DETECTION AND PREDICTION OF RISK FACTORS ASSOCIATED WITH PRODUCTION LOSSES USING PRODUCTION RECORDS ON COMMERCIAL PIG FARMS

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ABSTRACT

Japanese pork production remained flat in recent years, but number of pig farms have decreased and farm size in each farm has increased. In order to improve their production performance, many farms keep their records such as mating, farrowing, and weaning events of sows and mortality or daily gain of growing pigs as electronic files. However, the data used by producers has been still limited and most of the usages were basic with limited capacity for analysis. Big data collected from commercial pig farms can be transformed into useful information to improve decision making and maximize productivity. In swine production, big data application can be divided into two categories: explanatory model to detect risk factors that associated with disease occurrence and production losses, and predictive model to predict production parameter or events that will lead to disease occurrence and production losses. The explanatory model can be useful in interpreting what kind of risk factors affected disease occurrence and production losses, and producers should improve or modify their standard operating producer depending on the results of analysis. For example, inadequate management for heat stress can be reduced feed intake of sows during lactation that will decrease postweaning fertility or subsequent litter size. Low biosecurity level increases the probability of being introduced infectious disease into the farm. On the other hand, the predictive model can be useful in interpreting events likely to happen in the near future, and producers can use this information for decision making. For example, model-based monitoring by using sensors or ICT devises can be advised producers about what action to take. A computerized artificial insemination management system can determine optimal timing for insemination based on behavior analysis of sows. This manuscript addresses the use of data collected from commercial pig farms to improve farm productivity and decision making by detecting and predicting risk factors associated with production losses.

Keywords: Big data, epidemiology, machine learning, prediction, productivity, statistics

INTRODUCTION

Japanese pork production remained flat in recent years, number of pigs and sows are approximately 9 million pigs and 1 million sows, respectively. However, number of pig farms have decreased and farm size in each farm has increased. In the past 30 years, the number of pig farms decreased from 43,400 to 4470, whereas the number of pigs in each farm increased from 272.3 to 2,056 pigs/farm (Ministry of Agriculture, Forestry and Fisheries of Japan 2018; Figure 1). There are several reasons for reduction of number of pig farm, such as high feeding costs, increase of imported meat, and occurrence of infectious disease. In Japan, pork and chicken meats are main meat consumption, and annual meat consumption per capita is about 12.9 kg per person (Ministry of Agriculture, Forestry and Fisheries of Japan 2019). Japanese import volumes of fresh/frozen pork is about 932,000 tones, which is almost equivalent to volumes of domestic pork.

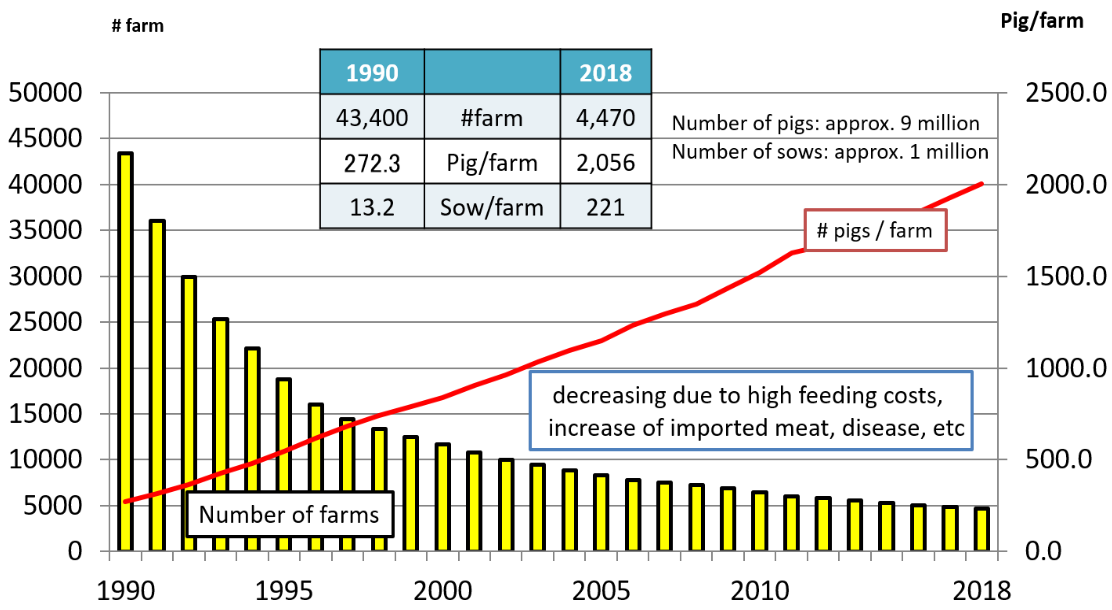

Figure 1. Number of pig farms and number of pigs and sows per farm in Japan in the past 30 years[a]

[a]Data were obtained from Ministry of Agriculture, Forestry and Fisheries of Japan (2018).

In Japanese pork industry, there are several problems that should be improved. At first, compared with USA or Europe, productivity in Japan is quite low. For example, average number of piglets born in 2017 in USA, Denmark and UK are reportedly 13.9 (Pork checkoff 2018), 16.9 (Hansen 2018) and 12.8 piglets (Agriculture and Horticulture Development Board 2018), respectively, whereas those in Japan was 11.1 piglets (Japan Pork Producers Association 2018). Most of feed ingredients such as corn and soybean meal and fuel such as gasoline and oil are imported from foreign countries, and changes in foreign exchange rate would be affected economic situation. In addition, due to an increase of average pig inventory, their management system has been changed. For example, many sow farm introduced batch management production system, which are formed into groups which allow mating and farrowing to occur at distinct intervals. One-week batch management system has one fixed day of weaning, and it is flexibility, limited peaks in labor requirement and the system is simple to operate (Vermeulen *et al.* 2017). However, producers have limited knowledge of those kind of systems. Furthermore, a free trade agreement such as Comprehensive and Progressive Agreement for Trans-Pacific Partnership (TPP11), the Regional Comprehensive Economic Partnership (RCEP) and the economic partnership agreement (EPA) have been concluded, and competitiveness of pork meat will be strengthened.

In order to improve their production performance, many farms keep their records such as mating, farrowing, and weaning events of sows and mortality or daily gain of growing pigs as electronic files. However, the data used by producers has been still limited and most of the usages were basic with limited capacity for analysis. Big data collected from commercial pig farms can be transformed into useful information to improve decision making and maximize productivity. This paper described how to apply pig data for decision making.

HOW TO APPLY PIG DATA

In general, swine data management systems would meet all the needs of the producers and consultants, such as descriptive analytics and the information flow to decision making. Piñeiro *et al.* (2019) defined a swine management system as "A system made up of tools (software and devices) that together with a working protocol and procedures, including the roles of users, can generate the necessary information to diminish the risk and uncertainties in decision-making." This system can be divided into four steps.

Step 1 is data collection. Data are the raw material of the system and can come from human inputs or sensor-robots. Data consisted only of numbers until now, but the sector is coming closer to the use of images and sounds (Piñeiro *et al.* 2019). Data can be collected from each single farm or several farms that used same recording software. At the data collection, it is important to maintain objectively and avoid bias with data. Database managed by local government or public institution include valuable data collected from various farms, but it should be paid attention to handling of personal information.

Step 2 is data check. Data check is related to the manipulation of data, including several tasks such as validation, sorting or aggregation, management of outliers and missing data. Field data sometimes includes missing or extreme data due to human error, recoding error or management responded to an emergency. The objective is to build databases with proper information generation, and it should be noted how many samples excluded based on each criterion.

Step 3 is data analysis. The way of data analysis should be selected based on the amount and quality of data collected. There are mainly two types of modeling: explanatory modeling and predictive modeling. Both modeling are useful for getting knowledge to improve productivity or management system. Meyer (2018) explained both modeling. Explanatory modeling is interested in identifying variables that have a scientifically meaningful and statistically significant relationship with an outcome. The primary goal is to test the theoretical hypotheses so there is an emphasis on both theoretically meaningful relationships and determining whether each relationship is statistically significant. Some of the steps in explanatory modeling include fitting potentially theoretically important predictors, checking for statistical significance, evaluating effect sizes, and running diagnostics. On the other hand, the goal of predictive modeling is to use the associations between predictors and the outcome variable to generate good predictions for future outcomes. As a result, predictive models are created very differently than explanatory models. The primary goal is predictive accuracy. Being able to explain why a variable "fits" in the model is left for discussion after work. Variables that are used in a predictive model are based on association, not statistical significance or scientific meaning. Until now, analytics were aimed at being mainly explanatory, but due to the amount of quality data available, predictive analytics is becoming a key step. The use of artificial intelligence such as machine learning (an application that provides systems with the ability to automatically learn and improve from experience without being explicitly programmed) or artificial neural networks (an information processing paradigm that is inspired by the way biological nervous systems process information) is expanding (Piñeiro *et al.* 2019).

Step 4 is the interpretation of the results and decision making. Information must be readable and understood by the recipient, and the recipient must have sufficient time to make key decisions. At the interpretation of the results, several factors should be considered to interpret appropriately: observational unit of analysis, time period of data collection, background of target, and so on. In addition, each knowledge obtained from analysis should be converted up to every work level, such as farm staff, farm manager, clinical veterinarian, and technical manager. It is also important to send the right information to the right person at the right time.

These steps will establish a robust information system that supports both production efficiency and the required quality standards. In swine production, big data application can be divided into two categories: explanatory model to detect risk factors that associated with disease occurrence and production losses, and predictive model to predict production parameter or events that will lead to disease occurrence and production losses. In the following paragraph, example of each model described.

ANALYSIS OF DATA COLLECTED OVER A PERIOD OF TIME

The explanatory model can be useful in interpreting what kind of risk factors affected production losses and disease occurrence, and producers should improve or modify their standard operating producer depending on the results of analysis. As an example, this section introduces three cases: analysis of production data in each farm, benchmarking, and epidemiological study to find risk factors associated with infectious disease.

Production data in each farm

This is the basic approach to find problems and factors that should be modified. In swine production, most farms keep their records such as mating, farrowing, and weaning events of sows and mortality or daily gain of growing pigs as electronic files. It is not difficult to collect their electronic files, analyze data, and obtain descriptive statistics for each performance.

The common ways to summarize data are longitudinal analysis and by-factor analysis. As a longitudinal analysis, figure 2 shows monthly average of farrowing rate in a certain farm. This figure was built by collection data of mating and farrowing from 2014 to 2018 in a certain sow farm. It is easy for farm staff, farm manager, clinical veterinarian, and technical manager to understand the change of farrowing rate over a period of time. In this point, the most important thing is to discuss what is the problem the farm has and how they improve this point.

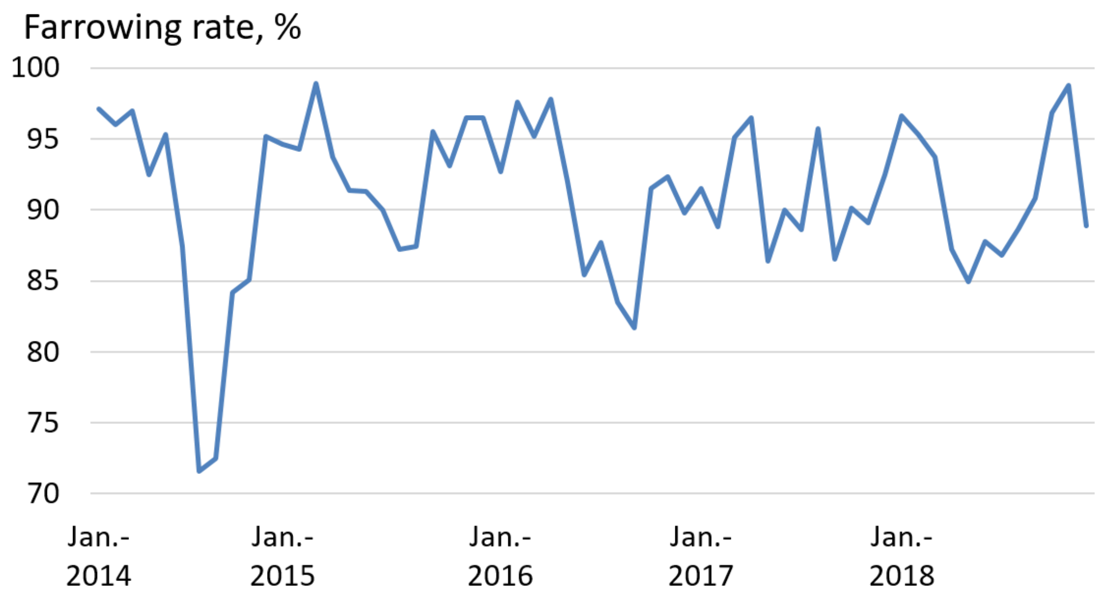

Figure 2. Monthly average of farrowing rate in a certain farm

A by-factor analysis can be obtained by comparing performance by several factors. As reproductive performance of sows, it is common to compare reproductive performance by parity. It is important to know the trend in reproductive performance by parity to design an optimal culling strategy and age structure of sow inventory. Table 1 shows comparisons of farrowing measurement by parity in a certain farm having Berkshire sows (Sasaki *et al.* 2014). This result showed that the pattern of measurements between parity groups in Berkshire sows is similar to that of F_1 crossbred animals (Clark and Leman 1987, Hoshino and Koketsu 2009).

Table 1. Comparisons of farrowing measurement by parity in Berkshire sows[a]

Parity	TPB[b], pigs	PBA[b], pigs	PBD[b], pigs	PBDP[b], %
1	8.2±0.04d	7.7±0.04d	0.5±0.02cd	6.6±0.25b
2	8.5±0.05c	8.1±0.04c	0.4±0.01e	4.4±0.19d
3	9.2±0.05b	8.7±0.05a	0.4±0.01d	4.7±0.18cd
4	9.3±0.05ab	8.8±0.05a	0.5±0.02c	5.2±0.20d
5	9.4±0.06a	8.8±0.06a	0.6±0.02b	6.1±0.24b
6	9.3±0.06a	8.7±0.06a	0.6±0.02b	6.2±0.25b
≥7	9.3±0.05ab	8.5±0.05b	0.8±0.02a	7.8±0.25a

a Data were obtained from a certain farm having Berkshire sows (Sasaki et al. 2014). b TPB: Total pigs born per litter, PBA: Pigs born alive per litter, PBD: Pigs born dead per litter, PBDP: Percentage of pigs born dead per litter

Values are expressed as the mean ± standard error of the mean (SEM).

Different letters indicate significant differences (a > b > c > d > e, P<0.05).

Benchmarking

Benchmarking is defined as continuous comparison and measurements in process and performance to obtain information and knowledge in order to improve their performance. These benchmarking concepts have been applied to agriculture animal herds for providing targets and standards of performance that can be used for comparison for continuous improvement (Koketsu 1999). Feasible targets and standards are necessary for producers and veterinarians to identify problem areas and improve their production in animal agriculture (Koketsu *et al.* 2010). Benchmarking also enhances our knowledge on a production system of the herd and how to improve the herd efficiency.

A method to identify a value for targets or standards is to rank the participating herds by the measurement, and obtain the several percentiles of the measurement (Koketsu *et al.* 2010). The 10, 25, 50, 75 and 90 percentiles of key measurements in the southern Kyushu, Japan are shown in Table 2. The percentiles of the ranked measurements indicate a herd's position within the participating herds indicating the studied population. Producers are able to find what percentile is close to their herd performance. Producers and veterinarians are also readily able to find which performance should be improved among the key measurements, comparing their performance to the standards and targets.

Table 2. Percentiles of key measurements in 2016 on 67 breeding farms located in the southern Kyushu, Japan

	Percentile				
Annual measurement	10th	25th	50th	75th	90th
Total pigs born, pigs	11.2	12.2	13.1	13.8	14.1
Pigs born alive, pigs	9.9	10.7	11.5	12.1	12.4
Pigs born dead, pigs	1.0	1.2	1.5	1.8	2.2
Number of pigs weaned, pigs	8.9	9.8	10.4	10.8	11.1
Preweaning mortality, %	4.5	7.0	9.3	12.1	15.7
Farrowing rate, %	77.9	85.1	88.8	91.2	93.5
Litters per sow per year	2.14	2.27	2.36	2.43	2.48
PWSY[a], pigs	18.3	22.4	24.4	25.8	26.5

[a] TPBPWSY: Pigs weaned per sow per year

In benchmarking analysis, it should be paid attention to interpret of the results because several factors that was not able to collect would be affected the result. For example, the difference of feed ingredients, genetics and health status would be biased the results. In addition, this is the simple comparison of the data, and the findings should be interpreted only as an association, not as indicators of biological causation.

Epidemiological study to find risk factors associated with infectious disease

It is very important to understand what kind of factors associated with infectious disease to prevent the introduction of pathogens. Epidemiological study can be identified the risk factors for infectious disease. Epidemiological steps of an outbreak investigation are three steps (Perez 2015). In first step, it is needed to investigate the extent of spatial and temporal dependence of disease incidence. In the second step, it is needed to quantify the association between epidemiological factors and disease. In the third step, it is needed to Assess the effect of outbreak on productivity and economic loss. These steps can be of great help to understand “the mechanisms for disease spread” and “the effectiveness measures implemented to prevent and control the disease”.

As an example of these step, research step about PED are described. Porcine epidemic diarrhea (PED) is caused by the PED virus, an enveloped and single-stranded RNA virus in the family Coronaviridae (Stevenson *et al.* 2013). The PED is an emerging disease of pigs in a number of countries in North America, Europe, and Eastern Asia. The PED virus recently emerged as a global threat to the swine industry, because a number of epidemics were reported in many important swine-producing countries of North America, that were previously believed to be PED virus-free, and in Eastern Asia (Mole, 2013, Stevenson *et al.* 2013, Chen *et al.* 2014, Hanke *et al.* 2015). In Japan, a new outbreak of PED was reported after an interval of 7 years (Sasaki *et al.* 2016). The virus rapidly spread across the country with 817 PED cases confirmed across 38 prefectures as of August31, 2014.

In first step, it is needed to investigate the extent of spatial and temporal dependence of disease incidence. Sasaki *et al.* (2017b) assessed the spatial dynamics of PED spread during the 8 months of the epidemic in the southern part of Kyushu between December 2013, the month observed first case in the studied region, and July 2014. Information on location and capacity of all farms in the prefectures (n = 1269) was obtained from a government database containing demographic information for livestock producers. Additionally, data on PED detection (positive or negative) was obtained from the regional Livestock Hygiene Service Center. The Cuzick-Edwards (CE) test, the Knox test, the directional test, and the permutation model of the scan statistic were used to assess the spatio-temporal distribution of the epidemic. PED cumulative farm level incidence was 19.5% (248/1269) through the study period. The highest density of positive farms was observed in the most farm-populated areas of the prefecture.

The CE test revealed an extensive degree of spatial clustering, with clustering of positive sites being significant (P<0.01) up to the 35th level of neighborhood (approximately 5 km in the studied data). The observed-to-expected ratio of cases was maximized at short spatio-temporal distances, with values of the observed-to-expected ratio of cases maximized when the thresholds were set at 2 km and 10 days, respectively. A significant (P<0.01) direction of spread was detected towards the northeastern direction. The permutation model detected five significant (P<0.01) clusters occurring at different stages of the epidemic wave. The strong spatio-temporal clustering of PED-infected farms during the first 6 months of the epidemic in the southern part of Kyushu is consistent with results obtained elsewhere and demonstrates the rapid spread of the virus in naïve populations. Results will help to understand the epidemiological dynamics of PED infection, to estimate disease impact, and, ultimately, to establish realistic objectives for the prevention or control of the disease. This results may also inform transmission models that could help in the development of control plans against highly transmissible viral diseases affecting the swine population in Japan.

In the second step, it is needed to quantify the association between epidemiological factors and disease. Sasaki *et al.* (2016) identified and compared risk factors associated with PED infection in locally and non-localized-exposed farms in Japan. A questionnaire was administered to a convenience selection of pig farms located throughout Japan. Questionnaires were administered between November 2013 (when the first case was reported in Japan) and August 2014. PED-positive farms (cases) were asked to provide information on their status (positive or negative) and select herd management practices for the two weeks prior to onset of PED clinical signs. Negative farms (controls) were given the same questionnaire and asked herd management practices for the two weeks prior to a given reference date. This date was assigned based on the date of PED occurrence in the town/prefecture in which the farm was located. Case and control farms were categorized as "locally exposed" if they were located within a 5 km radius from a PED-infected farm and "non-locally exposed", otherwise. Logistic regression analysis was used to identify factors associated with PED infection. Two separate regressions were done for locally exposed and non-locally exposed farms using PED status (positive/negative) as the dependent variable. PED in locally-exposed farms was associated (P<0.05) with increased farm size (in 100 pig increments), shorter distances to the closest PED-positive farm (less than1,001 m), and a disinfectant contact time of less than 20 min. In non-locally exposed farms, PED was associated (P<0.05) with increased feed truck visits to the farm, no visit of the veterinarian, and again a disinfectant contact time of less than 20 min. These findings suggest that the mechanisms of PED spread in Japan were different for farms closer to case-farms compared to farms that were further away from PED cases. These results will contribute to understanding the epidemiology of the disease in Japan and will ultimately aid in designing and implementing effective prevention and control strategies in Japan and other regions epidemically infected by the PED virus. In addition, Furutani *et al.* (2019) assessed the effect of biosecurity measures and intervention practices to control PED on time to absence of clinical signs (TAC) and number of dead suckling piglets during TAC. Farms were asked to provide information on farm characteristics and internal or external biosecurity measures during PED outbreak, as well as on intervention practices to control PED. The TAC was defined as the number of days from the date that clinical PED signs appeared to the date that clinical PED signs disappeared. The number of dead piglets per sow (DP/S) was calculated as the number of dead suckling piglets during TAC divided by the sow inventory. Regarding the effect of biosecurity measures during PED outbreak on TAC and DP/S, longer TAC was observed in *Actinobacillus pleuropneumoniae*–positive farms and farms outsourcing pig transport to the slaughterhouse (P<0.05). In addition, farms with divided truck entrances had lower DP/S than those without divided entrances (P<0.05). Regarding the effect of intervention practices to control PED on TAC and DP/S, farms that performed feedback at 2 weeks or later after PED outbreak had longer TAC and higher DP/S than other farms (P<0.05). Farms that fixed the hours staff worked in farrowing barn had lower DP/S than the other farms (P<0.05). In conclusion, variables associated with long TAC were *Actinobacillus pleuropneumoniae*–positive farms, farms outsourcing pig transport to the slaughterhouse, and farms performing feedback at 2 week or later after PED outbreak. Additionally, those associated with high DP/S were farms without divided entrances, farms without a fixed hours worked in the barn, and farms that performed feedback at 2 week or later after PED outbreak.

In the third step, it is needed to assess the effect of outbreak on productivity and economic loss. Regarding the effect of PED on productivity, Furutani *et al.* (2017) and Sasaki *et al.* (2017a) compared individual sow productivity of Berkshire sows exposed to PED virus at different stages of production, by using data obtained from a commercial farrow-to-finish farm in Kagoshima Prefecture, Japan. The sows were categorized into six groups based on the period in which they were exposed to PED virus: between days 0–30 (G1), 31–60 (G2), 61–90 (G3), or after 91 days of pregnancy (G4), during lactation (L), and after weaning (W). The control group was not exposed to PED during the period of PED outbreak. The sows of the G4 and L groups had the fewest piglets weaned (P<0.05) and the greatest pre-weaning mortality (P<0.05). The number of piglets weaned and pre-weaning mortality, however, did not differ among the G1, G2, G3, and uninfected groups. The G4 and W groups had slightly lesser farrowing rates than the uninfected group (P<0.05), however, similar subsequent piglet litter performance as the uninfected group. In addition, Furutani *et al.* (2018) compared individual sow productivity of F_1 crossbred sows exposed to PED virus at different stages of production. Compared with the uninfected group, there was no reduction in the number of pigs born alive in the G1–G4 groups. Sows of the G4 and L groups, however, had 4–9 pigs fewer pigs weaned, and a 36%–77% greater pre-weaning mortality than the uninfected group (P<0.05). There was no difference in farrowing rate and number of pigs born alive at subsequent parities among the sow groups. There were no interactions between sow groups and parity for sow productivity. Regarding the effect of PED on economics, Sasaki *et al.* (2019) estimated the economic impact of PED outbreak in Japan in 2013 and 2014 by using datasets from all pig farms were provided by Miyazaki (506 farms) and Kagoshima Prefectures (709 farms). Out of 250 farms infected with PED, farrow-to-finish and farrow-to-wean farms were 185, and the number of piglet mortality due to PED in these farms were 93,650. Total economic losses due to piglet mortality was 339,107 thousand Japanese Yen (JPY). Costs per farm due to implementation of enhanced biosecurity measures ranged from 159 to 2,585 thousand JPY. Costs of vaccination that newly started after PED outbreak per farm ranged from 4 to 289 thousand JPY. Total losses due to PED outbreak were 1,182 million JPY.

PREDICTION OF PRODUCTION LOSSES BY DATA COLLECTED BY HUMANS

The predictive model can be useful in interpreting events likely to happen in the near future, and producers can use this information for decision making. In this kind of model, producers can obtain knowledge to support decision making, both for daily decisions as well as strategic decisions. As new devises and communication technologies such as wireless connection, powerful mobile devices, sensors and cloud computing have been developed, data generation, processing, and use is easier than ever (Piñeiro *et al.* 2019). Data resource using the predictive model can be divided into two types: data collected by humans and collected by sensors. As an example of the predictive model by using data collected by humans, this section introduces three cases: prediction of farrowing rate, early detection of problems or disease by monitoring reproductive performance, and early detection of low productivity by monitoring growth performance.

Prediction of farrowing rate

In modern swine industry, many sow farm introduced batch management production system, which are formed into groups which allow mating and farrowing to occur at distinct intervals, leading to an all-in/all-out management (Lurette et al., 2008). One-week batch management system has one fixed day of weaning, and it is flexibility, limited peaks in labor requirement and the system is simple to operate (Vermeulen *et al.* 2017). In the batch management production system, it is important to predict farrowing rate because producers should change the number of gilts and sows being mated according to the prediction of farrowing rate in order to maximize farrowing space utilization efficiency (Koketsu *et al.* 2015).

In order to predict farrowing rate in each batch, it is recommended to construct the prediction model for farrowing rate by using artificial intelligence such as machine learning or artificial neural networks. Farrowing rate are reportedly associated with various factors such as season, parity, days from weaning to estrus and lactation feed intake. Among these factors, it is well known that pigs are sensitive to heat stress. Sasaki et al. (2018) assessed the effects of outside temperature on farrowing rate by using data obtained from 25 commercial farms, including 26,128 service records for gilts and 120,655 service records for sows. Results showed that in gilts, an interaction between climate conditions and service number was associated with farrowing rate (P<0.05). In the first service, farrowing rate decreased as climate conditions increased, whereas no relationship was found in the second service or later. In sows, farrowing rate at first service decreased as MAX increased from 22°C (P<0.05; Figure 3), but no apparent reduction under heat conditions was found in the second service or later. Additionally, effect of heat stress on farrowing rate in parities 1–2 was higher than those in parities 3–5 and ≥6 (P<0.05).

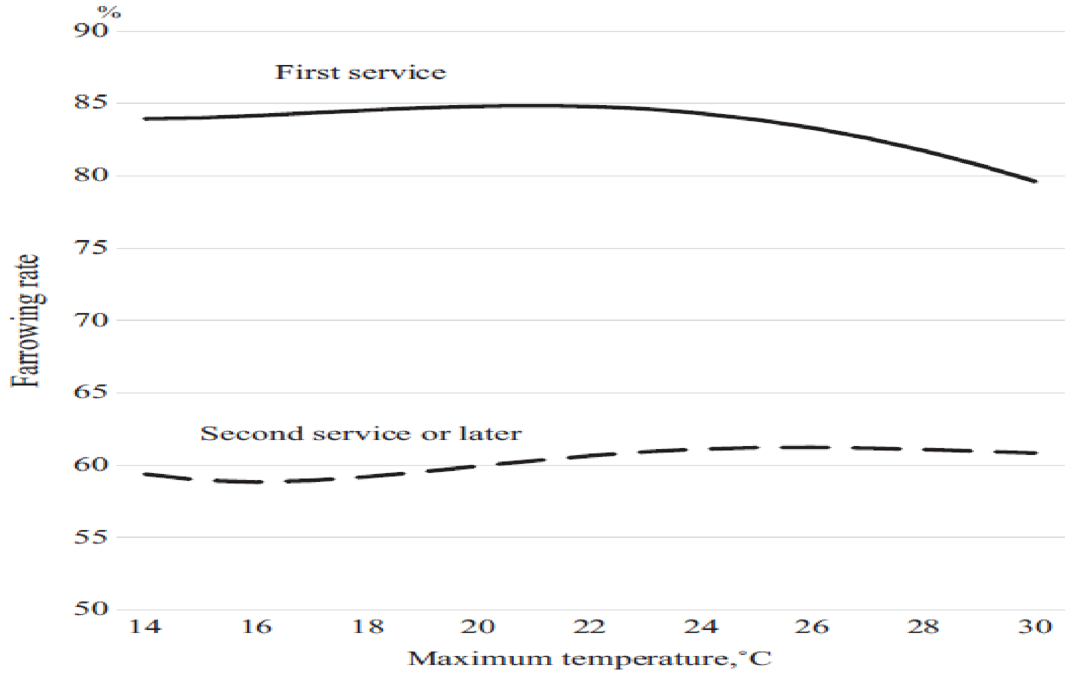

Figure 3. Predicted effect of maximum temperature for 21 days preservice on farrowing rate in different service number groups[a]

[a] This figure was cited by Sasaki *et al*. (2018).

Besides these factors, many variables were useful to increase accuracy of predicting farrowing rate. Low parity sows have lower farrowing rate, whereas mid-parity sows have higher farrowing rate (Koketsu *et al.* 2017). In addition, lower feed intake during lactation extended the days from weaning to estrus and consequently decreased farrowing rate (Koketsu *et al.* 1996).

Early detection of problems or disease by monitoring reproductive performance

Monitoring reproductive performance would be able to detect problems and disease occurrence. For example, Rashidi *et al.* (2014) developed a statistical method to distinguish healthy and disease phases and a method to quantify sows' responses to porcine reproductive and respiratory syndrome (PRRS) without having individual pathogen burden. An outbreak of PRRS decreases the number of piglets born alive, farrowing rate and feed efficiency, and increases pre- and postweaning mortality (Nieuwenhuis *et al.* 2012, Nathues *et al.* 2017, Silva *et al.* 2017, Nathues *et al.* 2018). Productivity losses in the United States swine industry are estimated to be $664 million annually (Holtkamp *et al.* 2013).

Rashidi *et al.* (2014) analyzed 10,910 sows with 57,135 repeated records of reproduction performance. Disease phases were recognized as strong deviation of herd-year-week estimates for reproduction traits using two methods: Method 1 used raw weekly averages of the herd; Method 2 used a linear model with fixed effects for seasonality, parity, and year, and random effects for herd-year-week and sow. The variation of sows in response to PRRS was quantified using 2 models on the traits number of piglets born alive and number of piglets born dead: 1) bivariate model considering the trait in healthy and disease phases as different traits, and 2) reaction norm model modeling the response of sows as a linear regression of the trait on herd-year-week estimates of number of piglets born alive. In both models, traits number of piglets born alive and number of piglets born dead was included as response variables to assess the ability of each trait in capturing the variation among sows in response to PRRS. Number of piglets born alive was chosen because most of the reproduction failures arising from PRRS would be expressed as a reduction in number of piglets born alive at farrowing (Figure 4). This paper showed that there is variation among sows in response to PRRS, implying possibilities for selection, and the reaction norm model is a good model to study the response of animals toward diseases.

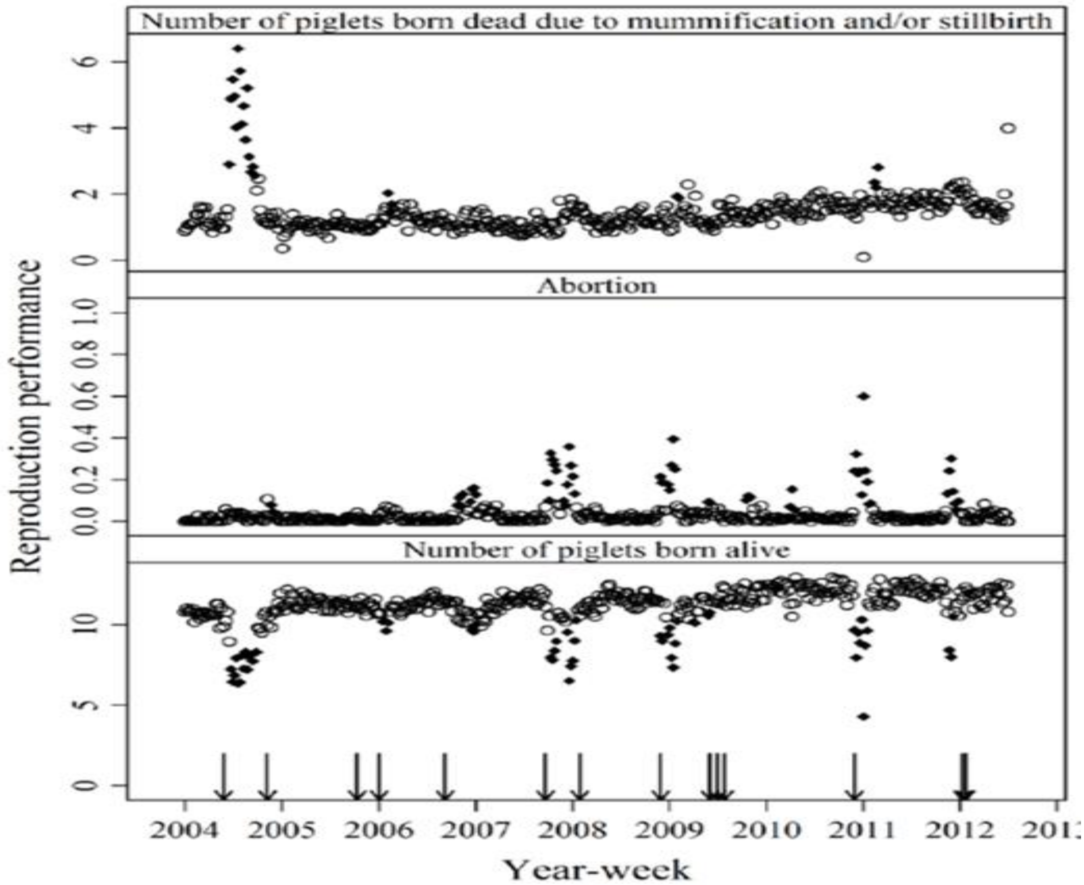

Figure 4. Predicted PRRS outbreaks using the linear model based on number of piglets born dead due to mummification and/or stillbirth, abortion, and number of piglets born alive. The solid diamonds show disease herd-year-weeks during an outbreak. The empty circles show healthy herd-year-weeks. The arrows show the weeks in which PRRS viruses were isolated from blood of sows[a]

[a] This figure was cited by Rashidi *et al*. (2014).

Early detection of low productivity by monitoring growth performance

As well as reproductive performance, monitoring growth performance would be able to detect problems and disease occurrence. For example, Stygar and Kristensen (2018) developed a new tool, built as a dynamic linear model (DLM) for systems with identified and unidentified pigs, used for frequent growth monitoring in pig production in order to alert farmers about deterioration in pigs' growth and to provide current and historical growth statistics for consecutive batches. The growth of pigs was described by parameters representing an initial body weight (BW), average daily gain and daily fluctuations in BW of pigs. Moreover, the constructed tool was built to account for increasing variation in BW of pigs over time as well as autocorrelation between BW measurements of observed individuals. The presented tool can be useful in obtaining growth statistics for systems where pigs are sold continuously. Frequent BW information can be useful in informing farmers about unexpected events influencing growth e.g. outbreaks of diseases or management problems. Moreover, the historical information on growth might be valuable in making optimal decisions regarding management.

With the exception of body weight, there are many indicators to detect low productivity in growing pigs. Feed intake is important indicator that strongly associated with growth performance. In the past, it is not easy to collect data of feed intake at real time, but the availability and the rapid development of new devices and emerging sensor technologies offer great potential for other measurements (e.g., body composition, physical activity, interactions among animals) that will allow more precise estimation of requirements and real-time animal monitoring (Pomer and Remus 2019).

PREDICTION OF PRODUCTION LOSSES BY DATA COLLECTED BY SENSORS

As mentioned above, data resource using the predictive model can be divided into two types: data collected by humans and collected by sensors. As an example of the predictive model by using data collected by sensors, this section introduces three cases: feeding machine, activity sensor to detect estrus, and biosecurity control.

Feeding machine for sows and growing pigs

In lactating sows, it is critical to optimize feed intake to increase their performance at weaning and at subsequent parity. Lower lactation feed intake is associated with lower average weaning weight of piglets, prolonged days from weaning to service, low farrowing rate, as well as more returns or more culled sows due to reproductive failure, and also fewer pigs born alive at subsequent parity (Koketsu *et al.* 1996). Currently, many type of electronic sow feeder systems are also available for lactating sows, which are individually housed. All these systems allow the producer to decide and adjust the amount of feed delivered to each sow. In particular, new options allowing the sow to choose how much and when to eat have recently arrived at the market (Gestal Solo, JYGA Technologies, Canada; Figure 5), thus enabling the farmer to know the lactation intake pattern. These data are very relevant since deviation from the ideal feed intake pattern can impair the productive performance of sows.

Figure 5. Electronic sow feeder Gestal Solo[a]
[a] This figure was cited by Jyga Technologies
(http://jygatech.com/wp-content/uploads/2019/07/EN_Solo-25-years-compressed.pdf)

In growing pigs, it is important to detect productivity problems in the barn as early as possible. Besides sows, it is difficult to monitor and evaluate feed intake in each growing pig. However, feeding pattern can be predicted by their eating behavior to the feeder that monitored by using an ear transponder with radio frequency identification (RFID). Maselyne *et al.* (2018) developed an automated monitoring and warning system based on measurements of the feeding pattern using an RFID system at the feeder, and found that the best performance was achieved for the Synergistic Control method on the number of RFID registrations per pig. Large inter- and intra-individual variation is present in the feeding pattern of individual pigs, justifying an individual monitoring approach. The obtained performance of the warning system is considered promising, but further improvements are still possible especially for the sensitivity and the precision.

Estrus detection by activity sensor

Estrus detection is one of the most important aspect in sow farm. Optimal timing of insemination can increase the probability of being conceived, and it is essential to predict the onset of estrus. In practical, the detection of estrus relies on visual observations such as a red and swollen vulva, mounting behavior, characteristic growl, nervousness, mucus discharge, and loss of appetite (Bonneville 2002). Combining sow variability and the difficulty of estrus detection, with the purpose of maximizing fertility, pig producers generally inseminate once every 24 h while the sow shows symptoms of estrus. This method usually delivers good results, provided that good estrus detection has occurred. However, it requires the presence of skilled individuals and multiple doses of semen (often two or even three inseminations per estrus).

Recently, new sensor technologies have been developed. Among them, PigWatch is a computerized artificial insemination management system designed to predict the best time to inseminate recently weaned sows (Klopfenstein *et al*. 2016). This system can determine optimal timing for insemination based on behavior analysis of sows. It consists of motion sensors installed on the top of every stall in the breeding area, a data analysis module and a software user interface. Motion sensors allow continuous and nonintrusive monitoring of sow behavior by assessing its real-time level of activity.

Furthermore, as is already known, the behavior of each sow is slightly different. Therefore, the first 2 days after weaning are used to learn about the normal behavior of animals when they are not in estrus. The algorithm looks for a significant increase in activity, which is characteristic of estrus (Figure 6; Piñeiro *et al.* 2019). As behavior data are collected, the algorithm analyzes the pattern of activity to predict the best moment to breed. Once the insemination is completed, the worker registers it in the software by triggering a switch on the sensor and all insemination request indicators disappear. This system is designed to be installed on commercial farms and has the potential to decrease dependency on skilled labor, improve reproduction, optimize the best use of the boars, and accelerate genetic improvement. Recent studies (Labrecque and Rivest 2018) used specialized algorithms that consider both sow behavior and worker observations to predict the best timing for insemination while maintaining good reproductive performance. These results proved how big data combined with artificial intelligence algorithms even under commercial conditions, can be transformed into useful information to improve decision making on pig farms.

Figure 6. Screenshot of control software for the PigWatch system. It shows sows already inseminated sows with one dose (blue drop), estrus evolution of the selected sow number (213) and the optimum recommendation for breeding (vertical green bar) or the preventive insemination, if not possible to inseminate at the recommended time (vertical green spotted bar). "Hands" in sows 207 and 210 shows manual recommendation of insemination since the pattern is not clear for the algorithm[a]

[a] This figure was cited by Piñeiro et al. (2018).

Biosecurity control

It is well known that infectious diseases decrease herd productivity and lead to economic loss. Disease prevention through biosecurity measures is believed to be an important factor for improvement of the overall health status in commercial herd production. Biosecurity is the term used in veterinary medicine to describe measures to prevent pathogens from entering farm premises or a group of animals, known as external biosecurity, or prevent the spreading of pathogens within farm premises or groups of animals, known as internal biosecurity (Amass and Clark 1999). To define biosecurity levels on commercial farms, it is important to quantify the biosecurity level in both external and internal aspects.

To date, most biosecurity program measures are based on scoring systems or survey forms. In US and Europe, a biosecurity assessment tool such as PADRAP (AASV: The American Association of Swine Veterinarians; Bottoms *et al.* 2013) and Biocheck (Ghent University; Postma *et al.* 2016) have been developed to measure biosecurity. These systems have risk-based weighted biosecurity scoring that translates questions regarding biosecurity into a score for internal, external and overall biosecurity status, and biosecurity level is assessed by interviewing the farmer regarding biosecurity practices and collecting data by visual inspection. This score aims at providing an objective, comprehensive and quantitative description of the level of biosecurity and can be used to inform the farmer on possible areas for improvements, and to compare his/her biosecurity level with that of other farms/herds.

A new approach addresses this issue by using real-time devices (B-eSecure System) to control the internal movement of farm staff. B-eSecure is an electronic system that besides external biosecurity, tracks and reports correct and wrong movements of people on farms and visualizes effects of biosecurity improvement on health status and production results (Geurts *et al.* 2018). Via installed tracking-devices, movements of people who wear personalized beacons are reported. Movements from grey to red were defined as safe and from red to grey and between red as risk respectively unsafe unless a hygiene-lock was used between them. B-eSecure is very helpful for visualization, implementation and improvement of biosecurity procedures. Linking the program with PRRSv prevalence data and production results helps to reach and maintain a high level of biosecurity. This new approach is very relevant since it generates data where previously there was none and can be used either as simple daily health controls to generate more sophisticated explanatory or predictive models that can help to control the main risk factors affecting internal biosecurity.

CONCLUSION

As a development of technologies, it has become easy to collect large quantities of data. It is useful for farm staff and clinical veterinarians to know about the factors affecting sow reproductive performance and growth performance in order to improve herd productivity. Further steps in this digitalization process will improve production efficiency, health, and welfare on farms under the quality standards that modern production requires (Piñeiro *et al.* 2019). This will bring unprecedented changes and advantages to the industry and huge opportunities for professionals in the global swine production sector. However, it is noteworthy that all of people related to commercial farm such as farm staff, farm manager, clinical veterinarian, and technical manager should be learned how to interpret the results of analysis or alerts given by the prediction model not to avoid misleading.

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