# IMPLEMENTING ARTIFICIAL INTELIGENCE AS A PART OF PRECISION DAIRY FARMING FOR ENABLING SUSTAINABLE DAIRY FARMING

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A R T I C L E  I N F O

Original Article

Received: *06 October 2020*

Accepted: *01 December 2021*

doi:10.5937/ekoPolj2104869R

UDC 004.8:[637.1:502.131.1]

***Keywords***:

*artificial intelligence (AI), precision agriculture, precision dairy farming, sustainable dairy farm, animal production, ammonium pollution*

***JEL***: *O13, Q13, Q16*

A B S T R A C T

The purpose of this paper is to consider implementation of Artificial Intelligence as a part of Precision Dairy Farming, as a way of processing, analysing and managing Big data, in order to enable sustainable dairy cattle farm. Increasing the volume of livestock production in the future and measuring the level of environmental impact becomes one of the most pressing concerns. The aim is to evaluate the impact of animal's production level on the ammonium pollution from dairy cattle farm using precision dairy farming technologies. The results indicate significant variability in estimated ammonium pollution from dairy cattle farms due to the animal's production indicating positive correlation between daily milk production and ammonium pollution. The test day records, as Artificial Intelligence application in precision dairy farming could be used both for assessing the ammonium pollution from farms and timely prevention and correction of inadequate management towards sustainable dairy production systems.



## Introduction

Using latest technology in precision dairy farming radically changes the agricultural production as it enables tracking, monitoring, processing and analyzing huge amount of various data concerning measuring numerous important activities and factors during the dairy cattle farm production process. This implementation of technology includes using Artificial Intelligence (AI) together with Machine Learning and other new technologies,

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with the purpose of efficient managing Big data, which provides immense advancement in productivity and enhancing total economic output in farming sector.

The implementation of AI and Big data, among other precision dairy farming (PDF) technologies, proves to be challenging in ever more complex and volatile natural, technological and market environment in the perspective of the need to produce high quality standardized and sustainable products.

Given the need to increase the volume of animal production in the future and, accordingly, the level of environmental impact, this paper aimed to evaluate the impact of animal's production level on the ammonium pollution from dairy cattle farm using the artificial intelligence that is one of the most frequently applied precision dairy farming technologies.

## AI as a key technology in the Fourth industrial revolution wave

It is widely recognized that Artificial Intelligence (AI) is one of the critical new technologies of the Fourth Industrial Revolution (IR4) or Industry 4.0. AI is defined as "the information-intensive transformation of manufacturing (and related industries) in a connected environment of Big data, people, processes, services, systems and IoT-enabled industrial assets with the generation, leverage and utilization of actionable data and information as a way and means to realize smart industry and ecosystems of industrial innovation and collaboration." (i-Scoop, 2020)

Klaus Schwab, who coined the term, in his seminal book *The Fourth Industrial Revolution* (Shwabb, 2016) claims that the IR4 is fundamentally different from the past three industrial revolutions. He stated that it is "characterized by a range of new technologies that are fusing the physical, digital and biological worlds, impacting all disciplines, economies and industries, and even challenging ideas about what it means to be human" (World Economic Forum, The Fourth Industrial Revolution, 2020). Industry 4.0 comprises high and dynamic interconnectivity of machines, products, components and humans. It has multiple benefits for the economy, which may be summarized as four main benefits: increased productivity, increased quality, increased flexibility and increased speed (i-Scoop, 2020).

According to BCG (BCG, 2020), nine core technologies are the crucial technological factors of Industry 4.0, capable of transforming industrial production: "a) Big Data and analytics; b) autonomous robots; c) simulation; d) horizontal and vertical system integration; e) industrial Internet of Things; f) cybersecurity; g) Cloud technology; h) additive manufacturing and i) augmented reality" (BCG, 2020).

Although AI was not specifically mentioned among those technologies, it permeates and links all segments and sectors of Industry 4.0 and enables radical transformation of the economy and society as a whole. It is difficult to define what AI exactly means, as it is no single technology, rather it comprises a set of technologies referring to image processing, self-learning, analytics, decision making and problem solving. AI is defined in many ways, based on a spectrum of views on AI as a body of knowledge, application, and a set of technologies or approach.

The definition of AI used by European Commission is rather comprehensive and practical: "AI refers to systems that display intelligent behaviour by analysing their environment and taking action – with some degree of autonomy – to achieve specific goals" (European Commission, 2018). European Parliament states: "AI is the ability of a machine to display human-like capabilities such as reasoning, learning, planning and creativity" (European Parliament, What is artificial intelligence and how is it used?, 2020).

The importance of AI lays in its extensive use (in various fields and sectors of economy and society), interconnectivity and its ability of self-learning, continual improvement and adaptability. The impact of AI on economy is disruptive in a way that it is revolutionizing every aspect of life and work. Implementation of AI in industry leads to radical transformation of the production process in all sectors of economy, especially in manufacturing, travel industry and transportation as well as agriculture. Hence, there is indication that AI is going to be crucially important for building "factory of the future". According to BCG: "Producers can generate additional sales by using AI to develop and produce innovative products tailored to specific customers and to deliver these with a much shorter lead-time. AI is thus integral to the factory of the future, in which technology will enhance the flexibility of plant structures and processes" (BCG, 2018).

Due to the complexity and extreme adaptability and applicability of AI in various sectors of economy, it is quite difficult to predict the future dynamics of the growth of global AI market. Hence, we see different reports on the future of global AI industrial growth. According to the Report of the Grand View Research By End Use, By Region, And Segment Forecasts, 2020–2027 (Grand View Research, 2020), the estimated value of the global AI market size in 2019 was USD 39.9 billion. The expectation is that it will grow at a compound annual growth rate (CAGR) of 42.2% from 2020 to 2027.

According to PwC Report named "Sizing the prize", *Global Artificial Intelligence Study: Exploiting the AI Revolution: What is the real value of AI for your business and how can you capitalize?* (PwC, 2017), the expected global GDP in 2030 could be up to 14% higher as a result of AI usage. That would be a potential contribution to the global economy of 15.7 trillion US dollars by AI. Looking at regional distribution, the study shows that the biggest gain from AI in 2030 will be in economies of China (boost of up to 26.1% GDP) and North America (boosting 14.5% of GDP).

PwC study concludes that the great impact of AI on the global economy will be the result of these three main factors: a) improved productivity; b) increased consumer demand and c) some job displacement but also new employment opportunities.

Having understood the relevance of the AI as a key driver of the economic and social development and digital transformation of the EU economy as a whole as well as of its member states, European Commission has established the "European approach to Artificial Intelligence". This approach is based on three pillars (European Commission, 2020):

- Being ahead of technological developments and encouraging uptake by the public and private sectors;
- Prepare for socio-economic changes brought about by AI;
- Ensure an appropriate ethical and legal framework.

## Implementation of AI in precision dairy farming

Use of AI has already revolutionized agriculture in many ways. The concept of precision agriculture was developed as a result of designing and transforming agriculture upon the digital transformation principles and by usage of AI and other core technologies of the industry 4.0. According to International Society of Precision Agriculture (ISPA), the precision agriculture is defined as "a management strategy that gathers, processes and analyses temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production" (International Society of Precision Agriculture, ISPA, 2020).

Precision dairy farming (PDF), as a sector of precision agriculture, is described as "the use of information and communication technologies for improved control of fine-scale animal and physical resource variability to optimize economic, social, and environmental dairy farm performance" (Eastwood et al., 2012). By another, more concise definition, the precision dairy farming "involves the use of technologies to measure physiological, behavioural, and production indicators on individual animals" (Precision Dairy Farming, 2020).

AI is intrinsically connected to Big data. AI enables effective and efficient use of the huge mass of data that we have as input in businesses. In addition, AI's need for Big data is limitless; in fact, there is a reciprocal relationship between AI and Big data – the more data enters, the more efficient AI is in analysing that quantity of data. There is a trend of converging AI with Big data technology. Yet, Thomas Siebel (Siebel, 2019) goes further and writes about converging of four essential technologies: Big Data, IoT, AI and Cloud computing. According to Radun, "the huge potential of AI in contributing to the improvement of performance, i.e. the growth of productivity, rationalization, business efficiency, rests on its *power of intelligent automation*. AI radically pushes the boundaries of automation and is able to make breakthrough in various areas of the economy, automating and accelerating the way of collecting and analysing data, business processes, ways of organization, decision-making, prediction capabilities, etc. From this point of view, the effects of AI are not only direct, through the direct implementation of a particular AI application in business, but also indirect, which lay in the unimagined possibilities of creating completely new products, services and branches in the future, resulting from applying AI as universal ability of intelligent, self-learning factor" (Radun, 2019).

There are great many biological and physical processes that should be observed and optimized in the dairy farming sector of agriculture. That is exactly why the role of AI, together with machine learning (subset of AI, sometimes used as synonym of AI), Big data, IoT, Cloud computing and other technologies is essential in processing, analysing and managing plenty of data occurring in the dairy farming production process.

Technologies used by farmers serve to observe many parameters about their cattle and working process. Among those parameters recorded by the PDF technologies are "daily milk yield, milk components, step number, temperature, milk conductivity, automatic estrus-detection monitors, and daily BW measurements… Proposed parameters include jaw movements, ruminal pH, reticular contractions, heart rate, animal positioning and activity, vaginal mucus electrical resistance, feeding behaviour, lying behaviour, glucose, acoustics, progesterone, individual milk components, colour (as an indicator of cleanliness), infrared udder surface temperatures, and respiration rates" (Borchers, Bewley, 2015).

The main purpose of implementing AI, machine learning, Big data, IoT and related technologies in PDF is to feed the system with as many data as possible (variables, parameters), including the ability to forecast changes in those data (weather, conditions, parameters) by which system may be trained, processing the great database of information, learning and finding the best solution.

For the producer, the decision to involve precision dairy farming technologies is a strategic issue. That is why it is crucial to observe the benefits and advantages of the technologies of the PDF. According to Precision Dairy Farming network, the main goals of implementing PDF may be various, and they can be summarized as the following ones: maximize production of animals, early detect the disorders or diseases on the individual level, early detect health and production problems on a herd level, as well as minimize the treatment costs by application of adequate preventive measures (Precision Dairy Farming, 2020).

The primary advantage of using PDF technologies is attaining greatly efficient, high-quality, sustainable dairy farming production, while keeping minimal bad environmental impact and enriched animal health. The PDF technologies, including AI, can help producers (dairy farmers) make decision-making processes more objective, improve the productivity and quality of the animal production and reduce the need for extra labour in animal management.

The second goal of the 2030 Agenda for Sustainable Development (United Nations, The 17 Goals) declares, "End hunger, achieve food security and improved nutrition and promote sustainable agriculture". In accordance with that specific goal, FAO states: "FAO works to enhance livestock's contribution to the Sustainable Development Goals (SDGs) by supporting the transformation of animal production systems – small and large – in ways that are economically, socially and environmentally sustainable" (FAO, 2020).

The application of artificial intelligence in animal production in some way implies usage of different precision technologies in order to detect animal's characteristics related to production, physiology and behaviour. These characteristics could be used in forecasting of the parameters related to enablement of production systems sustainability from the aspects of economic efficiency and impact on the environment. The impact of animal production on the environment, particularly in the light of climate change is one of the main points in the light of the forecasted increase in livestock production. According to FAO (FAO, 2006), the animal production sector will continue to be the most productive agricultural sub-sector considering global milk production is forecasted to increase to 1043 million tonnes in the following period till 2050.

This production increase need to be followed by appropriate environment protection measures (minimization of greenhouse gasses emission). In The Netherlands, for instance, the dairy farms are under monitoring using the content of urea in milk (Bijgaart, 2003). This way of controlling permits the determination of potential pollution sources and notifies farms regarding precautionary actions. In Europe, the optimum amount of urea content in milk is in the interval from 15 to 30 mg/dL (Ruska et al., 2017). Milk urea content could be used for estimation of ammonium pollution from daily farms. The reduction of ammonium pollution from dairy cattle farms represents major part in enablement of environmentally sustainable production systems.

Considering the necessity of timely information and reaction in animal production, the hypothesis of this research was that the application of technologies of precision dairy farming could contribute to more objective and successful management and overall economic and environmental sustainability of dairy cattle farms.

Furthermore, regarding the need to increase the volume of animal production in the future and, accordingly, the level of environmental impact, this *paper aimed to evaluate the impact of animal's production level on the ammonium pollution from dairy cattle farm using the artificial intelligence that is one of the most frequently applied precision dairy farming technologies*.

## Material and methods

For statistical analysis, the test-day records of Holstein first parity cows recorded in the ten years' period (2004 to 2013) were analysed. Test-day records were recorded during the regular milk recording conducted by the Croatian Agricultural Agency according to the alternative milk recording method (AT4 / BT4) on dairy cattle farms in Croatia. At each milk recording, measuring of milk yield and milk sampling were conducted during the morning or evening milking. The SAS software was used for the Big data managing, logical control, formulation of new variables, development and testing of statistical model. The test-day records outside logical defined values (lactation stage in (< 5 days and > 90 days), age at first calving in (< 21 and > 36 months)), with missing information on parity, breed, and daily milk traits, were removed from the dataset. After logical control (for milk trait values ICAR standards were used; ICAR, 2017), the database consisted of 105,033 test-day records from 50,218 first parity Holsteins reared on 4,693 dairy farms.

The calculation of the content of milk urea nitrogen (MUN) was done on the basis of the content of milk urea (UREA) using the mathematical expression:

MUN (mg/dL) = UREA * 0.46 (Spiekers & Obermaier, 2012)

Furthermore, the ammonium emission (A-EMISSION) was computed based on the content of milk urea nitrogen (MUN) using the mathematical expression:

A-EMISSION (g/cow daily) = 25.0 + 5.03 * MUN (Burgos et al., 2010)

In accordance with the production level (daily milk yield – DMY), the animals were divided into five classes: I (DMY ≤ 15 kg); II (DMY > 15, ≤ 20 kg), III (DMY > 20, ≤ 25 kg), IV (DMY > 25, ≤ 30 kg) and V (DMY > 30). In addition, the test day records, regarding the date of milk recording, were separated into 4 seasons (spring (months III, IV, and V), summer (VI, VII, and VIII), autumn (IX, X, and XI) and winter (XII, I, and II)).

Basic statistical parameters of daily milk production (daily milk yield and contents (fat, protein, and urea), daily content of urea nitrogen in milk and daily ammonium emission is shown in *Table 1*.

**Table 1.** Basic statistical parameters of analysed elements (daily milk traits, milk urea nitrogen and ammonium emission)

| Variable | N | Mean | SD | CV | Minimum | Maximum |
|---|---|---|---|---|---|---|
| DMY | 1719033 | 23.17 | 7.19 | 31.03 | 3.00 | 70.40 |
| DFC | 1655847 | 4.01 | 1.00 | 24.99 | 1.50 | 9.00 |
| DPC | 1670025 | 3.04 | 0.35 | 11.54 | 1.20 | 6.94 |
| UREA | 1465628 | 21.65 | 9.47 | 43.73 | 0.50 | 60.00 |
| MUN | 1465628 | 9.96 | 4.36 | 43.73 | 0.23 | 27.60 |
| A-EMISSION | 1465628 | 75.10 | 21.91 | 29.18 | 26.16 | 163.83 |

*Note*: DMY – daily milk yield (kg); DFC – daily content of fat in milk (%); DPC – daily content of protein in milk (%); MUN – content of urea nitrogen in milk (mg/dL); A-EMISSION – ammonium emission (g/cow daily)

The assessing of the impact of production level on the variability of analysed traits (daily milk yield; milk urea content, milk urea nitrogen content and ammonium emission) in first parity cows of Holstein breed, was performed by applying the subsequent statistical model:

$$y_{ijklmn} = \mu + b_1(d_i/305) + b_2(d_i/305)^2 + b_3 \mathrm{h}\,(305/d_i) + b_4 \mathrm{h}^2(305/d_i) + S_j + A_k + P_l + e_{ijklm}$$

where $y_{ijklm}$ = estimated trait (daily milk yield; milk urea content, milk urea nitrogen content and ammonium emission);

μ = intercept;

$b_1, b_2, b_3, b_4$ = regression coefficients;

$d_i$ = stage of lactation in days, i (i = 5 to 90 day);

$S_j$ = fixed effect of season of milk recording, j (j = spring, summer, autumn, winter);

$A_k$ = fixed effect of animal's age at first calving in months, k (k = 21 to 36 month);

$P_l$ = fixed effect of animal's production level, l (l = I., II., III., IV. and V.);

$e_{ijklm}$ = residual.

Scheffe's method of multiple comparisons (in PROC GLM / SAS (SAS (SAS Institute Inc., 2000)) was applied in order to test the significance of the differences between the analysed traits due to the defined classes of animals' daily milk production.

## Results and discussion

The statistical analysis revealed statistically highly significant impact ($p < 0.001$) of all model's effects (age at first calving, stage of lactation, recording season, and level of animals' daily milk production) on analysed traits (daily milk yield; milk urea content, milk urea nitrogen content, and ammonium emission). Ruska et al. (Ruska et al., 2017) also found the significant impact of season on urea content in milk with higher content during the summer months. The LSMs of analysed traits, classified in production level classes (I, II, II, IV and V), are shown in *Table 2*.

**Table 2.** LSMs of daily milk yield, contents of milk urea and milk urea nitrogen as well as ammonium emission of first parity Holsteins regarding the production level

| Production level | DMY | UREA | MUN | A-EMISSION |
|---|---|---|---|---|
| I. | $12.03^{A}$ | $20.72^{A}$ | $9.53^{A}$ | $72.94^{A}$ |
| II. | $17.85^{B}$ | $20.44^{A}$ | $9.40^{A}$ | $72.29^{A}$ |
| III. | $22.56^{C}$ | $21.35^{B}$ | $9.82^{B}$ | $74.39^{B}$ |
| IV. | $27.43^{D}$ | $22.71^{C}$ | $10.45^{C}$ | $77.55^{C}$ |
| V. | $34.32^{E}$ | $24.02^{D}$ | $11.05^{D}$ | $80.59^{D}$ |

*Note*: DMY – daily milk yield (kg); UREA – daily content of urea in milk (mg/dl); MUN – daily contnet of urea nitrogen in milk (mg/dl); A-EMISSION – ammonium emission (g/cow daily); LSMs marked with different letters (A, B, C, D, E) differ statistically significant ($p < 0.001$)

The daily milk yield differed highly significantly, in statistical terms ($p < 0.001$) regarding the daily milk production level. The statistically highly significant ($p < 0.001$) lowest value of urea content in milk was determined in animals that had daily milk production under 20 kg. Similarly, those animals had lowest daily values of urea nitrogen content in milk as well as the lowest values of ammonium emission. Furthermore, the highest urea content in milk, urea nitrogen content in milk as well as ammonium emission was observed in animal with highest daily milk production. These results indicate that the amount of estimated ammonium pollution highly depends on animal's production level.

Spohr, Wiesner (1991) and Spann (1993) determined that increased milk urea content indicate complication related to feeding of highly productive dairy cows. In order to control the animal feeding, urea content in milk (UREA) is used in Europe (Kohn et al., 2002; Bucholtz et al., 2007) while in the USA the urea nitrogen content in milk (MUN) is commonly applied (Aguilar et al., 2012). Furthermore, Godden et al. (Godden et al., 2001) and Haig et al. (Haig et al., 2002) stated that in the countries that evaluate the usage of nitrogen and feeding efficiency, the urea content in milk is recommended as an indicator for optimization of farm management.

## Conclusion

Our study showed the statistically highly significant ($p < 0.001$) impact of age at first calving, stage of lactation, season of milk recording and the level of animals' daily milk production on all analysed traits (daily milk yield, urea content in milk, urea nitrogen content in milk and ammonium emission). The highest content of urea and urea nitrogen in milk as well as ammonium emission was observed in animals with daily milk production higher than 30 kg. The results point to significant differences in ammonium pollution depending on the animal's production showing a positive association between daily milk production and ammonium pollution. The hypothesis of the research that the application of precision dairy farming technologies can contribute to more objective and successful management and overall economic and environmental sustainability of dairy cattle farms was confirmed. Furthermore, the test day records as a way of artificial intelligence (AI) application in animal farming (precision dairy farming) could be used for evaluating and monitoring the ammonium pollution from dairy cattle facilities as well as for timely prevention of inadequate management and enablement of sustainable dairy production systems. The results of the analysis indicate that the implementation of AI, Big data, IoT, Cloud computing and related technologies as new technologies within the precision dairy farming could have great perspective in enabling effective and sustainable dairy farming for the benefit of both producers and consumers.

## Acknowledgement

The authors would like to thank Croatian Agency for Agriculture and Food for permission to use recorded animal production data in the statistical analysis.

### Conflict of interests

The authors declare no conflict of interests.

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