total poultry supply in specific regions, the total amount of imported eggs, and so on.

Modeling commercial egg production is a complex and challenging task, mainly because of the nonlinear nature of the egg production curves (Ahmad 2011). Many mathematical and statistical models have been used to describe the egg production curve (Grossman and Koops 2001; Álvarez and Hocking 2007; Kebreab et al. 2016). In these ways, egg production performance can be predicted, however, it is significantly difficult to measure and compare overall system profitability between various parts of poultry supply interact.

To date, both simulation and machine learning technologies have been used as efficient alternatives to predict poultry breeds or egg production performances. Muramatsu et al. (1994) constructed a computer simulation model that could predict both the egg production and the growth of egg-laying hens and could depict the complex relationship between the physiological, environmental, and productive states during the egg-laying periods. Ahmad (2009) developed various neural network models of poultry growth using the simulated data of different growth periods obtained from public literature. Ahmad (2011) compared neural network models with mathematical and statistical models for predicting egg production in layers and proposed an efficient model that balanced the feed and nutrient intake, improved the environment, and enhanced the farm profits. Therefore, it appeared that there was no application relating to the poultry breeds of complex long-term egg production systems, which could measure and compare overall system profitability between various parts of poultry supply interact.

In this study, a hybrid modeling approach has been developed as a tool for the economic analysis of poultry breeds used in complex long-term egg production systems. The factors considered in this study were the stored and collected internal operational data that related to the within-breed historical life-cycle reliability; additionally, the related economic data having a major influence on egg prices and poultry life spans from a poultry farm were considered. In the designed simulation models, the forecasted egg sales prices from a machine learning algorithm (MLA) were incorporated to evaluate the economic analysis of specific poultry breeds. The analysis results demonstrated that the simulation could be combined with machine learning to serve as a powerful large-scale data analysis tool for poultry breeds of complex long-term egg production systems, measuring and comparing overall system profitability between various parts of poultry supply interact. The combination of machine learning and simulation was motivated by fostering a data-based hybrid modeling approach that could benefit complex long-term production systems by providing a realistic knowledgebase of data schema for testing and understanding overall system profitability of different species in the context of overall poultry supplies.

2 MACHINE LEARNING–ASSISTED SIMULATION

Simulations have played an important role in operations management as a means for evaluating systems, comparing alternatives, and optimizing configurations. Symbiotic simulation is a methodology for rapidly assessing and predicting the impact of changes in complex manufacturing systems (Gaku 2020). A symbiotic simulation driven by real-time or near real-time data enables cooperation between the virtual and physical systems. Simulation with various data sources can enable better performance prediction of utilization areas and bottlenecks. Furthermore, effective data flow can be applied to the simulation modeling of an entire product life cycle and its value chain.

Information technologies, such as machine learning, are extremely important for enhancing the performances of simulations or augmenting a model's intelligence to provide potential benefits. Ruedem et al. (2020) described a conceptual framework for the modeling approaches that pair machine learning and simulation in the context of Industry 4.0. Therefore, advances in machine learning have propelled simulation processes into a new position as decision-making tools in Industry 4.0 applications. In other words, to enable better performance prediction of the utilization areas, simulations need various data sources, such as parameters and data generated by an MLA (Gaku et al. 2021).

Machine learning technologies can generally be used for three types of integrations as follows:

- Integrate or generate synthetic input data elements or input parameters from various data sources to enhance simulation performances.
- Embed MLAs in simulation models to capture the complex and optimal decision logic with near real-time execution.
- Analyze simulation results to detect the patterns or the intelligence in simulation result data as a solution to support decision-making.

Generally, machine learning and simulations have similar features; both of them deal with huge amounts of data. A variety of data sources can be collected and shared efficiently through powerful computing resources in today's business environment; therefore, all types of machine learning integrations require large-scale data analysis methods before, during, or after performing symbiotic simulation models. Technological advancements for both simulations and machine learning models have greatly simplified the collection and sharing of large volumes of data; these advances have also facilitated the application of these data to models and have evaluated various possible scenarios to predict and drive outcomes (Sturrock et al. 2018).

3 DATA-BASED HYBRID MODELING APPROACH OF COMPLEX LONG-TERM EGG PRODUCTION SYSTEMS

3.1 Input Data

Tables 1 and 2 show an example of the selected resultant input data for the symbiotic simulation applications of complex long-term egg production systems. Table 1 shows part of the internal operational data within biological constraints established by the life cycles of specific breeds.

Table 1: Part of the internal operational data.

(a) Historical Poultry Viability (percentage/week)

Week 1	Week 2	Week 3	…	Week 68	…
0.9996	0.9988	0.9978	…	0.9011	…
0.9991	0.9985	0.9977	…	0.8994	
0.9998	0.9995	0.9990	…	0.8878	…
…	…	…	…	…	…

(b) Historical Poultry Intensity (percentage/v

Week1	Week2	Week3	…	Week68	…
0.0000	0.0087	0.1299	…	0.8529	…
0.0001	0.0024	0.0709	…	0.8443	…
0.0026	0.0407	0.1951	…	0.8071	…
…	…	…	…	…	…

(c) Historical Percentage of Egg S

Egg sizes / Weeks	SS	S	MS	M	L	LL
…	…	…	…	…	…	…
Week 5	0.0314	0.5164	0.4343	0.0178	0.0000	0.0000
Week 6	0.0009	0.1562	0.7092	0.1330	0.0006	0.0000
Week 7	0.0001	0.0560	0.6646	0.2765	0.0029	0.0000
…	…	…	…	…	…	…

Here, (a) historical poultry viability, (b) historical poultry egg-laying intensity, and (c) historical percentages of egg sizes are used to extract data from the historical business data warehouse. Table 2 shows the related external economic data sample that has a major influence on egg prices and poultry life spans, such as the egg sales prices of poultry farms and egg dealers, the total poultry supply in specific regions, and the amount of domestic import of eggs. These data are the external constraints from the business environment. Furthermore, these data are responsible for generating and providing synthetic input data elements to enhance the simulation performances. For example, the data elements of the egg sales prices of poultry farms and egg dealers can be forecasted using linear regression models based on the (a) historical egg sales prices in specific regions, (b) poultry supply in specific regions, and (c) volumes of imported eggs.

In the current age of Industry 4.0, a variety of data types relating to both the external economic environment and internal business operations can be collected and shared efficiently through powerful computing resources. The data-based hybrid modeling approach combines machine learning and simulation and is useful when the processing capabilities of simulations cannot handle the indispensable dimensionality of large-scale data, for example, in an actual complex long-term egg production system.

Table 2: Selected related external economic data.

(a) Historical Egg Sale Prices of Specific Regions

Year	Month	Egg Price (¥/kg)
…	…	…
2012	1	149
2012	2	185
2012	3	178
2012	4	182
2012	5	168
2012	6	161
2012	7	160
2012	8	157
2012	9	176
2012	10	193
2012	11	209
2012	12	230
2013	1	171
2013	2	190
2013	3	175
2013	4	172
2013	5	164
2013	6	155
2013	7	157
2013	8	175
2013	9	211
2013	10	220
2013	11	260
2013	12	280
…	…	…

(b) Poultry Supply of Specific Regions

Year	Month	No. of Laying Hens (thousands)
…	…	…
2012	1	7965
2012	2	7948
2012	3	8554
2012	4	8450
2012	5	8404
2012	6	8181
2012	7	8191
2012	8	7238
2012	9	7716
2012	10	8215
2012	11	7991
2012	12	7762
2013	1	7728
2013	2	7796
2013	3	7976
2013	4	8272
2013	5	8289
2013	6	8302
2013	7	7592
2013	8	7123
2013	9	8368
2013	10	7734
2013	11	8240
2013	12	8103
…	…	…

(c) Domestic Egg Importing Volume

Year	Month	JA Egg Import (ton)
…	…	…
2012	1	12025
2012	2	8569
2012	3	11140
2012	4	8642
2012	5	10438
2012	6	10317
2012	7	10240
2012	8	11300
2012	9	13179
2012	10	13255
2012	11	11819
2012	12	9053
2013	1	8470
2013	2	8361
2013	3	8092
2013	4	11715
2013	5	9722
2013	6	8013
2013	7	9474
2013	8	11113
2013	9	8720
2013	10	10706
2013	11	10275
2013	12	10011
…	…	…

Competitive egg production operations typically have a life cycle of more than 2 years; therefore, the inherent life-cycle reliabilities of different breeds have a competitive advantage in long-term poultry production operations. In this study, simulation models of poultry breeds of complex long-term egg production systems were designed to obtain related large-scale data from the Excel data tables shown in Table 1; this table shows the (a) historical poultry viability, (b) historical poultry egg-laying intensity, and (c) historical percentage of egg size. The use of Excel data tables is an important part of data-driven modeling because object breeds can be changed to extract data of different breeds with good flexibility; the designed models are powerful. For example, different breeds need to be analyzed when each breed has a different life-cycle reliability. The input data configuration is similar, but the contents of the related data are different. Figure 1 shows the average intensities of the HD and HH breeds from the beginning of the laying period. Naturally, when the laying hens finish the pullet phase, the egg laying by all the breeds starts from 0% to 5% in week 1, which is the the beginning of the laying period. Growth intensifies until weeks 45 and 46. Then, the peak mortality decreases and later increases. After the mortality period, the egg-laying intensities decrease and finally stop. The egg-laying intensities of the HD and HH depend on the differences in breeds and poultry viabilities.

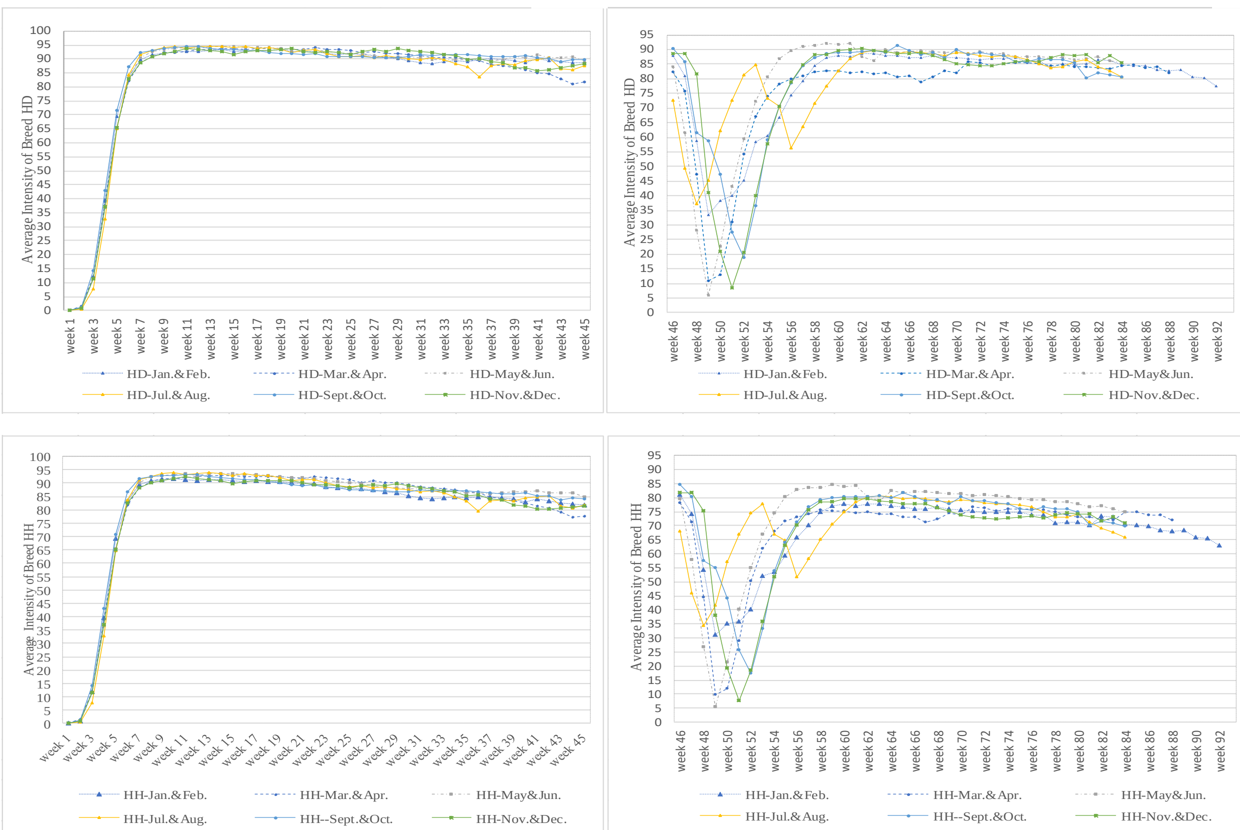


Figure 1: Average intensities of different breeds.

3.2 Modeling

A modeling approach of specific simulation models was applied according to the complexity levels of the system structures and the data properties of real-world systems. As illustrated, the goal of this study is to mimic complex long-term egg production systems, also provide a realistic knowledgebase of data schema for testing and understanding overall system profitability of different species in the context of overall poultry supplies. Therefore, it is of consequence that simulation is used within egg production systems for different breeds considering various types of business data efficiently and effectively.

A valid simulation model was one that accurately represented the relevant characteristics of the object or decision problem being investigated. In this study, the profit of specific egg-laying hen breeds and their relevant characteristics based on each life-cycle span are considered. If Y represents the profit from a specific egg-laying hen breed based on the life-cycle span, the relevant characteristics of the complex long-term egg production systems are represented as follows:

$$Y = f\ (L, V, I, N, F, E, P, C), \tag{1}$$

where $C =$ *Fodder trade prices*
$E =$ *Distribution of egg sizes*
$F =$ *Fodder consumption for each hen per day* (g)
$I =$ *Average egg laying intensity*
$L =$ *Level of poultry input* (*thousands*)
$N =$ *Percentages of normal egg laying*
$P =$ *Egg trade prices*
$V =$ *Average poultry viability*

To forecast *Y* using independent variables, such as *L*, *V*, *I*, *N*, *F*, *E*, *P*, and *C*, the mathematical form of the function *f* is quite complicated because actual data of each independent variable changes frequently according to both the biological constraints of the poultry's life span and the external influence on the egg trade prices.

Figure 2 shows how to describe the relationship between the dependent variable *Y* of the complex egg production systems and the independent variables *L*, *V*, *I*, *N*, *F*, *E*, *P*, and *C*. In general, at the end of each week, actual internal operational data are collected and stored based on daily egg production operations. Related external economic data, which have a major influence on egg prices and poultry life spans are also collected regularly .

Data-based modeling usually focuses on poultry breeds of one sort and another. To reflect the relevant characteristic of complex egg production systems, various data elements from various data sources should be integrated. The three types of independent variables are as follows:

- The first step of *L* is usually under the manager's control.
- *V*, *I*, *N*, *F*, and *E* of each week could reflect the fundamental characteristics of the biological constraints of different breeds and could provide insights into the within-breed historical life-cycle reliability.
- *P* and *C* are the characteristics relating to the external influences on the length of poultry's life span.

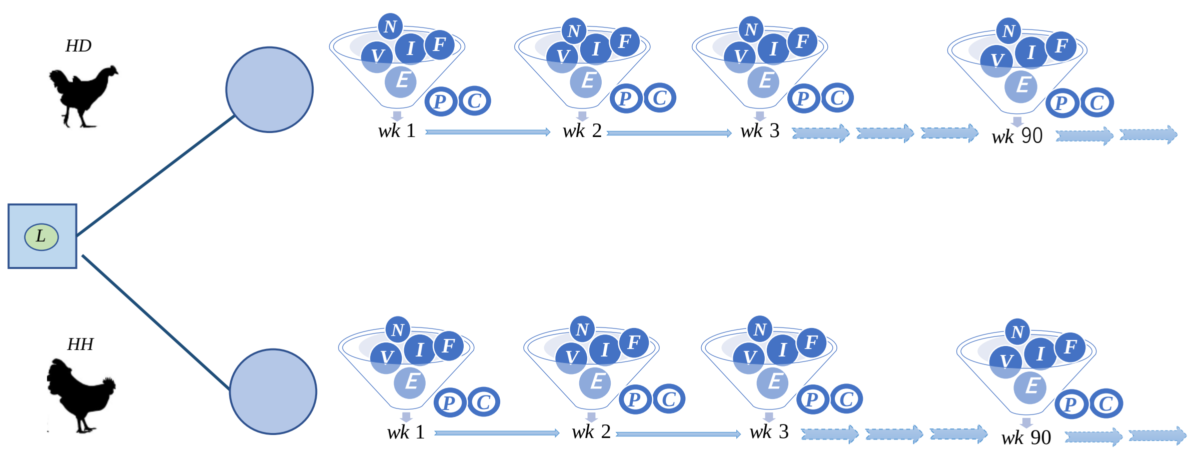


Figure 2: Relationships between the different types of variables.

4 APPLICATIONS

Poultry production has important economic and social benefits and plays a significant role in both human nutrition and agricultural development. The diverse agroecology and agronomic practices in many poultry farms could increase the contribution of poultry to agricultural outputs and could improve performance in decision-making in the production and operational planning phases.

Figure 1 shows the general life cycle of poultry production activities. In this case, when the laying hens finish the pullet phase, a laying phase starts at 112 days of age with an egg-laying intensity of 0%–5% (Gaku et al. 2011). In this section, the proposed data-based hybrid modeling approach using machine learning and simulation was applied to real poultry farms with complex long-term egg production systems.

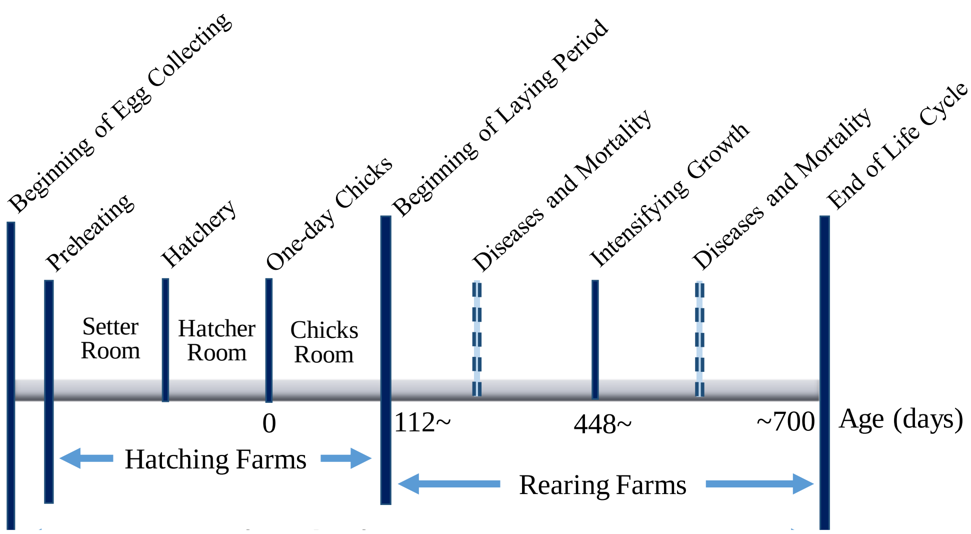


Figure 3: General life cycle of poultry production activities.

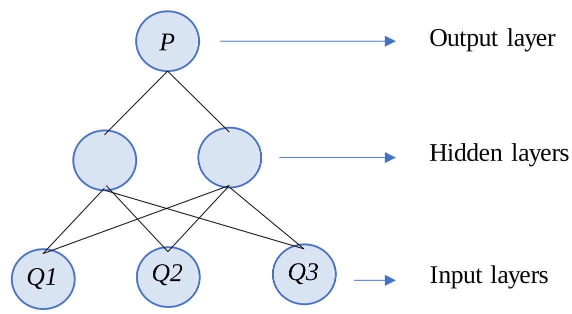
The academic–industrial cooperation project was started in 2014, and the object farms have continually provided diverse operational data recorded in daily long-term egg production. This study aimed to analyze cost-efficient methods of two major poultry breeds with complex egg production systems based on the production cycles of historical poultry breeds. The goal is to make more accurate estimates of how good egg products could be obtained from different breeds and what financial results would be obtained at the end of each production cycle. The data elements considered for the economic analysis were both stored and collected internal operational data related to the within-breed historical life-cycle reliability and to the economic data that had a major influence on egg prices and poultry life spans.

This section describes how to apply the data-driven hybrid modeling approach using machine learning and simulation. In the first stage, a linear regression model is predefined to adapt related historical economic data. Whereas a traditional statistical model could apply a predefined relationship to forecast egg sales prices, a machine learning algorithm can learn patterns directly from the latest input datasets without assuming a priori particular relationship. Datasets for the MLA using linear regression models were prepared to forecast the egg sales prices between poultry farms and egg dealers (P); these datasets included external historical economic data involving historical egg sales prices in specific regions ($Q1$), poultry supplies in specific regions ($Q2$), and egg importing volumes ($Q3$).

Figure 4 shows the schematic view of a neural network designed to forecast the egg sales prices using related historical economic data. The latest data sources to improve the forecasting accuracy without reprogramming show that the future egg sales prices between poultry farms and egg dealers could be forecasted more accurately and timely.

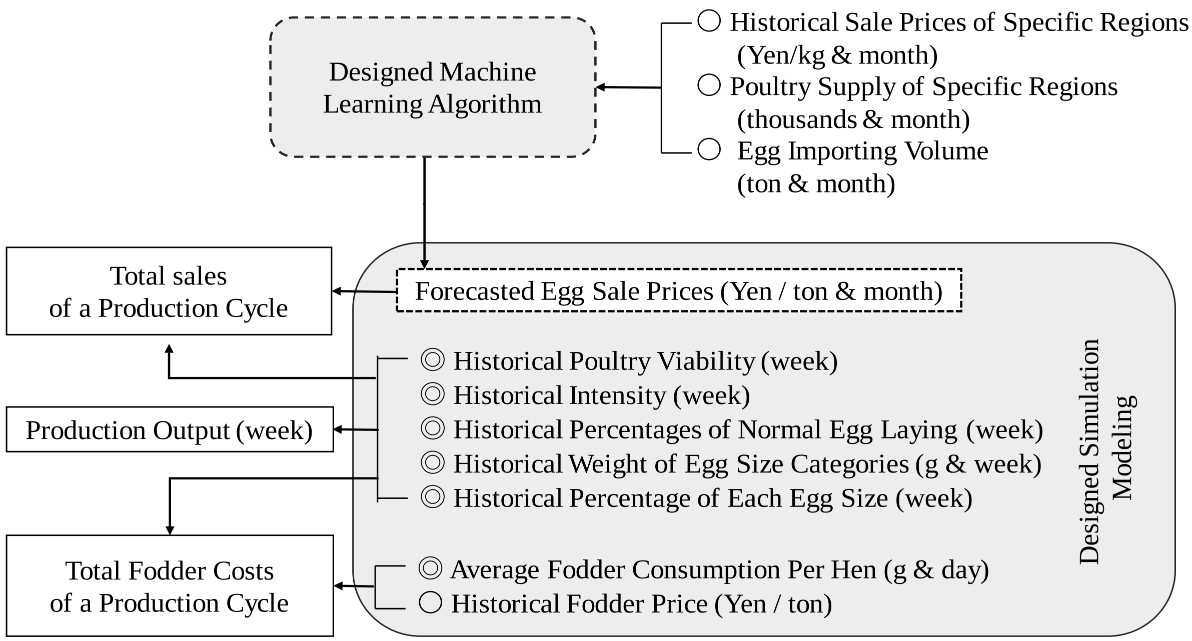
Figure 5 desciribes relationships between machine learning algorithm and simulation modeling.Here, data analysis using machine learning was responsible for providing a portion of the appropriate input data for the simulation models, as shown in Figure 5.

In the second stage, in the designed simulation models, the forecasted egg sales prices from the designed MLA were incorporated to allow the evaluation of economic analysis for each of the poultry breeds. The process of simulation modeling could embed the same cost-efficient decision logic into the model and separately consider the different data elements of specific poultry breeds. The simulation models were constructed using the Simio simulation software version 14.230. Figure 6 shows one part of the simulation logic of this study. The relationships between the inputs and outputs of the specific poultry breeds could be established by incorporating MLAs into the simulation and by using the appropriate data utilization method.



$Q1$: Historical egg sale prices of specific regions
$Q2$: Poultry supply of specific regions
$Q3$: Egg importing volumes
P : Egg sale prices between poultry farms and egg dealers

Figure 4: Schematic view of a neural network.



○ : Related Economic Data ◎ : Historical Operational Data

Figure 5: Relationship between machine learning algorithm and simulation modeling.

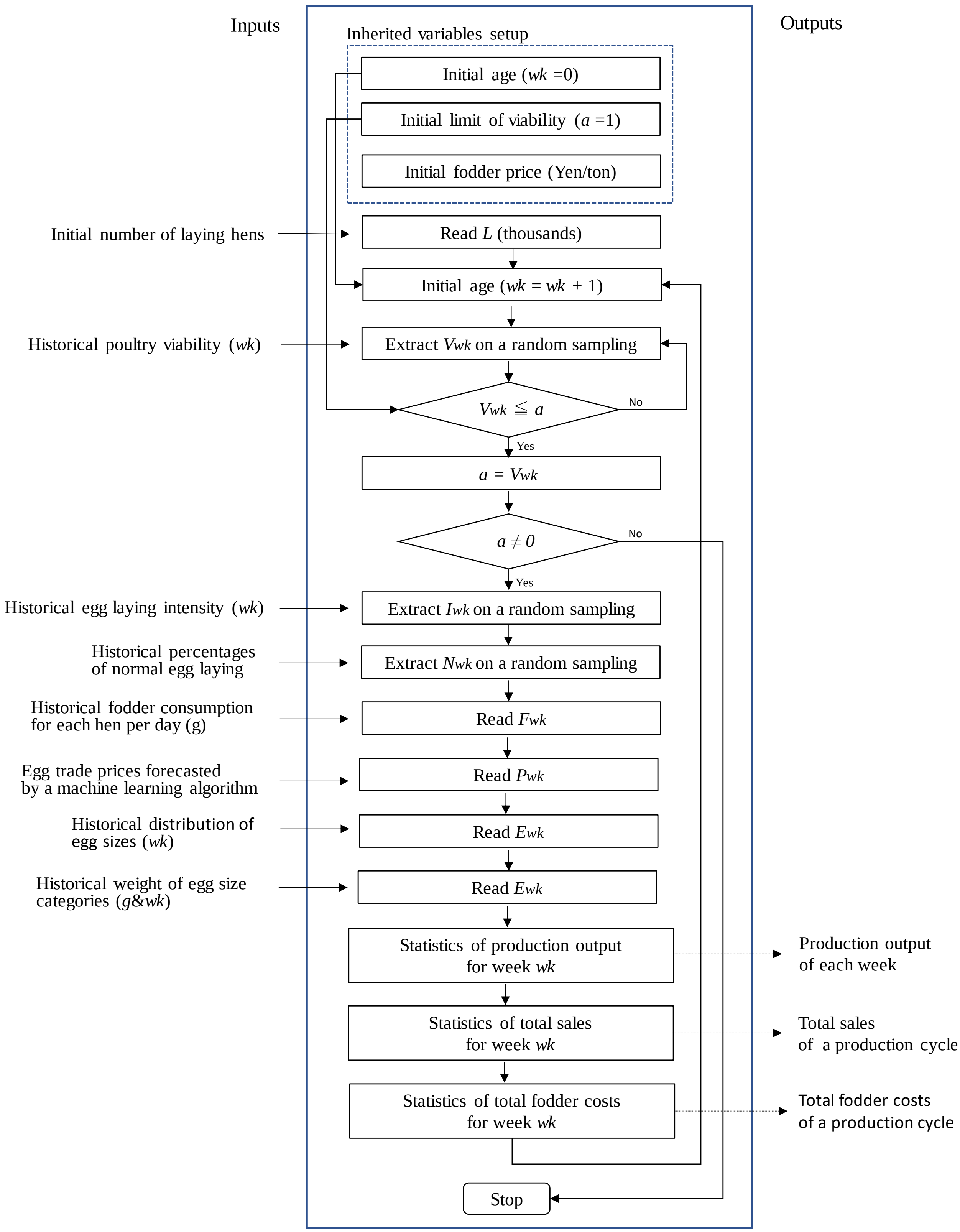


Figure 6: Part of the simulation logic in simulation models of complex long-term egg production systems.

Here, external economic data were collected from Ja.z-tamago.co., Ltd., which had overall charge of the egg products supply in Japan. Various internal operational data were provided by the actual egg production farms called Ainan Farms, which are engaged in hen breeding for the production of eggs for consumption. Overall, the modeling flexibilities of machine learning and simulation can be key drivers to dramatically innovate and aid long-term production and operational planning in the poultry industry (Gaku et al. 2021).

Table 3 shows the actual parts of the input data used for simulation models of the different breeds provided by Ainan: (a) historical poultry intensity of the breed HD and (b) historical poultry intensity of the breed HH.

To measure and compare overall system profitability between various parts of poultry supply interact, a realistic knowledgebase of data schema is actually considered and provided to real poultry farms of Ainan, Japan. Figures 7 and 8 show the egg revenue for each week based on the life cycle of breed HD and HH. The analysis results prove that the simulations could be combined with machine learning to serve as a powerful large-scale data analysis tool for poultry breeds used in complex long-term egg production systems.

Table 3: Actual parts of the input data for data-driven simulation models of two types of breeds.

(a) Historical data of breed HD (%)

	Week 1	Week 2	Week 3	Week 4	Week 5	…	Week 36	Week 37	Week 38	Week 39	Week 40	…
HD	0.0	1.0	11.9	39.8	69.5	…	89.7	90.0	89.9	89.5	88.5	…
	0.1	1.5	12.0	39.0	65.4	…	89.2	88.1	87.4	86.8	86.1	…
	0.0	1.1	11.5	36.7	65.6	…	89.7	89.5	89.9	90.8	90.6	…
	…	…	…	…	…	…	…	…	…	…	…	…
	0.0	0.5	7.9	32.7	65.0	…	83.7	87.6	88.4	88.0	89.5	…
	0.1	1.3	14.4	43.1	71.5	…	91.2	91.0	90.7	90.9	91.2	…
	0.0	1.0	11.5	37.0	65.5	…	90.1	88.9	88.6	86.9	86.9	…

(b) Historical data of breed HH (%)

	Week 1	Week 2	Week 3	Week 4	Week 5	…	Week 36	Week 37	Week 38	Week 39	Week 40	…
HH	0.0	1.0	11.9	39.7	69.2	…	84.8	84.8	84.6	84.0	82.9	…
	0.1	1.5	12.0	38.9	65.2	…	86.3	85.0	84.2	83.4	82.6	…
	0.0	1.1	11.5	36.6	65.5	…	86.4	86.0	86.3	86.9	86.6	…
	…	…	…	…	…	…	…	…	…	…	…	…
	0.0	0.6	7.9	32.7	64.8	…	79.7	83.2	83.9	83.3	84.5	…
	0.1	1.3	14.4	42.9	71.0	…	86.7	86.4	86.0	86.1	86.3	…
	0.0	1.0	11.5	36.9	65.2	…	85.5	84.2	83.8	81.7	81.5	…

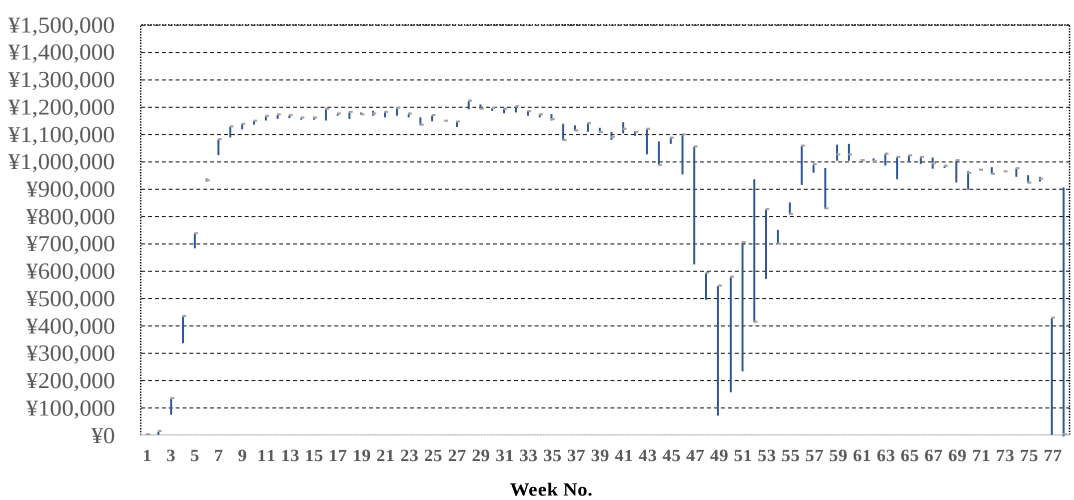


Figure 7: Egg revenue for each week based on the life cycle of the HD breed.

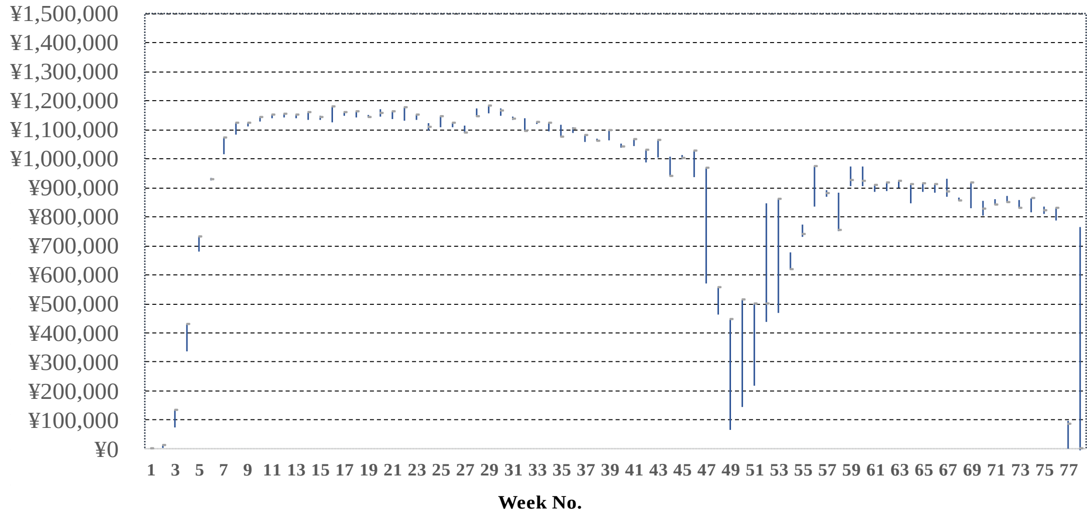


Figure 8: Egg revenue for each week based on the life cycle of the HH breed.

5 CONCLUSIONS

In this study, data analysis was conducted using machine learning to provide a portion of the appropriate input data on the egg sales prices for the simulation models constructed to represent the actual egg production operation activities of specific poultry breeds. Besides the input data forecasted by the designed MLA, the simulation input data included other kinds of data, such as the historical egg-laying intensity, poultry viability, and other information required by managers. The proposed hybrid modeling approach could be implemented as an excellent tool for the economic analysis of specific poultry breeds used in complex long-term egg production systems. It can be used to compare the economic effects of different poultry breeds or swine breeds based on their production life spans.

In future studies, the proposed data-based hybrid modeling approach proposed in this study will be used for economic analyses that emphasize the different seasonal beginnings of the laying period on a specific poultry breed in terms of the related datasets. This can be an agile analysis tool to evaluate the decision timings made to molt or to replace the flock.

ACKNOWLEDGMENTS

We would like to thank Mr. Daishi Saito who continues to provide actual business data for this study. A special thanks to Mr. David T. Sturrock from Simio LLC for his advice about simulation modeling and scheduling application.

This research is supported by Grants-in-Aid of the Japan Society for the Promotion of Science (JSPS) for Fostering Joint International Research(A) (Grant Number: 17KK0078).

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