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MODERN MANAGEMENT METHODS IN THE SWINE SECTOR – A REVIEW

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Abstract

Precision livestock farming (PLF) and information and communication technology (ICT) tools are revolutionizing pig production with various technologies, such as sensors, data analytics, and monitoring systems. These tools enable real-time and continuous monitoring of pig health, behavior and production parameters. ICT tools, including advanced data analysis algorithms and decision support systems, interpret the collected data and assist in making informed management decisions. By optimizing critical aspects of pig production, including feed management, environmental control, disease detection, and overall herd health management, these technologies are paving the way for a more profitable and sustainable future in precision livestock farming. The result is improved feed efficiency, reduced environmental impact, enhanced animal welfare, and increased profitability, offering a promising outlook for the industry.

Key words: precision livestock farming, intensive production, animal welfare, modern technology, sensors, pig, microclimate monitoring

In the 1990s, the transition from extensive to intensive rearing caused changes at every stage of pig production. The changes do not only include the range and size of pig performance parameters (breeding, reproduction, rearing, fattening and slaughter) but also the scale of production, i.e., the increased stocking density. The rearing period was also shortened to a minimum of 21 days, translating into an increase in farrowing frequency from 2.0 per year to 2.2–2.5 (Jensen and Recien, 1989; Andersen et al., 2008). Pigs in intensive rearing also have improved growth potential and feed conversion rates (FCR). These alterations result in a shorter fattening period from 7–8 months to 3–4 months. Increasing the level and scale of production caused more frequent rotation of pigs on the farm and their higher concentration (Jun et al., 2018; Maes et al., 2020; Kashiha et al., 2013 a, b; Girard and Bee, 2020; Hintze et al., 2013; Olejnik et al., 2022). Due to further intensification of production and legal changes (welfare, Animal Health Act), the technological standards of pig rearing are raised, among others, by modernizing livestock housing to improve animals' living conditions. The purpose of the introduced changes, in addition to pig welfare conditions, is to increase the profitability of production and improve the health status of kept animals (Hemsworth and Barnett, 2001).

The intensification of pig production should be based on aspects related to sustainable agriculture in the following areas: economic, environmental and social. These sectors include monitoring and controlling as many animals as possible at one time and operating the livestock facility in the ideal social, natural environment, which is a challenge for pig production these days (Beluhova-Uzunova and Dunchev, 2019).

One of the solutions for problems with effective herd management in intensive production scale is the use of PLF (precision livestock farming) method, which aims to develop technology and tools for online monitoring of livestock continuously throughout their lives, i.e., within the functioning in a technological group and in a fully automatic manner, to support the farmers by providing quantitative information about the condition and utility of the animal (Tzanidakis et al., 2021; Banhazi et al., 2011; Banhazi and Black, 2009).

Production using PLF seems to combine several areas for business, including economy, IT sector and technology providers, based on pig herd maintenance, namely

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food safety, animal welfare, pig health, environment and sustainability. Importantly, as noted by Banhazi et al. (2012), this approach has the potential to significantly increase profitability, making it an attractive prospect for the industry.

The idea of precision agriculture (PA) was first introduced in the early 1990s in the US. In 1997, the House of Representatives described PA as 'an integrated information- and production-based farming system that is designed to increase long-term, site-specific and whole farm production efficiency, productivity and profitability while minimizing unintended impacts on wildlife and the environment' (Beluhova-Uzunova and Dunchev, 2019).

Previously, the assessment of biological processes involving live animals (organisms) seemed too complex to track with automated tools that would control animal production online. Emerging technologies allow tools to control multiple production processes, excluding visual observation conducted 24 hours a day (Banhazi et al., 2011).

PLF is a technological system for real-time monitoring of livestock, which aims to manage the basic production unit, the animal, in the most efficient way (Berckmans, 2017; Norton et al., 2019). Management in the PLF concept takes into account an integrated, automated system for controlling and monitoring reproduction, rearing, fattening, animal health, welfare, and the impact of livestock maintenance on the environment in real-time (Berckmans, 2015; Vranken and Berckmans, 2017).

A system that meets these conditions must be based on three assumptions. The first is related to the continuous monitoring and control of variables relating to environmental conditions, the animals themselves, and the consistent data analysis. The second assumption must incorporate realistic expectations and forecasts of the variability of the animals' individual performance and their response to changes in environmental conditions. The third is incorporating expectations, forecasts, and digital measurements into an analytical algorithm for herd management and online monitoring of pig health and welfare conditions (Yu et al., 2021).

PLF is a part of the management process because, with the acquired data, it is possible to develop an overall schedule including a sequence of logical actions, processes and decisions, for the application of which resources are needed (raw materials, biological, i.e. the animals themselves), people, capital or organizations intended to provide conditions for their effective operation in a specific market environment, leading to the achievement of the set goals. Therefore, PLF serves not only to monitor pigs daily at every stage of production regardless of the number of pigs kept, but it is also an early response tool which emphasizes the individual variability of animals (Hemsworth and Barnett, 2001; Beluhova-Uzunova and Dunchev, 2019; Tzanidakis et al., 2021; Banhazi et al., 2011, 2012; Banhazi and Black, 2009).

The PLF concept is relatively new to the European swine industry, but the first pig farmers are beginning to use it today. Some PLF technologies, such as monitoring pigs' coughs, automatic weighing devices, and monitoring camera systems, are already available on the market (Banhazi et al., 2022; Tucker et al., 2023; Reza et al., 2024). Automated welfare assessment based on electronic sensor data has also been developed.

In precision livestock production, traditional environmental measurements of microclimate (temperature, humidity and CO_2) are being augmented with measurements of animal response using feed intake sensors, growth monitors, cameras and microphones. The animal in this process serves as a "sensor" and the specific behaviors of pigs are crucial in finding optimal indicators for an individual farm (Lucy and Szafranski, 2017).

In this review, we present and discuss available technologies that can be applied to pig production systems to control pigs' environment, health, and welfare more accurately. We describe areas where PLF can be used and the potential impact of such technologies on production levels and animal welfare status.

Tools used to monitor behavior and production parameters

Housing and microclimate control

Optimal temperature in livestock building is one of the most important factors for maintaining the health, welfare and desired productivity of pigs across various stages of production. Newborn piglets, particularly vulnerable to temperature fluctuations, require a warm and controlled environment to prevent hypothermia and support early growth (Villanueva-Garcia et al., 2021; Yu et al., 2021). During pregnancy and lactation, sows also demand specific temperature conditions to support reproductive performance and milk production (Lucy and Szafranski, 2017). Furthermore, temperature management is essential during the growing and finishing phases to mitigate stress and enhance feed efficiency (Renaudeau et al., 2008). Many indicators define the thermal comfort range, considering various parameters (Rodrigues et al., 2011). For example, the calculation of lower critical temperature for each stage is based on body weight and age (Fournel et al., 2017). In order to meet the appropriate conditions, piglets are usually kept under heat lamps or on heating mats. Zheng et al. (2021) also proposed a modern solution in the form of an Automatic Thermal Control and Management System (ATCMS) that allows adjustment and maintenance of the desired conditions based on the real-time collected data. Due to rising energy costs, maintaining thermal balance is a serious challenge. An economically advantageous solution to the problem might be to use a geothermal heat pump (Macdonald et al., 2000). Mahfuz et al. (2022) report that geothermal heating with the additional sunlight-based system as a heating source in incubators resulted in electricity use of 64.8% compared with commonly used incubators. According to Mun et al. (2020), a geothermal heat pump tested during winter months decreased harmful gas emissions (NH_3, H_2S), reducing them by an average of 47% (18% in growing

and 52% in the finishing stage). Carbon dioxide concentrations were also significantly lower, with almost 39% reduction compared to a control group with conventional heating at every production stage. From the point of view of herd management, what is also worth mentioning is the significant reduction in electricity consumption by approximately 39%, which is undoubtedly important for long-term profitable production. In the summer period, it allowed maintaining a lower temperature during the finishing period by 15.6% (Mun et al., 2021). Information and communication technology (ICT), defined as tools that allow for collecting, storing, transmitting and analyzing data (OECD, 2015), such as environmental sensors and automated climate control systems, has led to an advanced temperature monitoring in swine facilities. These tools enable real-time data collection, allowing farmers to precisely regulate temperature parameters, optimize energy efficiency, and promptly address deviations (Mahfuz et al., 2022). Andersen et al. (2008) used tags that continuously measured ear skin temperature, which allowed the determination of the behavioral pattern of diurnal rhythm depending on microclimate conditions. As swine production evolves, a comprehensive understanding and precise management of temperature conditions through ICT tools become pivotal for sustainable and efficient pig farming practices (Racewicz et al., 2021). Deploying advanced sensors and data analytics also allows real-time surveillance of humidity levels in swine facilities, creating the opportunity for farmers to address potential issues such as respiratory diseases proactively. Thermal stress, connected with high humidity levels, is a direct cause of several problems, negatively affecting production indicators and significantly impairing welfare and production efficiency (Ross et al., 2015). One of the helpful indicators is the temperature-humidity index (THI) (Gaughan et al., 2012) or enthalpy, thanks to which it is possible to assess potential heat stress (Rodrigues et al., 2011; Luis De Castro Júnior et al., 2022) and, therefore, take appropriate actions by efficiently handling the herd (Chu and Jong, 2008). Monitoring temperature and humidity is particularly valuable in the face of global warming and unpredictable weather conditions (Kuczynski et al., 2011). Automated ICT-driven ventilation systems can dynamically adjust airflow based on humidity data, ensuring optimal conditions for swine welfare (Mahbub et al., 2020; Shin et al., 2023). Integrating innovative tools in humidity monitoring enhances precision and allows tracking trends over time, facilitating the implementation of targeted interventions for improved pig welfare appropriate for specific technological groups (Brown-Brandl et al., 2013). The continuous assessment of key parameters, including temperature, humidity, and air quality, empowers farmers to make informed decisions for ventilation adjustments (Mahbub et al., 2020). Intensive animal production contributes greatly to greenhouse gas emissions. Meticulous management of gas levels, especially ammonia, is essential to protect pig health and productivity and improve farms' environmental sustainability (Philippe et al., 2011). As described in the literature, there are several reasons for the problem, i.e. manure repository (Philippe et al., 2011), the type of flooring (Wang et al., 2017) and the level of feed balance and utilization (Aarnink and Verstegen, 2007). Elevated ammonia concentrations cause multiple issues and respiratory challenges and compromise the overall welfare of pigs (Banhazi et al., 2008; Schillings et al., 2021). Technological advancements in the form of ICT have resulted in innovative tools such as gas sensors and automated ventilation systems, offering real-time monitoring capabilities. Yoon et al. (2022) developed an ammonia monitoring system consisting of a Livestock Odor Management System (LOMS) and a Livestock Odor Control System (LOCS). Due to the combination of electrochemical sensors, data transmission and trend analysis can be treated as a management supporting tool in the decision-making process dedicated to microclimate control. For example, Enviro-Detect (PLF Agritech, Edinburgh, United Kingdom), linked with the Automated Data Analysis and Management System (ADAMS) (Kopler et al., 2023; Banhazi et al., 2024), provides information on not only ammonia levels but also carbon dioxide, dust, temperature and humidity (inside and outside the livestock building), ventilation speed. Implementing reliable information sources for proactive management ensures optimal conditions for the swine, reducing the risk of respiratory issues and stress, and contributes to resource efficiency and sustainability in swine production and desired welfare.

Weight monitoring

In large-scale production, data obtained from body weight monitoring are essential to estimate the feed conversion rate, revealing that feed/water intake plays a crucial role in precise animal management and efficient production from an economic point of view (Atsbeha et al., 2020). According to an experiment conducted by Meiszberg et al. (2009), water intake based just on animal observation might be misleading, and more precise methods are needed to estimate the actual intake more accurately. Using an algorithm developed from top-view video recordings and subsequent behavioral analyses of fattening pigs, Kashiha et al. (2013 a) estimated water intake with compliance of 92% compared to real consumption. In the case of feed intake surveillance, ear tags are widely used. Based on the experiment conducted on pregnant sows, feeding pattern was dependent on rank in the group (Chapinal et al., 2008). Using a single electronic feeder (Fitmix, Mannebeck Landtechnik GmbH, Schüttorf, Germany) and ear tags (HP HDX, Allfex Europe) used for individuals' identification, it was possible to determine that dominant sows spent significantly more time at the feeder and accessed it earlier than the rest of the herd, thus potentially leading to undesirable fluctuations in growth between individuals caused by uneven feeding frequency (Jia et al., 2021).

Technological integration facilitates not only the streamlined collection of weight data but also its seamless analysis for comprehensive insights into growth patterns and overall herd performance (Fournel et al., 2017). From the farmer's point of view, body weight is significant because it determines the length of the production cycle. Weighing animals using standard methods is stressful for the animals and time-consuming, and requires several handlers at once (Kashiha et al., 2013 b; Kollis et al., 2007; Aquilani et al., 2022). Banhazi et al. (2011) developed a system for non-contact body weight assessment based on body size measurements obtained through image analysis, including parameters such as maximum length, minimum width of the front, rear and mid sections, total areas of the front and rear and mid sections. The measurement error in relation to the actual body weight was approximately 1.18 kg. The correlation between measured features and pigs' weight was the highest for maximum width, maximum rear width and total area (R2 equal to 0.965, 0.964 and 0.974, respectively). Jun et al. (2018), based on the measurements of pigs in the fattening phase on 2D images, obtained a correlation with the results of the control group at the level of R2 = 0.79.

Currently, a whole spectrum of automatic methods of body weight monitoring is used (Wang et al., 2008). Multiple commercially available solutions like Weight Detect, eYeScan, eYeNamic, Pigwei, WUGGL, or OptiScan were previously described by Vranken and Berckmans (2017). By leveraging the potential of these tools, pig producers can implement targeted strategies for optimal nutrition, health management and performance evaluation (Banhazi et al., 2012). The synergy between weight monitoring and use of other ICT tools not only enhances the efficiency of data-driven decision-making but also empowers pig producers to make informed choices that contribute to the swine's overall welfare and productivity (Ellis et al., 2020). As these technologies continue to evolve, integrating novel weight monitoring methods with ICT tools promises to refine further and advance the precision of swine farming practices. Ongoing research in this domain is the key to shaping the future landscape of weight management in swine production.

Localization and activity tracking

In pig production, understanding locomotion and implementing effective activity-tracking methods is not just important, it is crucial for ensuring the welfare and productivity of the animals (Matthews et al., 2016). A method of determining herd dispersion based on a combination of video recordings, image analysis and machine learning, described by Nilsson et al. (2015), is a valuable welfare assessment tool, mainly when heat stress occurs. Locomotion also plays a crucial role in assessing the overall health of pigs, appropriate for the group's behavior, as abnormal gait or movement patterns can indicate underlying health issues or lameness (Guesgen and Bench, 2017). Ahrendt et al. (2011) proposed a system dedicated to loose-rearing housing conditions that tracks the movement of up to 3 individuals at a time in real-time without losing them in a larger group. Modern technologies such as accelerometers and computer vision systems are increasingly employed to monitor and manage locomotor activities in pig farming (Tzanidakis et al., 2021). These tools enable farmers to track pig movement, identify changes in behavior, and detect signs of distress or illness early on. Kashiha et al. (2014), with the use of an ellipse as a more accurate body model recorded with a camera from the top view, achieved movement tracking accuracy at level 89.8%. However, this technique was inadequate in correctly identifying the difference between standing and lying down, as well as lying in a group, related to the overlap of ellipses, thus distorting the reading. Nasirahmadi et al. (2015) successfully solved the problem with the Delaunay triangulation. Delaunay triangulation (DT) is a method of dividing a set of points on a plane into triangles so that no point lies inside the circumcircle of any of these triangles. This method maximizes the smallest angle in the triangles, avoiding very narrow triangles.

Employing advanced technologies such as accelerometers (Darr and Epperson, 2009; Cornou and Lundbye-Christense, 2012; Brown et al., 2013; Escalante et al., 2013; Oczak et al., 2016; Bahlo et al., 2019) and radio-frequency identification (RFID) tags (Jin et al., 2006; Kapun et al., 2020; Kapun and Gallman, 2017) facilitate real-time and precise tracking of pig movement patterns and overall activity levels.

Integrating both aforementioned ICT tools and complex system like tracking models ensures accurate data collection and enables farmers to gain insights into individual and group behaviors (Benjamin and Yik, 2019; Kim et al., 2022; Zhou et al., 2023). Machine learning algorithms further enhance these capabilities, allowing for the identification of subtle changes indicative of health issues, environmental stressors or behavioral anomalies of individual animals (Matthews et al., 2017; Liakos et al., 2018).

Diseases detection and hygiene maintenance

Within the domain of swine production, the integration of precision livestock farming methods has emerged as a critical driver for disease detection and hygiene maintenance (i.e. securing health status) (Neethirajan et al., 2017). Employing advanced technologies such as sensors, cameras, and data analytics, enables real-time monitoring of swine health parameters and the early detection of potential disease outbreaks (Gómez et al., 2021). ICT tools facilitate continuous health surveillance, allowing prompt intervention and preventive measures (Alarcón et al., 2021). Integrating machine learning algorithms further refines disease prediction models, providing farmers with proactive insights into possible health risks. Using deep learning, Yin et al. (2021) developed an algorithm that, based on audio recordings, allows cough detection and overall classification of wet/dry cough with an accu-

racy of 96.8% and 95.4%, respectively. Sound recording might be a supportive tool in decision-making processes (Cordeiro et al., 2018) and an effective disease prevention tool. Hong et al. (2020) achieved 94.7% accuracy for cough, grunt and scream detection via the Mnas-Net, a lightweight anomaly detection system. Common problems with cough and swine production led to the development of SoundTalks (SoundTalks NV, Leuven, Belgium – a commercially available tool for continuous monitoring based on microphones and artificial intelligence data analysis). The potential of deep learning is described in more detail by LeCun et al. (2015). Combining it with collecting biometric data allows the herd to be sorted into healthy and potentially infected clusters (Lee et al., 2017), thus contributing significant value to disease spreading prevention. Another form of health surveillance is infrared technology (IFR), which is based on measuring the surface body temperature of pigs in a non-contact, real-time, and long-distance manner. Both the method of operation and the potential of IFR have been described by Cook (2012). As shown by Rosengart et al. (2022), measurements made using thermal imaging combined with analyses performed by artificial intelligence might be used as a tool for the identification of sows' postpartum dysgalactia syndrome (PDS), allowing for quick detection of problems with the accuracy of automatic temperature measurement comparable to a more labor-consuming rectal examination method. However, environmental factors such as humidity and temperature inside livestock buildings might affect the measurements (Church et al., 2014). Martínez-Avilés et al. (2017) used the system developed within the EU Rapidia Fields project, based on a combination of accelerometers, biosensors in the form of ear tags for temperature surveillance and video monitoring to determine the effect of African swine fever on infected individuals. Thanks to automatic measurements, the increase in temperature was detected up to 2 days earlier, and the decrease in mobility was recorded at the same time as in the case of manual measurements, thus being an additional parameter indicating a potential health problem.

We previously mentioned that data obtained by Chapinal et al. (2008) shows feeding patterns and might also constitute the basis for a faster response to potential problems in the herd. In the research of Brown-Brandl et al. (2013), time spent at the feeder registered with the use of RFID ear tags was found to be a specific determinant of welfare and decreased pneumonia problems in individuals. Similar conclusions were also reached by Madsen and Kristensen (2005), who by observing piglets' water consumption, could predict a diarrhoea outbreak even one day in advance.

The comprehensive approach of ICT tools in disease detection and hygiene maintenance safeguards swine health and ensures a clean and biosecure environment, thereby promoting swine herds' overall welfare and productivity. As technological advancements persist, ongoing research endeavors promise to enhance further the precision and effectiveness of these disease management strategies in swine production.

Limitations and perspectives

An essential element in improving herd monitoring is greater access to precision breeding methods and convincing potential buyers of its purchase and rightness of use. This purchase should be influenced by improved production efficiency, i.e. better production parameters and the possibility of earlier reaction from herd managers. PLF tools are widely used in the case of environmental monitoring or automation of feeding of individual production groups. However, some areas have yet to be discussed, i.e. devices for monitoring litter size during the rearing period or precise monitoring of pig weight during the fattening period relating to each pig in a pen. These parameters directly affect the profitability of production (they mainly concern the breeding herd and the fattening pigs). The impression is that such essential aspects of closed-cycle and open-cycle production are overlooked or under-researched.

A key element influencing the spread of PLF equipment is its affordability and shorter-term return on investment, often not possible in organic farming or herds with smaller animal numbers.

Another aspect influencing the spread of precision equipment in the piggery is the improvement of animal welfare. The Common Agricultural Policy (CAP), as of January 1, 2023, aims to shape changes in agriculture to strive for a modern European agricultural sector sustainably. Under the reformed policy, funding for small and medium-sized farms will be more equitable. In addition, farmers will receive financial support if they innovate their pig production in precision agriculture and agroecological production methods. The new CAP aims to support food security and farming communities in the European Union by supporting specific measures in these and other areas.

The regulations and conditions for joining the program are presented, and a wide field is provided for manufacturers to use PLF devices (Ehlers et al., 2022). Unfortunately, one crucial detail is omitted here. Do farmers or producers receive a higher price for a fattening pig raised under the welfare subsidy? Unfortunately, no. The subsidy alone is insufficient to cover all the costs associated with the higher welfare requirements, so joining the producer or farmer system, especially for sows, is not very popular (Kopler et al., 2023). The program has the right ideas, but more detailed regulations from the EU are needed here to make the system more widespread and cost-effective. There is a lack of integration with the meat industry, i.e. a higher price per 1 kg of livestock/percent share of meat in the fattener carcass in the case of so-called "welfare", as well as information for consumers on whether the raw material comes from such a program.

One of the main challenges today in implementing the elements of sustainable agriculture is to look at swine production more broadly than just the piggery and the

animals in them. A sustainable production environment includes nutrition, crop cultivation, waste management, supply chains, and processing. All of these elements must be consistent with each other and work toward a single goal; otherwise, any changes in a particular area will not affect the overall sustainability.

Precision equipment used in production should, therefore, form an integral whole of the interests and needs of animals, producers and consumers alike, and be closely linked. Consumers, in particular, are looking for credible arguments to confirm their purchase from a production based firstly on the humane and friendly treatment of animals and secondly on the conduct of animal production in fully sustainable relations with the natural and social environment.

Conclusion

Numerous data are automatically recorded (by internal control computers) and stored on the farm's computer. However, in practice, pig producers rarely use this information because the price of precision equipment is still out of reach for them due to the break-even point. As a result, pig owners lose money because discrepancies in the production process are not noticed or are noticed too late. PLF is the best solution in systemically solving the problem of food insecurity and is ideally suited to the concept of sustainable agriculture, which is starting to become mandatory – from monitoring the environment (nutrition and microclimate) to assess welfare, behavior, and health to controlling body weight, daily gains, heat detection or feed consumption to improve herd prevention programs (Hemsworth and Barnett, 2001; Renaudeau et al., 2008; Rodrigues et al., 2011).

All the systems described in the article used in pig production are equipped with early warning systems, either as system alerts in production or apps that directly notify the producer via smartphone. These systems enable quick objectified decision-making, which improves the producer's farm and herd management system. The information contained in the review will be helpful to both future researchers and pig producers in improving pig farm management.

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