Decision-Making Strategies on Smart Dairy Farms: A Review

L. Krpalkova, N. O' Mahony, A. Carvalho, S. Campbell, G. Corkery, E. Broderick, J. Walsh

***Abstract*—**Farm management and operations will drastically change due to access to real-time data, real-time forecasting and tracking of physical items in combination with Internet of Things (IoT) developments to further automate farm operations. Dairy farms have embraced technological innovations and procured vast amounts of permanent data streams during the past decade; however, the integration of this information to improve the whole farm decision-making process does not exist. It is now imperative to develop a system that can collect, integrate, manage, and analyze on-farm and off-farm data in real-time for practical and relevant environmental and economic actions. The developed systems, based on machine learning and artificial intelligence, need to be connected for useful output, a better understanding of the whole farming issue and environmental impact. Evolutionary Computing (EC) can be very effective in finding the optimal combination of sets of some objects and finally, in strategy determination. The system of the future should be able to manage the dairy farm as well as an experienced dairy farm manager with a team of the best agricultural advisors. All these changes should bring resilience and sustainability to dairy farming as well as improving and maintaining good animal welfare and the quality of dairy products. This review aims to provide an insight into the state-of-the-art of big data applications and EC in relation to smart dairy farming and identify the most important research and development challenges to be addressed in the future. Smart dairy farming influences every area of management and its uptake has become a continuing trend.

***Keywords*—**Big data, evolutionary computing, cloud, precision technologies.

I. Introduction

THE world of dairy farming is complex and changing fast. Dairy sector economics comprises knowledge from many different angles and sources [1]. The way animals are raised on farms has changed greatly over the past century including growth in farm size and increased technology [1]. The main characteristics of an ideal dairy system identified by the respondents in a study by Cardoso [2] were related to animal welfare from two perspectives: consideration for the quality of life of the animals based on ethical arguments and the consequences of animal care on the quality of milk. In recent years, the world has witnessed a change in purchasing patterns, involving the consumer who is increasingly attentive to their health and to the quality of the food they buy [3]. Starting from the assumption that people are not consumers but citizens, the concept of Food Democracy is born, in which food is not considered a consumer good but a right and, as such, must be safe and nutritious, as well as produced and enjoyed in respect of the environment and of those who cultivated it [4]. Intercepting this need with a view to market opportunities leads the agri-food business to embrace the quantity-quality duo and to undertake sustainable production paths and voluntary traceability tools able to witness these choices. Voluntary traceability has two main objectives: food safety and quality [3].

Innovative systems are required, to reconcile the need for farmers to earn a decent living, meet consumer demand for affordable and quality dairy products, reduce the environmental impact of dairy farming and improve animal health. Management decisions can be informed by near-real-time data streams to improve the economics, sustainability, environment, quality of final product, overall health and welfare of dairy herd [5].

Decision support tools can use data and analytics from the farm and other available and useful sources [5]. As smart machines and sensors become more common on farms and farm data grow in quantity and scope, farming processes will become increasingly data-driven and data-enabled. Continuous developments in IoT and cloud computing are leading the phenomenon of what is called Smart Farming [6]. While Precision Agriculture is concerned with in-field/herd variability, smart farming goes beyond that by basing management tasks not only on location but also on data (enhanced by context) and situation (triggered by real-time events) awareness [7]. Real-time assistant reconfiguration features are necessary in a smart farming system in order to carry out agile actions, especially in cases of changed conditions on dairy farms or other circumstances (e.g., weather,

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disease alert, feeding system and diet). These features typically include intelligent assistance in implementation, maintenance and use of the technology [6]. Fig. 1 summarizes the concept of smart dairy farming, incorporating smart connected devices, which inform control of the farm system. Smart devices extend conventional tools (e.g., rain gauge, milking parlor, tractor, notebook) by adding autonomous context-awareness with a suite of sensors and actuators with built-in intelligence, capable of executing autonomous or remote actions. Robots will play an important role in the control of the future dairy farm, but humans will always be involved in the whole process at a much higher intelligence level. The smart dairy farming cycle becomes almost autonomous and helps stabilize farmers' income and maximize profit and sustainability of the dairy sector. Additionally, farmers of the future will be able to share information with different personnel, consultants, or others while being able to easily manage the level of data access [6].

Industry 4.0 stems from the 4th industrial revolution and is defined as a process that leads to fully automated and interconnected industrial production [3]. Some of the technological phenomena typical of Industry 4.0, such as the IoT and analytics, are the most relevant in terms of impact on the market and will act as a driving force towards a real '4.0 transformation' during the next 10-15 years [3]. In the era of the 4th industrial revolution, the use of digital technologies, thanks to the integration of data and the connection of resources, will allow the creation of an efficient and sustainable farm system.

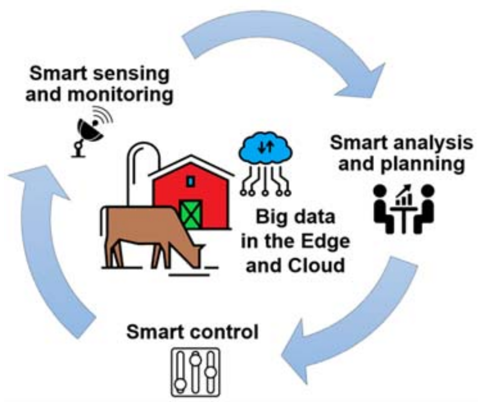

Fig. 1 The cycle of smart dairy farming enhanced by cloud-based event and data management

The transfer of the Industry 4.0 paradigm to the agri-food industry will allow farmers to act concretely on the factors of production, speed up and improve the innovation process already introduced by the precision agriculture paradigm and bring overall benefits to this industry [8]. All these data generated from new technologies offer an opportunity for development of farm-specific models to help in the management decision-making process [9]. With the increasing amount of data available at the farm, there is a critical need to automatically integrate the different data sources within decision-making tools that can provide integrated advice to farmers and lead to more efficient dairy farm management [5]. The existing whole-farm models have structural and functional limitations and are inflexible in their structure and options, i.e., with regard to being able to integrate new modules. Furthermore, documentation and reported evaluations for existing whole-farm models are often incomplete and/or insufficient to support higher level of system management [9]. The lack of integration and subsequent separated analysis generate different problems, such as suboptimal use of on- and off-farm resources, increased risk of mistakes and failure, delays in optimal actions, lack of understanding for complex environmental and market issues, narrow vision of opportunities for improvement, and, ultimately, suboptimal profitability and consequently decreased sustainability and resilience [9]. Agricultural models present a number of difficulties with regard to optimization. These problems include complex relationships which are not conducive to the simpler forms of economic modelling, biological variability modelling, or the identification of suitable variables to be optimized. The high degree of complexity in these systems translates to high dimensionality of the search-space. Furthermore, the search-space may contain multiple local optima, as very different combinations of management options can have similar economic outcomes [10]. Models of agricultural systems range widely on both temporal and spatial scale. Farm-level systems have typically been investigated, but models also range out to regional, industry and national scales. Short-term (within-year) profitability and cash-flow issues are common, but the timeframe can be extended to more years, to investigate sustainability and long-term effects. Any selected optimization method is required to deal with all these problems, and reliably returns the solution for the global optimum. Generally, evolutionary algorithms have proven superior for these tasks [10].

Big data and smart farming are relatively new concepts and their implications for research and development will continue to spread. Smart machines and sensors are improving and changing rapidly in this area and the state-of-the-art of that will probably be outdated soon after this paper is published. This review aims to provide an insight into the state-of-the-art of big data in relation to smart dairy farming and to identify the most important research and development challenges to be addressed in the future. The paper will be structured as follows: in the introductory section, the scenario of the current situation in dairy farming is reported. In the second section, the area of Big Data, Precision Livestock Farming, Edge and Cloud Computing and Smart Dairy Farming Management are discussed. Finally, the future trends and challenges in Dairy Farm Management and Evolutionary Computing are debated.

II. BIG DATA

In general, big data is a term for data sets that are so large or complex that traditional data processing applications are inadequate [11]. Big data is changing the scope and organization of farming through a pull-push mechanism and often includes data with sizes that exceed the capacity of traditional software to process within an acceptable time and value [7]. Big data is diverse, complex, and of a massive scale, and it means that such datasets require a set of techniques and technologies with new forms of integration to reveal insights from datasets. Big data represents the information that requires specific technology and analytical methods for its transformation into value [11]. Big data challenges include not just the obvious issues of scale, but also heterogeneity, lack of structure, error handling, information privacy, updating, data source, capturing data, data storage, data analysis, search, sharing, transfer, querying and visualization, at all stages of the analysis pipeline from data acquisition to result interpretation. When we handle big data, we observe and track what happens [11]. Global issues such as food security and safety, sustainability, environmental impact and as a result efficiency improvement are currently being enhanced by big data applications. These issues mean that the scope of big data applications extends far beyond dairy farming alone but covers the entire supply chain including customers' requests. Thankfully we now have IoT in action. All kind of objects and devices that are producing many new and real-time accessible data are connecting wirelessly [7]. This applies to all stages in the smart dairy farming cycle (Fig. 1). Analytics is the main success factor in creating value out of these data. Many innovative start-up companies are eager to sell and deploy all kinds of applications (e.g., sensor deployment, benchmarking, predictive modeling, and risk management) [6].

III. Precision Livestock Farming

Precision livestock farming can be defined as real-time monitoring technologies aimed at managing the temporal variability of the smallest manageable production unit, known as 'the per animal approach'. With intense advancements in Computer Vision (CV) and Artificial Intelligence (AI), there has arisen an array of opportunities for these technologies to become even more useful in monitoring the needs and behavior of every animal and also allow robotics to interact with animals safely. Applications include the automatic monitoring of cattle by intelligent camera surveillance technology, and the automation of tasks such as herding, milking, feeding, and bedding. This indicates that the automated device could be used to measure the body condition of cows accurately and objectively with little effort [12]. Further, automatically recorded longitudinal sensor data could be a proper alternative for cow phenotyping in extensive grassland systems, aiming towards an accurate data basis for genetic evaluations [13]. Finally, some of the smart farm decision technologies will be able to substitute actual farm management and will learn as it goes by applying complex machine learning approaches and exploiting the interdependencies of the complex integrated biological, physical, technological, environmental and informational dimensions of dairy farm systems [5]. The system can be organized from tissue level going down to cell, organelle, and molecule and could also go up to organ, organism, and herd levels—eventually simulating an entire farm or even an entire region [9]. AI will be used to predict the outcome of various management options more accurately and also evaluate the achievement and sustainability of farmers' targets [5]. According to Grinter et al. [14], it is important to validate all precision dairy technologies to understand their precision and accuracy before taking measurements or applying them to cattle management or research.

Machine-generated (MG) data is typically well-structured and derived from the vastly increasing number of sensors and smart machines used to measure and record farming processes. The IoT boosted this development. MG data are well-structured and suitable for computer processing, but its size and speed are beyond traditional approaches, and therefore, it is becoming an increasingly important component of farming to store and process this information in the proper manner [6].

IV. Edge and Cloud Computing

The computing platforms can be added to the agricultural systems, but they are not architected to process MG volumes of data in real-time. It is also expensive and difficult to scale them up to the level required for training highly iterative data-driven machine learning models and algorithms. Cloud computing platforms are perfectly suited for such tasks due to their scalability and elasticity. However, this requires sending large volumes of MG data to the cloud [15]. However, many recent user centric IoT applications are latency sensitive or require real-time data analysis and decision making, scenarios where cloud computing could not be applied due to latency problems [16].

Also, large amounts of data are transmitted to the cloud, used only once without providing much insight, and it is not possible to leverage the same in the future for additional analysis. Hence, processing such data at the edge and transmitting only the data insights can help in saving the cost of data transmission and storage [15].

Cost of data transmission is sometimes the most critical factor determining the adoption of edge computing for certain scenarios. This is especially important for use-cases, where data are collected at high frequencies and the cost of such data transmission is very high. In such scenarios, the industry is moving towards adoption of Edge Computing to make analysis and decisions at the edge, and only transmit alerts and notifications related to security incidents to the central hub [15].

These solutions are typically used in vertically integrated applications. The processing and analytics of the data happens on the edge device and the cloud is used for coordination and data archival [15]. The central cloud piece is still necessary to help coordinating all the edge activity [16]. These advancements benefit the development of smart dairy farming cycle (Fig. 1), a technology where every physical entity has a digital twin in the virtual world, and also enable the move from centralized control, configuration and management of machines to autonomous and decentralized solutions [15].

V. Smart Dairy Farming Management

According to Wolfert et al. [6] management or control processes ensure that the business process objectives are achieved, even if disturbances occur. A controller that measures system behavior corrects if measurements are not compliant with system objectives.

The breadth of the areas of management which can be influenced by smart dairy farming continues to grow. Table 1 provides an overview of current big data applications in relation to different elements of smart dairy farming.

The main data products along the big data value chain are (predictive) analytics that provide decision support to dairy farm processes at various levels. The first prerequisite is that these analytics based on sensor or similar data must somehow fit into existing or reinvented dairy farm processes [6].

TABLE I
EXAMPLES OF BIG DATA APPLICATIONS/ASPECTS IN SMART DAIRY FARMING PROCESSES

Cycle of Smart Farming	Applications
Smart sensing and monitoring	Accelerometers (behavior) [11], [14], [35] Biometric sensing [33] Body Condition Score [12] Farm's carbon footprint [26] GPS tracking [33] Growth of dairy calves [31] Health [18], [29] Locomotion Score [12], [36] Milk robots and production [12], [20] Monitoring (identification of cows, safety, and quality of final product) [12], [25], [32] Phenotyping [28] Reproduction [40]
Smart analysis and planning	Body Condition Score [12] Breeding and genetic [5], [17], [20] Efficiency in production [24] Growth of dairy calves [31] Health [5], [17], [24], [28] Locomotion Score [12], [36] Milk robots and production [5], [12], [17], [23], [27] Monitoring (identification of cows, safety, and quality of final product) [12], [34] Nutrition and feeding [5], [17] Phenotyping [21] Reproduction [30], [40] Whole-farm system [5], [11], [23], [37]
Smart control	Autonomous vehicles [12] Body Condition Score [12] Health [22], [30] Locomotion Score [12], [36] Milking robots and production [12], [22], [30], [33] Monitoring (identification of cows, safety, and quality of final product) [12] Nutrition and feeding [22], [30] Whole-farm system [5], [9], [17], [37]
Big Data in the Edge and Cloud	Farm's carbon footprint [26] Health [30], [31], [34] Milk robots and production [5], [17], [20], [22] Monitoring (identification of cows, safety, and quality of final product) [25], [32] Nutrition and feeding [5], [17] Whole-farm system [15], [38], [39]

According to Wolfert et al. [6], the smart dairy farming management system must have a feedback loop in which a norm, sensor, discriminator, decision-maker, and effector are present.

A. The Current State of Dairy Management

Dairy producers make strategic management decisions based on separate software tools with some even having computers dedicated to specific farm software [17]. The tools are not connected to each other even though all the data streams are interrelated. Farm managers need to visualize and interpret each of all these data streams and make integrated decisions. As an example, we can provide some analysis that comes from a milking and feeding system (Fig. 2), a reproduction monitoring system (Fig. 3), and health recording system (Fig. 4). When analyzed independently, the disparate data streams are informative and describe many of the activities that take place on a dairy farm (e.g., feeding management decisions, heat detection, somatic cell count in milk etc.).

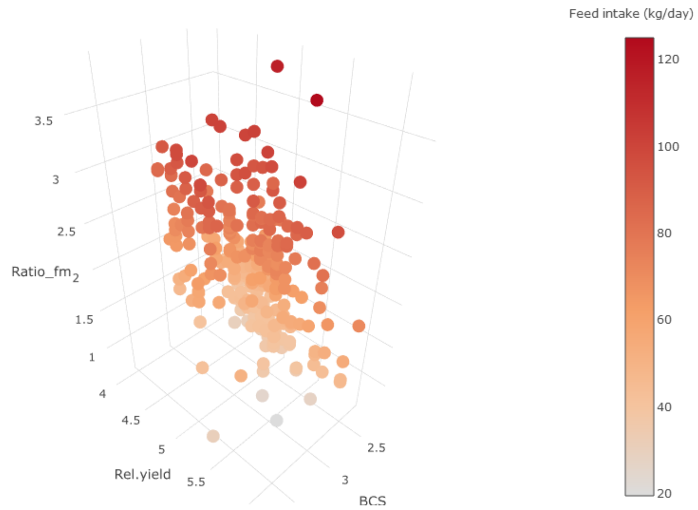

Fig. 2 Analysis of feed intake (kg/day), ratio of feed per 1 kg milk yield, relative milk yield (milk yield per 100 kg of body weight) and body condition score (sample analysis)

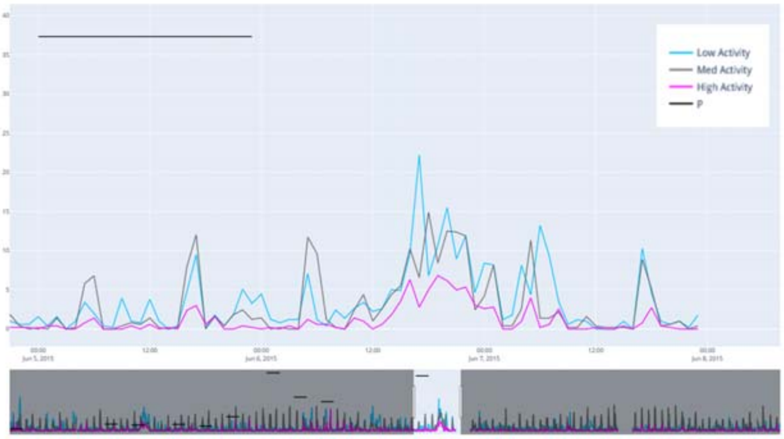

Fig. 3 Detection of heat using machine learning based on activity and progesterone data (sample analysis)

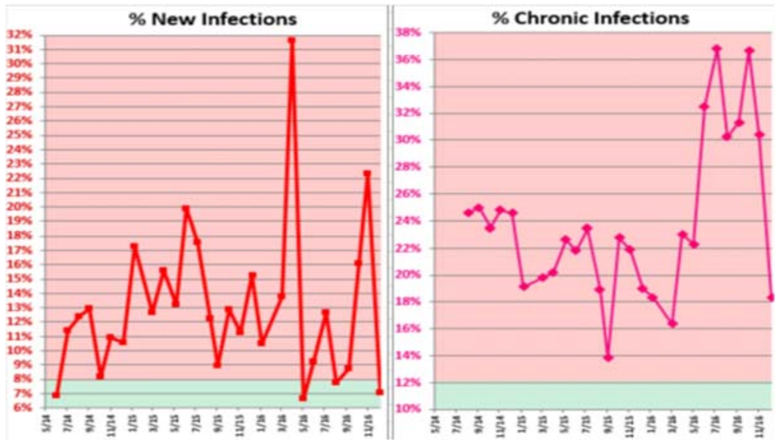

Fig. 4 Analysis of somatic cell count (sample analysis)

However, when they are integrated, they can generate even more important insights of different situations happening at the farm and improve decision making and farm management [17]. According to Græsbøll et al. [18], the productivity of the individual dairy cow is of central importance to dairy farmers: the most important metrics being her milk production, reproductive performance, and somatic cell count. Predictions of dairy farm productivity are important for making decisions on culling and replacements, feed management or health problems and these have a substantial influence on the economy of the farm. Cabrera et al. [17] added that decision making is crucial in business. Taking the right decision at the right time leads to success. The right decision alone is not sufficient, it has to be taken at the right time [17].

New technologies are becoming available and are being developed to help the dairy industry improve the welfare and productivity of individual animals on dairy farms. They are "smart" but again they are not speaking to each other. The data are generated every day and farmers need to see the current situation on the farm every day without waiting or comparing a few analyses or even some written notes. In the future, the system needs to be able to filter out the noise and attach identifiers to each type of data and finally integrate this information to improve whole-farm decision-making in real-time [5]. AI and machine learning approaches can be applied to all of a dairy farm's data streams to analyze those data [17]. However, real-time integration of these data to improve whole-farm management, leading to data-driven decision making in farming, has proven challenging [17].

VI. Future Of Dairy Farm Management

Whole-farm models are valuable because they can evaluate different management strategy on farm and provide overall process control systems for sustainable production, environmental quality, water and nutrient use efficiency, energy efficiency and long-term profit. Whole-farm models will provide novel information to the scientific community about managing dairy production at a farm level instead of optimizing single-farm operations [9].

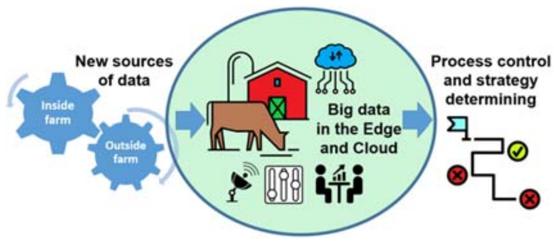

Fig. 5 New challenges of smart dairy farming

Fig. 5 summarizes the challenges of smart dairy farming in the near future, which mean that new sources of data and setting up a continuous process of data integration and analysis will substantially improve prediction abilities of a farm model. Furthermore, this next-generation model should be able to incorporate data of newly developed sensors and take full advantage of big data artificial intelligence, which will be the part of modern dairy farm systems. Data mining and deep learning will guide model development and validate performance. The "Inside farm" submodules will use data of soil and water composition, feed nutrition and energy, animal status (health, behavior, genetic, production, and reproduction) and barn ventilation/insulation. The newly developed sensors, laboratory techniques and subsequently developed algorithms will be able to control wellbeing of livestock (e.g., with algorithms for grouping strategies of cows). Insights gained on processes in animal tissues, organs and metabolisms will be used to evaluate which functionalities are important for high production, environmentally friendliness and good quality dairy products. The "Outside farm" submodules will use data of weather, market, possible diseases alerts, offer of new technologies and their impact on farm management practices, welfare, safety and health standard of humans and animals and including the evaluation of societal benefit of more efficient production systems while reducing negative environmental impacts. Process control and strategy determination can be evaluated for one dairy farm, a few farms or all farms in a region, country, or world. The process control will vary from relatively simple feedback mechanisms to deep learning algorithms (e.g., to implement the right management or scheduling). The evaluation of short-term and long-term effects of the mentioned submodules will also help better inform farmers, industry, and policy leaders on the environmental and economic impacts of adding, removing, or changing one or multiple dairy farm practices. The system in the future should be able to manage the dairy farm as well as an experienced dairy farm manager with a team of the best agricultural advisors. All the integrated information from the data will be able to improve whole-farm decision-making as well as improve the welfare of animals, food safety and quality. The final step will be to apply all found algorithms (inside and outside farm submodules) to create intuitive, cloud-based decision-support tools that allow farmers to use real-time data from their farms to make smarter and complex management decisions with emphasis on either the short-term or long-term effect.

Maintaining a flexible architecture is a critical design component to maintain relevance in an evolving digital landscape. The challenges associated with scaling a service are certainly multifaceted, but when building an API-based system where data integration and processing is the primary value-add, there must be a high level of coordination between participating entities to begin with. There must exist an ontology between data generators along the entire dairy management chain [5].

VII. Evolutionary Computing

The whole-farm model should provide all three types of analytics: descriptive, predictive, and prescriptive. Descriptive analytics often take the form of key performance indicators and provide some summarization, which in the dairy industry might include income over feed costs, feed efficiency measures, or disease occurrence. Predictive analytics involve forecasts of what they are likely to be in the future, rather than a summarization of their values in the past. Prescriptive analytics often tackle more complicated decisions and trade-offs and can integrate one or more predictive analyses or data streams to inform how to best reach a goal [5]. Especially with the last analysis, evolutionary algorithms and scheduling can be very useful in these applications. An example could be to suggest and predict:

1. What is the optimal vehicles driving cycle on the farm?
2. What herd health level, herd size, breed composition (breeding values), nutrition efficiency and weather conditions are needed to reach targeted production or profitability?
3. What to use for farm strategies concerning the different market, environment, climate condition, customers' demand, farm sustainability and future development (short-time or long-time effect)?
4. How to improve the quality of milk (milk composition, SCC)?
5. How to improve the health of dairy cows?
6. How to improve supply chain management among suppliers, facilities, warehouses and customers with the objectives of minimization of cost and maximization of customer services?

In conclusion, the whole-farm model should be able to make optimal decisions in the short, medium and long-term to meet operational, tactical, and strategic goals and also learn as it goes by applying complex machine learning approaches and exploiting the complex interdependencies between inside and outside submodules (Fig. 5). According to Kebreab at al. [9], the prediction accuracy will improve as more data and more integrated live data streams become available.

Evolutionary computing (EC) is effective in finding optimal solutions and is able to answer previous questions. EC is a type of machine learning that uses principles from nature to evolve solutions. In the case of genetic algorithms, there is a strong effect of randomness in EC. That means we use concepts from nature to help our software evolve a solution to a problem.

The concept includes natural selection, which involves fitness, passing genes down from generation to generation via genetic crossover, and even passing genes with genetic mutations [15]. The genetic algorithm and genetic programming can be used in wide variety of situations not directly related to the nature. EC is very effective in finding an equation to fit a set of data, in a process control, problem design, task scheduling, finding the optimal combination of sets of some objects and finally, in strategy determination. According to Meyer [10], when using EC, it is possible to develop complex logic solutions, given a set of inputs. In this case a programmer can allow the genetic program to "play" and develop a solution by itself.

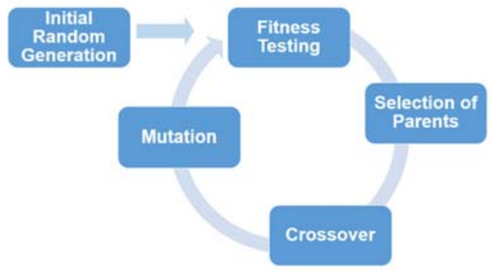

Fig. 6 The Process of Genetic Computing

Fig. 6 shows how genetic computing works. The genetic algorithm and genetic programming begin by defining an initial population of randomly generated candidate solutions. The fittest candidates are selected for reproduction by some fitness function. Two parent candidates are crossed to form two child candidates for the next generation, and occasionally mutation is applied. The process is repeated until after a certain number of generations, the candidate with the best fitness is chosen as the ultimate solution to the problem.

A. Genetic Algorithm vs. Genetic Program

In a genetic algorithm each candidate contains data in a linear form. The candidate data is interpreted in some way to determine fitness, which is typically a fairly simple process, and, since we are dealing with a particular set of data, the solution is always an answer to one particular problem rather than a general approach. Genetic programming contains computer instructions rather than data, and those instructions are arranged in a tree form. To test the fitness of a candidate, the program is actually run, sometimes inside of a simulator, sometimes stand-alone. The final, best solution found can then be used with different parameters like any other sub-routine or program [19].

B. Solution Space and NP – Hardness

The solution space is a set of possible solutions to a given problem. Most of the problems typically have a small solution space. For example, for writing an application to collect data from a user and store it in database, there are not a lot of distinctly different approaches to solve that problem. The solution space is therefore said to be small. There are, however, entire classes of problems with very large solution spaces, meaning there are many viable solutions. It can be, for example, for strategy determination for a dairy farm (Fig. 5).

There is a branch of mathematics that studies this type of problem, which is often referred to as NP-hard or NP-hardness, which is short for non-deterministic polynomial-time hardness. NP-hardness refers to a class of problems that are difficult to find a solution for. Non-deterministic means that for any given attempt to solve a problem you may end up with a different solution. The polynomial-time refers to measuring how long it takes to find a solution. Obviously, the bigger your solution space, the more important the time it takes to find a solution [10].

Regarding agricultural systems models, increasingly more researchers are finding that mathematical programming methods are not well suited. In some situations, these methods contribute adequate strategies, but there are many cases where these assumptions lead to very poor (high cost) solutions to the real problem. Having invested considerable time and effort in the planning, formulation, verification, and validation of a general farm model to simulate the target system, there is the next problem of optimization. Searching the feasible space of available management options and coming up with the global optimum is a difficult task, especially as the data streams and complexities of the problem increase. However, EC appear well-suited for this task, as they are amongst the most efficient of the available optimization methods. Overall, by considering a population of solutions, they allow for the identification and investigation of near-optimal strategies, which may also be of interest to the dairy farm manager [10].

VIII. Conclusion

Big data and EC will cause major changes in the scope and organization of a dairy farm. Resilience, sustainability, quality, well-being for humans and animals are keywords for the future of the dairy sector. The data analytics are being developed at a scale and speed that has never been seen before. Referring to Fig. 1 and Fig. 5, it can be expected that farm management and operations will drastically change by accessing real-time data, real-time forecasting and tracking of physical items and IoT developments in further automating farm operations. However, all these changes should bring permanent operational and strategic decision-making benefits to farmers to help them earn a decent living, manage consumer demand for affordable and good quality dairy products, and adhere to environmental/animal health requirements.

Future publications are expected to bring more practical details about the application of the EC techniques to smart dairy farming.

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References

[1] T. Garnett, M. C. Appleby, A. Balmford, I. J. Bateman, T. G. Benton, P. Bloomer, et al.," Sustainable intensification in agriculture: Premises and policies", Science, vol. 341, no.6141., pp. 33-34, Jul 2013.

[2] C. S. Cardoso, M. Jose Hotzel, D. M. Weary, J. A. Robbins, and M. A. G. von Keyserlingk," Imagining the ideal dairy farm", J. Dairy Sci., vol. 99, no.2., pp. 1663–1671, Jan 2016.

[3] A. Corallo, M. E. Latino, and M. Menegoli, "From Industry 4.0 to Agriculture 4.0: A Framework to Manage Product Data in Agri-Food Supply Chain for Voluntary Traceability World Academy of Science, WASET, Int. J. of Nutrition and Food Engineering, vol. 12, no. 5., pp. 146–150, Apr 2018.

[4] B. R. McFadden and S. Stefanou, 'Another Perspective on Understanding Food Democracy,' Choices, vol. 31, no. 1, pp. 1–6, 2016.

[5] M. C. Ferris, A. Christensen, and S. R. Wangen, "*Symposium review*: Dairy Brain—Informing decisions on dairy farms using data analytics, J. Dairy Sci., vol. 103, no. 4., pp. 3874–3881, Apr 2020.

[6] S. Wolfert, L. Ge, C. Verdouw, and M. Bogaardt, "Big data in Smart Farming – A review", Agricultural Systems., vol.153, pp. 69–80, May 2017.

[7] J. Wolfert, C. G. Sørensen, and D. Goense, "A Future Internet Collaboration Platform for Safe and Healthy Food from Farm to Fork", Global Conference (SRII), 2014 Annual SRII. IEEE, San Jose, CA, USA, pp. 266–273.

[8] A. T. Balafoutis, B. Beck, S. Fountas, Z. Tsiropolous, J. Vangeyte, T. van der Wal, I. Soto et al., "Smart Farming Technologies – Description, Taxonomy and Economic Impact" In: Pedersen S., Lind K. (eds) Precision Agriculture: Technology and Economic Perspectives. Progress in Precision Agriculture. Springer, Cham, 2017.

[9] E. Kebreab, K. F. Reed, V. E. Cabrera, P. A. Vadas, G. Thoma, and J. M. Tricarico," A new modeling environment for integrated dairy system management ", Animal Frontiers, vol. 9, pp. 25-35, Dec 2019.

[10] D.G Mayer, "*Evolutionary Algorithms and Agricultural Systems*" Kluwer Academic Publishers: Dordrecht, 2001, ISBN 0792375750.

[11] A. De Mauro, M. Greco, and M. Grimaldi, " A formal definition of big data based on its essential features", Libr. Rev. vol. 65, no3., pp. 122 - 135, Apr 2016.

[12] N. O' Mahony, S. Campbell, A. Carvalho, L. Krpalkova, D. Riordan, and J. Walsh, "3D Vision for Precision Dairy Farming**"**, IFAC-Papers OnLine, vol. 52, no. 30., pp. 312 – 317, 2019.

[13] M. Bohlouli, S.Alijani, S.Naderi, T.Yin, and S.König, "Prediction accuracies and genetic parameters for test-day traits from genomic and pedigree-based random regression models with or without heat stress interactions" J. Dairy Sci., vol. 102, no.1., pp. 488–502, Jan 2019.

[14] L. N. Grinter, M. R. Campler, and J. H. C. Costa, "Technical note: Validation of a behavior-monitoring collar's precision and accuracy to measure rumination, feeding, and resting time of lactating dairy cows", J. Dairy Sci., vol. 102, no. 4., pp. 3487–3494, Feb 2019.

[15] A. Carvalho, N. O'Mahony, L. Krpalkova, S. Campbell, J. Walsh and P. Doody, "Farming on the edge: Architectural Goals,*" 2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics),* Istanbul, Turkey, 2019, pp. 1-6, doi: 10.1109/Agro-Geoinformatics.2019.8820424.

[16] M. A. Zamora-Izquierdoa , J. Santaa,∗ , J. A. Martınezb, V. Martınezc , A. F. Skarmetaa, "Smart farming IoT platform based on edge and cloud computing", Biosystems Engineering, vol. 177, pp. 4-17, Jan 2019.

[17] V. E. Cabrera, J. A.Barrientos-Blanco, H. Delgado, and L. Fadul-Pacheco, "Symposium review: Real-time continuous decision making using big data on dairy farms" , J. Dairy Sci., vol. 103, no. 4., pp. 3856-3866, Apr 2020.

[18] K. Græsbøll, C. Kirkeby, S. S. Nielsen, T. Halasa, N. Toft, and L. E. Christiansen, " Models to Estimate Lactation Curves of Milk Yield and Somatic Cell Count in Dairy Cows at the Herd Level for the Use in Simulations and Predictive Models", Frontiers in Vet. Sci., vol.3, pp. 115, Dec 2016.

[19] S.B. Mat Sah, V. Ciesielski, D. D'Souza, M. Berry, "Comparison between Genetic Algorithm and Genetic Programming Performance for Photomosaic Generation" In: Li X. et al. (eds) Simulated Evolution and Learning. SEAL 2008. Lecture Notes in Computer Science, vol 5361. Springer, Berlin, Heidelberg

[20] J. S. Vuppalapati, S. Kedari, A. Ilapakurthy, A. Ilapakurti, and C. Vuppalapati, "Smart Dairies — Enablement of Smart City at Gross Root Level," *2017 IEEE Third International Conference on big data Computing Service and Applications (BigDataService)*, San Francisco, CA, pp. 118-123, 2017.

[21] J. Koltes, J. B. Cole, R. Clemmens, R. N. Dilger, L. M. Kramer, and J. K. Lunney, "A Vision for Development and Utilization of High-Throughput Phenotyping and big data Analytics in Livestock" Front Genet., vol. 10, pp. 1-14, Dec 2019.

[22] C. Kulatunga, L. Shalloo, W. Donnelly, E. Robson, and S. Ivanov, "Opportunistic Wireless Networking for smart dairy farming," in *IT Professional*, vol. 19, no. 2, pp. 16-23, Mar-Apr 2017.

[23] R. Chudasama, S. Dobariya, K. Patel, and H. Lopes, "DAPS: Dairy analysis and prediction system using technical indicators," 2017 Third International Conference on Sensing, Signal Processing and Security (ICSSS), Chennai, 2017, pp. 176-180.

[24] C. Hudson, J. Kaler, and P. Down, "Using big data in cattle practice," In Practice, vol. 40, no. 9., pp. 396 - 408, Oct 2018.

[25] R. S. Alonsoa, I. Sittón-Candanedoa, Ó. Garcíaa, J. Prietoab, and S. Rodríguez-Gonzáleza, "An intelligent Edge-IoT platform for monitoring livestock and crops in a dairy farming scenario" Ad Hoc Net., vol. 98, Mar 2020.

[26] E. Mieras, A. Gaasbeek, and D. Kan, "How to Seize the Opportunities of New Technologies in Life Cycle Analysis Data Collection: A Case Study of the Dutch Dairy Farming Sector" Challenges, vol. 10, no. 1., pp. 8, Jun 2019.

[27] W. J. Yan, X. Chen, O. Akcan, J. Lim, and D. Yang, "Big data analytics for empowering milk yield prediction in dairy supply chains," 2015 IEEE International Conference on big data (big data), Santa Clara, CA, pp. 2132-2137, 2015.

[28] J. Horvath, B. Banhelyi, T. Csendes, and E. Miko," Professional and economic reasons for adoption of precision dairy farming" Lucrari Stiintifice Seria I, Management Agricol. vol. 21, no. 2., pp. 39-43, 2019.

[29] E. A. Eckelkamp and J. M. Bewley, "On-farm use of disease alerts generated by precision dairy technology", J. Dairy Sci., vol. 103, no. 2., pp. 1566-1582, Feb 2020.

[30] L. M. Mayo, W. J. Silvia, D. L. Ray, B. W. Jones, A. E. Stone, I. C. Tsai, J. D. Clark, J. M. Bewley, and G. Heersche, "Automated estrous detection using multiple commercial precision dairy monitoring technologies in synchronized dairy cows", J. Dairy Sci., vol. 102, no. 3., pp. 2645-2656, Feb 2020.

[31] M. C. Cantor, C. H. Pertuisel, and J. H. C. Costa, "Technical note: Estimating body weight of dairy calves with a partial-weight scale attached to an automated milk feeder2", J. Dairy Sci., vol. 103, no. 2., pp. 1914-1919, Feb 2020.

[32] S. F. Wamba and A. Wicks, "RFID deployment and use in the dairy value chain: Applications, current issues and future research directions," *2010 IEEE International Symposium on Technology and Society*, Wollongong, NSW, 2010, pp. 172-179.

[33] S. Sonka, "big data and the Ag Sector: More than Lots of Numbers", *Int. Food & Agri. Management Rev.,* vol. 17, no. 1., pp. 1-19, 2014.

[34] J. B. Cole, S. Newman, F. Foertter, I. Aguilar, and M. Coffey, "Breeding and Genetics Symposium: really big data: processing and analysis of very large data sets", J. Anim. Sci., vol. 90, no. 3., pp 723–733, Mar 2012.

[35] J. Werner, C. Umstatter, L. Leso, E. Kennedy, A. Geoghegan, and L. Shalloo, M. Schick, B. O'Brien, "Evaluation and application potential of an accelerometer-based collar device for measuring grazing behavior of dairy cows," Animal, vol. 13, no. 9., pp. 2070–2079, Feb 2019.

[36] L. Krpalkova, A. Murphy, L. Zavadilova, N. O' Mahony, A. Carvalho, S. Campbell, and J. Walsh, "Detection, prevention and impact of lameness in dairy cattle management**",** Int. J. of Advances in Sci. Eng. and Tech., vol. 8, no. 1., pp. 2321 –9009, Jan 2020.

[37] M. O. Akbar, M. S. Shahbaz khan, M. J. Ali, A. Hussain, G. Qaiser, Maruf Pasha, U. Pasha, M. Saad Missen, N. Akhtar, "IoT for Development of Smart Dairy Farming", J. of Food Quality, vol. 2020, pp. 1-8, Mar 2020.

[38] C. Lokhorst, R. M. de Mol, C. Kamphuis, "Invited review: Big Data in precision dairy farming", Animal, vol. 13, no. 7, pp. 1519-1528, 2019 Jul.

[39] M. Taneja, N. Jalodia, J. Byabazaire, A. Davy, C. Olariu, "SmartHerd management: A microservices-based fog computing-assisted IoT platform towards data-driven smart dairy farming", Softw Pract Exp, vol. 49, no. 7, pp. 1055-1078, Jul 2019.

[40] L. Krpálková, N. O' Mahony, A. Carvalho, S. Campbell, J. Walsh, "Evaluating the economic profit of reproductive performance through the integration of a dynamic programming model on a specific dairy farm", Czech J. of Animal Science, vol. 65, pp. 124-134, Apr 2020.