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Decision support in precision sheep farming

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Abstract While the 7 million-head French sheep industry is contracting, the average herd size is rising, providing challenging issues to maintain and improve its productivity. Precision Livestock Farming has allowed the sheeps and herds to be equipped with sensors and has a result the amount of data to be processed by farmers has surged. We argue that in order for the farmers to take appropriate actions there is a need for the development of a decision support system that take into account not only real-time data but also expert knowledge. In this work, we first highlight the specific challenges presented by the field of precision sheep farming to the development of a Cyber-Physical and Human System. We then introduce a methodology to implement a decision support in this context.

Keywords: Precision livestock farming, Decision support system, Collective Decision, Interoperability, Heterogeneous data,

1. INTRODUCTION

For the past 20 years, the French sheep industry has seen an overall reduction in the number of sheep in the country. Indeed, the national livestock of 10 million heads in 1996 has been cut down to only 7.2 million. This is also reflected in the loss of nearly 54,000 farms between 2000 and 2016. Based on these observations, the sheep industry has launched a program [1] around two major issues:

- Producing more lambs and milk to meet demand and create more jobs throughout the country,
- Increasing farmer's incomes while improving working conditions and the attractiveness of the sheep breeder profession.

This context is also widespread at the European level, with the creation of an EU Sheep Forum [2] and a thematic network H2020 SheepNet [3] which define the recommendations to be applied to reinvigorate the sector. Responding to the global stakes of the sheep industry will require foresight to improve the technical and economic performance of sheep farms. It is necessary to produce more, produce better: the sector is thus moving towards a greater production of lambs, with fewer inputs (food autonomy, reduction of medicinal and phytosanitary inputs) which is part of an agroecological approach which aims to improve economic, environmental and social performance.

Precision Livestock Farming (PLF) deeply change the farmers working processes (Hostiou et al., 2017) by providing new information – often in large quantities – on the health status of the animals, their welfare, and their food requirements to preserve and improve the technical, economic and environmental performances of farms (Panell, 1999). One could says that the agricultural sector is experiencing a similar trend to what the industrial world has experienced since the 90s. It is confronted with similar issues concerning capitalization and exploitation of knowledge generated within PLF, to those induced by the arrival of Information and Communication Technologies (ICT) in the industry. The sheer amount of data collected and the diversity of sources render the comprehension and control of the system by human operators very complex. That is why Decision Support Systems (DSS) are required to collect, synthesize and pre-analyze all available data, to make them intelligible to Decision Maker (DM) and to help him/her in his/her choices. Therefore we argue that there is a need to transfer and adapt methods and tools from industrial engineering decision support to agricultural organizations (Panell, 1999; Ruiz-Garcia et al., 2009; Banhazi et al., 2012; Terrasson et al., 2017).

In the case of sheep industry, compared to other sectors, the available courses of actions are limited. Adapting sensors to sheep specificities is an issue at stake to better control the breeding (health disorders, reproduction/struggle, calving...). Indeed, there has been an increase in average herd size for several years, which reduces the time that farmers can spend on individual observation of their animals throughout the sheep production cycle. This increase leads to a real need to improve the performance control that allows farmer to better control their herds. This need can be split into major challenges such as individual monitoring of ewes, phenotype estimation of each animal, solutions to improve the gimmer sorting and culling man-

[1] Program Inn'Ovin (http://www.inn-ovin.fr/)
[2] The EU sheep meat forum (https://ec.europa.eu/agriculture/sheep-goats/forum_en)
[3] SHaring Expertise and Experience towards sheep Productivity through NETworking (https://ec.europa.eu/eip/agriculture/en/find-connect/projects/sheepnet-sharing-expertise-and-experience-towards)

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agement, identification of animals requiring specific cares (health problems, lambing assistance, ...), lamb growth monitoring, and milk production monitoring for each ewe. However, these applications have common issues, related to the large amount of capitalized data, the heterogeneity of data sources, and the system complexity. In this context, decision making is difficult because breeders can no longer have a global vision of the system and we argue that a DSS become essential.

For that purpose, we first describe the issue of decision making in PLF and identify the main scientific challenges to be considered to help breeders in their work (section 2). We then look into current approaches proposed in the literature that address these challenges (section 3) and propose a methodology for decision support in the context of PLF (section 4).

2. DECISION IN PLF

2.1 A multidisciplinary concern

PLF solutions are based on several ICT such as sensors, information systems, decision-making algorithms and human machine interfaces. This technological aggregation provides new services to farmers. These help them in their decision-making process by enhancing both the management of their daily tasks and the supervision of their herd.

In this context, one of the most common technology employed in PLF is the Radio Frequency Identification (RFID) tagging of animals which is mainly used to identify them (Bocquier et al., 2014). RFID also offers to farmers a way to guarantee the traceability throughout the feed-animal-food chain, and the ability to better manage individual production and feeding of each animal. Other PLF solutions are based on collars equipped with sensors which are able to transmit data wirelessly (Brown et al., 2013; Collins et al., 2015; Llaria et al., 2015; Terrasson et al., 2016). These collars allow the acquisition and transmission of data regarding animal localization and behavior. By means of all these data, the main decisions that can be assisted in sheep farming concern early detection of ewe diseases, limitation of antibiotics use to improve the meat quality, overall productivity, and the reduction of the breeder workload – both physical and more importantly cognitive. All these decisions must be taken into consideration while ensuring the livestock welfare.

Consequently, the exploitation of collected data requires tools to formalize, interpret and help end-users (farmer, veterinarians) to take appropriate decisions. In this frame, decision support has to face up multiple challenges such as the heterogeneity of the data and their reliability. Indeed, data are to be provided not only by sensors, but also by existing information systems or directly from experts – e.g. veterinarian or ethologist. Thus, the design of decision-making process is also subjected to the capacity of each data source and information systems that compose a PLF solution to be interoperable. All the while guarantying that the decision-making process is adapted to the end-user needs.

Therefore, the issue of decision support for PLF and, more accurately, for Precision Sheep Farming (PSF), is therefore at the crossroad of a number of technologies where humans must be considered as a main part of this global Cyber-Physical and Human System (CPHS) (Terrasson et al., 2017).

2.2 Breeder: an expert at the heart of the collective decision

In the context of PLF we define here breeders as Decision Makers (DMs) since they can be perceived as experts in their field, driving their production, monitoring the risk indicators, managing the amount of data useful to their control.

In this scope, we will define our case study as pertaining to the well-known approach in the field of decision based on Multi Criteria Decision Making (MCDM). MCDM refers to decision making in the presence of multiple criteria usually in conflict (Zanakis et al., 1998). More specifically, decision taken by the breeder relates to the field of Multi Attribute Decision Making (MADM) when the decision is based on a discrete and usually limited number of predefined alternatives requiring inter and intra-attribute comparisons that involves the realization of a trade-off by the DM (Yoon and Hwang, 1995).

This type of decision model involves, for the DM, the exploration of a "universal set" –i.e. the set of criteria and alternatives. In connection with this type of decision-making process, Miller et al. (2013) offer a review of the literature that allows them to highlight characteristics for DMs : (1) DMs are adaptive, (2) DMs' choices are based on their awareness, (3) DMs are subject to contextual preference reversals, and (4) that DMs' preferences can be viewed as stochastic processes.

The first point highlights the iterative aspect of this type of decision, as regards the second focus on awareness called in some communities "situational awareness" and which leads globally to a so-called informed decision (Abi Akle et al., 2017b). Points three and four introduce the complexity of decision-making related to DM preferences. Indeed, in addition to introducing the stochastic dimension, the DM preferences must be generally managed in a decision-making situation in a collective context.

A decision in a collective context can be defined according to three modalities : codecision, cooperative decision, or collaborative decision. Seguy et al. define these three forms of collective decision :

- *"Codecision: a joint decision following the involvement of several actors with sharing resources and goals, and where each actor is involved in the decision making,*
- *Cooperation: a simple juxtaposition of individual and sporadic activities, without sharing an objective,*
- *Collaboration: shared production and shared objectives, where each actor performs a part of the work with resources, benefits or risks sharing"* (Seguy et al., 2010).

From our point of view, it is not only a matter of sharing a certain amount of information but also of understanding it. For Karacapilidis and Papadias (2001), the collaborative decision is an argumentative process where every actors

must take into account each other to understand the problem constraints and solutions, along with the interests and priorities of each. Jankovic et al. (2007) nuances the point of view of Karacapilidis & Papadias by adding a dimension of conflict risk. Indeed, they define collaborative decision as an activity where everyone has different and often conflicting objectives with the other actors involved in the decision-making process.

In our opinion, we can place our case study as being in a either situation of co-decision or collaborative decision – e.g. the objectives of the veterinarian and the breeder can sometimes be common and sometimes conflicting. This variation in the situations implies to design a DSS that is flexible and adaptive.

3. MAIN CHALLENGES

Taking decision in PSF presents several challenges that a DSS designed to assist farmers must consider and integrate. In this section we translate those into three main challenges for the design of such DSS – heterogeneous data processing, interoperability between information systems and user integration in DSS – and studies the methodologies proposed in the literature to address these.

3.1 Heterogeneous data

Knowledge management is critical in any DSS. Indeed, the notion of choice, which is central in decision support, implies a mastery and an understanding of the knowledge to characterize the studied problem –in particular its context, the alternatives as well as the indicators or decision criteria to be optimized. The concept of knowledge integrates three levels:

- Knowledge about the objects, concepts and various entities that forms the studied system. In our case, this level includes among other things the breeders, and the animals and their different observable physiological characteristics.
- Knowledge coming from system observation –events, state change and interactions between objects in the system. In our case, this level includes the evolution of the physiological characteristics observed via sensors, the databases about milk production and births or the breeder observations on animal behavior.
- Know-how on the system as a wider human perspective on the functioning of similar systems to our case study. In our case, this level consists in part of the breeder's expertise about their herd and the expertise of the veterinarian.

Knowledge modeling –i.e. its representation in a formal framework allowing the establishment of reasoning mechanisms such as inference mechanisms– is a critical step in the construction of a DSS. The chosen formalism should exhibit the following properties :

- Heterogeneity representativeness: it should allow the representation of knowledge resulting from heterogeneous sources – e.g. sensor data, information systems, business tools or human expertise. Furthermore it should allow the definition of fusion mechanisms that will be implemented to hybridize knowledge from technological sources (databases, sensors ...) and from human sources (veterinarians, breeders ...)
- Uncertainty resilience: it should take into account the uncertainty inherent in human knowledge and consider the need to infer from this knowledge through a computer system. Multiple issues should be addressed at this stage relative to uncertainty modeling of:
  - Technological data: reliability of transmitted or stored data, sensor failures or errors...
  - Human knowledge: trust in the expert, confidence of the expert in its evaluation, intuition modeling.
- User centered: it should be designed with the goal to fulfill farmer needs in their decision making process.

Thus the chosen formalism should be identified or developed according to the user needs, the characteristics of collected data and interoperability constraints. Probabilistic methods, possibilistic theory, evidential theories are possible solutions, as are all combinations of these approaches (Dubois and Prade, 2009).

3.2 Interoperability

Interoperability is usually described as the capacity for two (or more) systems to exchange information and to reach their functionalities reciprocally (Bourey et al., 2007).

There exist three approaches that avoid problems of incompatibility between systems, which is the main cause of non-interoperability:

- "Integrated approaches" are based on the definition of a shared format for all models, and correspond to the implementation of dedicated interfaces between one system and the shared format;
- "Unified approaches" are based on the characterization of a shared meta-model for the mapping of the concepts based on a semantic point view; one way to define a meta-model is to use ontologies concepts;
- "Federated approaches" is generally more complex to implement and allows the systems to dynamically adapt themselves to the received data from other systems. An ontology (Wache et al., 2001) is used to structure knowledge of the working domain then to manage a dynamic mapping between the concepts of both systems.

Several ontologies for agriculture exist with dedicated knowledge domain such as Agrovoc (Soerge et al., 2004) or AgOnt (Hu et al., 2011) – specially dedicated to agriculture IoT.

One important issue to address is to take into account the different aspects of interoperability: data, service, process, and business; as well as the different levels of problems of incompatibility: conceptual, technological, and organizational. It is recognized that interoperability cannot be solved by taking into account only the technical aspects – e.g. the technological and conceptual problems. Based on the Model Driven Architecture®(MDA) approach, defined by the Object Management Group (Object Management Group, 2003), we consider a multi-level modeling approach (Merlo et al., 2014) to formalize this interoperability problem:

- A business level, in order to characterize the different stakeholders (humans and sensors) of the studied system, their role and relationships, their business processes and the decisions they make;
- An information system level, dedicated to data, information and knowledge identification and the information flows between human and sensors stakeholders –including IT tools, in order to characterize the collaborations and especially the exchanges between them. It is the functional description of the whole IT platform;
- A technological level, which introduces the technical constraints for the specifications and the implementation of the future IT platform, integrating the DSS.

Consequently, technical solutions for the studied DSS must be defined in correlation with organizational models (Baina, 2006) from business and information system levels.

3.3 Uses and users

Human-machine interfaces (HMI) and more precisely graphical supports for decision making require adapting to different phases of the decision-making process for the user. This includes three main phases that we call: (i) Awareness, (ii) Warning and (iii) Strategy.

For *Awareness*, it is necessary for the user to gain situational awareness, especially by observing the interactions between the different decision variables (Ireson, 2009). In this phase, users must be able to detect insights to have knowledge of the situation and therefore the HMI support must offer them an overview of these data which are a vector of decision.

The second phase called *Warning* implies for the user a narrowing activity. At this stage, DMs go deeper into the data set to get more details. It is for them to identify specificities and therefore to be able to focus on a particular point. The HMI should allow DMs to analyze a reduced set of data to analyze the sensitivity of the decision variables. In general, it is in this phase that the DMs carry out comparison actions of an alternative with respect to all the others by considering each decision criterion one after the other. It is therefore important to make the focus possible through the decision support (i.e. avoid noise).

Finally the phase called *Strategy* –also known in decision engineering as the selection (or choice) is crucial because it is there that the DMs make the trade-off. We are talking about strategy because we have to select one of several alternatives that can meet the constraints and satisfy the preferences of DMs. Thus, the HMI must allow the user to compare all the alternatives, remaining at this stage, among them on all the decision criteria (in the previous phase the comparison is done on each criterion independently) (Abi Akle et al., 2017a).

While farmers are experts of the decision in the PLF context, they are most certainly not expert in DSS as users. Thus we must guard ourselves against the pitfalls of human-machine system design. Indeed the HMI design is crucial for the development of the DSS since it conditions the acceptability by the DMs. In turn the use of the IT platform will impact the acquisition of observations from the farmers which will be feed back into the decision system. Thus as for the design of the formalism, the HMI design should be based on following the best practices of engineering of HMI .

4. PROPOSED METHODOLOGY

This section presents the methodology underlying the DSS that needs to be developed. This methodology is based on a decision process (section 4.2) and exploits data flows (section 4.1) to enable the functioning of this decision process.

4.1 Data flows

We introduced in section 3.3 a three-phase process (Awareness, Warning and Strategy) that allows the users to move from elementary observations to a fully understood decision. This evolution is made possible by data flows in figure 1.

The stakeholders identified as data providers (in blue in figure 1) in the system: the sheep – either as an individual entity or as a herd – the farmers, the veterinarians and all the experts with relevant knowledge related to sheep farming – professional association, research institute, certification organisms, etc.

The data acquisition elements that feed the decision process (in orange in figure 1) can be divided into three groups:

- Sensors attached to sheep or present in their environment capture the behavior of the system,
- User interfaces enable the farmer to provide their observations on the system,
- Elicitation mechanisms extract knowledge from the analysis of the system by the experts.

Data and knowledge from these elements are stored in several databases and can be classified as follow :

- Data labeled as *technological* from the sensors (*e.g.* heart rate, body temperature...) or from the farmer (*e.g.* apparent animal state) is first stored in a *real-time* database then through an experience feedback process (not present in the figure 1) is structured and summarized in an *historical* database (*e.g.* average heart rate of the herd, sheep emotional state model)
- *Expert knowledge* collected from the elicitation of expert opinion is either used directly in the decision process or is combined with the *historical technological data* from the experience feedback process to produce business rules (*e.g.* IF the sheep seems weak AND her temperature is above 40 THEN called the veterinarian). These rules are used in the decision process.
- Finally, *structured data* is the rules produced by the experience feedback process from the *historical technological data* and the elicited *expert knowledge.*

As the user moves through the three decision phases (Awareness, Warning and Strategy) two artificial intelligence mechanisms are deployed : whistle-blowing and decision support. These unfold in the three phases as follow:

(1) The whistle-blowing mechanism analyses the *real-time* data under the light of the *expert knowledge* and

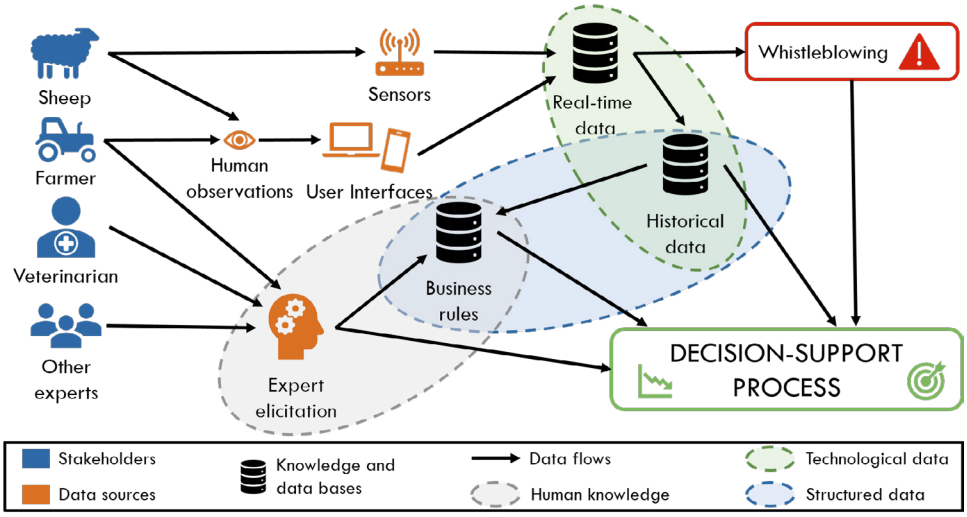

Figure 1. Data flows for the decision support system

upon the detection of an anomaly about one animal (sickness, birthing) or about the herd (predators) sends an alert to the user.

(2) The user analyses the problem or consult specialists to add new *expert knowledge* to the system.

(3) The decision support process help users to take appropriate actions based on the *technological* data (observations), the *expert knowledge* and the *structured data.*

This decision support process is described in more details in the next section. While figure 1 only describe the data flow necessary for the decision making process, there is also a flow related to the experience feedback process. Its goal is to log all the observations produced in the system along with the analysis, choices and action taken by the users. This data will feed and maintain the *structured database.*

4.2 Decision support process

The proposed decision support process based on work by (Villeneuve et al., 2017) is depicted in figure 2.

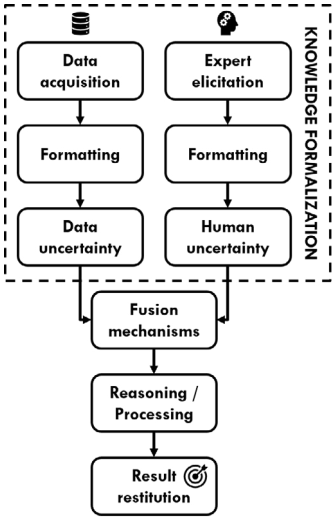

Figure 2. Decision support process

It can be summarized in four main steps:

(1) The knowledge formalization consists in the acquisition of technological and structured data and expert opinions, in the formatting of these data by using a formalism (to be determined) which respects the constraints set out in section 3.1 and in the introduction of uncertainty by weighting or adapting data using business rules stored in knowledge bases.

(2) The fusion aims to concatenate the all the knowledge without loosing information about uncertainty. The choice of fusion mechanisms is totally dependent of the chosen formalism for knowledge representation.

(3) The processing allows the introduction of formalized knowledge into the decision support model and the inference of this knowledge to compute indicators for decision support.

(4) The result restitution allows the indicator formatting so that they can be interpreted by the human DM.

This process will be implemented by choosing a knowledge representation formalism and by building a realistic model with the help of users and experts in the PLF field (farmers, veterinarians ...).

5. CONCLUSION

In this paper, we argue that Precision Sheep Farming (PSF) must be considered as a CPHS (Section 2). The design and the development of a Decision Support System (DSS) in this context offers a concrete example of collaboration and codecision for problems specific to CPHS. In particular, tackling the challenges of heterogeneous data processing, interoperability between information systems and user integration in DSS (Section 3) is relevant to any CPHS.

Our methodology (Section 4) thus can be applied beyond the case study of the PSF and that could be applied to any CPHS. This methodology will be validated through an implementation in the PASTORE project – funded by the French government – that brings together academic and industrial partners to cover the whole data flows presented in figure 1 – IoT sensors, breeders, veterinarians and data scientists. Several herd will be equipped with sensor, along with the deployment of an interoperable system of data

storage and analysis. Finally an DSS application will be developed and tested on the field to evaluate the proposed mechanisms.

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