A Learning Model for Intelligent Agents Applied to Poultry Farming

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Abstract: This paper proposes a learning model for taking-decision problems using intelligent agents technologies combined with instance-based machine learning techniques. Our learning model is applied to a real case to support the daily decisions of a poultry farmer. The agent of the system is used to generate action policies, in order to control a set of factors in the daily activities, such as food-meat conversion, amount of food to be consumed, time to rest, weight gain, comfort temperature, water and energy to be consumed, etc. The perception of the agent is ensured by a set of sensors scattered by the physical structure of the poultry. The principal role of the agent is to perform a set of actions in a way to consider aspects such as productivity and profitability without compromising bird welfare. Experimental results have shown that, for the decision-taking process in poultry farming, our model is sound, advantageous and can substantially improve the agent actions in comparison with equivalent decision when taken by a human specialist.

1 INTRODUCTION

The use of learning systems based on intelligent agents (Castelfranchi, 1997; Maes, 1995) is an alternative to address a number of computational problems, such as vehicle control (Au et al., 2014), games and robotics (Bachrach et al., 2014; Cobo et al., 2013), vehicular traffic control (Ribeiro et al., 2012; Jiang et al., 2014), collective decision making (Ribeiro and Enembreck, 2013; Ribeiro et al., 2013), etc. In this work, we propose a learning model using intelligent agents supported by learning techniques based on instances (Aha et al., 1991). Our approach has the advantage of providing flexibility to construct data models and training sets, eliminating the need of a prior heuristic.

The proposal to be described can be summarized as follows. We aim to generate action policies from historical data of broiler management, emerging an expert system able to assist poultry farmers in the decision-making process. Usually, predictive systems require distributed and flexible approaches to become usable in industrial scale, since they are required to adapt themselves to dynamic environments. In this context, agent-based approaches are appropriate for the construction of open, distributed, heterogeneous and flexible architectures, that can offer a variety of services without imposing architectural constraints. Thus, the incremental development of the agent in the decision making process based on machine learning algorithms becomes easier (Enembreck and Barthès, 2005). The agent developed in this paper takes results from a machine learning process, including the extraction of knowledge from database of previous production systems.

Pragmatically, it has been implemented machine learning techniques to extract information from historical data of broiler management, providing the agent with such information and examining its behavior in the decision-making process. The decision-making itself occurs on a set A of activities performed in broiler management (Ferket and Gernat, 2006).

Activities that define A involve actions occurring throughout the broiler chicken life cycle, which interfere on factors such as: amount of consumed feed and water, light, ventilation, humidity, resting time, and temperature control. These factors directly impacts on the amount of food that is consumed, with respect to the amount of meat that is produced. This relation is called *Feed Conversion Ratio* (Fontana et al., 1992) and is crucial to the success of the broiler production system.

The decision-making process is the result of the agent's action policy in the environment (aviary). An action policy represents the behavior that the action causes, e.g., increasing, maintaining or decreasing the

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temperature, the humidity, the amount of food, etc. These actions interfere on the productivity indicators. To define an action policy, the agent receives a set of resources, such as qualitative characteristics of the environment or knowledge bases containing actions from previous managements. A *good* action policy is achieved when the productivity is somehow improved, in terms of feed conversion.

In the paper, we evaluate and validate our estimations by comparing them against field tests, conducted using real data from poultry farming. The behavior observed from the agent has been confronted against empirical decisions taken by human experts (farmers) when handling the process. The same configuration has been assumed for the scenario. To classify optimized actions, we apply an instance-based algorithm over historical data.

The manuscript is structurally organized as follows: Sections 2 and 3 respectively introduce basic concepts on poultry farming and related machine learning techniques. Section 4 presents the proposed model, which is experimentally evaluated in Section 5. Finally, Section 6 presents some conclusions and perspectives.

2 POULTRY INDUSTRY

Poultry farming is the raising domesticated birds. Among the birds in poultry stand out the species *G. gallus*, subspecies *G. g. domesticus* with trinomial name of *Gallus gallus domesticus* - or simply *chicken*. When it is raised for meat production it is called broiler poultry (Charles and Stuart, 2011). On a smaller scale, there are also bred birds such as ducks, goose, quail, turkeys, ostriches, pheasants etc.

The broiler poultry farming is an economic activity increasingly important worldwide. In 2013, the world chicken meat production accounted 82,178 (1,000 MT), being 16,958 (USA); 13,500 (China); 12,308 (Brazil); 9,750 (EU- 27); 3,420 (India), and 28.242 (others). In Brazil, the production of the subspecies *G. g. domesticus* reached 12.30 million tons in 2013, corresponding to a growth in comparison with 2012, when 12.23 million tons were produced. With this performance, Brazil is getting close to China, currently the second largest world producer, whose production in 2013 summed up 12.550 million tons, only behind the United States, with 16.648 million tons, according to projections from the US Department of Agriculture (USDA)[1].

[1]Brazilian Poultry Association (2014). "Annual Report", 2013/2014. www.brazilianchicken.com.br.

The growth in 2013 was largely driven by the increased consumption of chicken meat and the 5.1% expansion in exports, with a total 3.8 million tons of chicken exported to more than 150 countries. Out of the total national production of chicken, 69% was intended for domestic consumption, and 31% for exports.

The growth and economic impact of broiler poultry farming shows its importance. Increased productivity, reduced costs and environmental aspect and well-being of animals has forced the industry to modernize processes, with public and private investments in genetic improvement research (Closter et al., 2012); immunology, health and disease (Lee et al., 2011);quality programs and good manufacturing practices (Northcutt and Jones, 2004); metabolism and nutrition (Shariatmadari, 2012); physiology, endocrinology and reproduction (Bakst et al., 2012); modernization of industrial processes, e.g. processing, products and food Safety (Tavarez et al., 2011); and the development of computer-aided solutions. The development of expert system is the scope of this work.

(Arowolo et al., 2012) developed an expert system for diagnosing poultry diseases which could also be used both by the farmer and the experts to train their students. The knowledge (elicited from the experts and literature review) was represented in the system using a rule-based approach. The *Unified Modeling Language* was used to describe the design of the system. The expert system was tested using design criterion and knowledge-base expert system for stratified root.

(Maseleno and Hasan, 2012) built a web mapping and Dempster-Shafer theory as an early warning system of poultry diseases. Dempster-Shafer theory combines beliefs in certain hypotheses under conditions of uncertainty and ignorance, and allows quantitative measurement of the belief and plausibility in identification result. Web Mapping is also used for displaying maps on a screen to visualize the result of the identification process. The result reveal that poultry diseases warning system has successfully identified the existence of poultry diseases and the maps can be displayed as the visualization.

(Schmisseur and Pankratz, 1989) proposed an expert/knowledge-based microcomputer program to the diagnose layer management problems and recommend expert remedial management advice. The program also provokes management action by calculating the economic loss attributed to major management problems. It analyzes data generated by a commercially marketed layer performance financial microcomputer program and has demonstrated the ability to emulate poultry management experts in the diagnoses of 80 individual layer management problems. The program provides scarce expert poultry management advice to poultry layer managers regardless of size and scale of operation.

In spite of the extensive options of poultry farming technology, few computer systems are specialized in applying machine learning techniques to automate the decision-taking process. In the following, we present some alternatives that have been used for that purpose in industry, highlighting the novelties and benefits brought by this particular paper.

3 AUTOMATIC LEARNING

Techniques based on imperative programming, combined to empirical knowledge and formal methods (Teixeira et al., 2014) can be applied to coordinate sequences of operations in factory automation. Such sequences can then be commanded by conventional tools and technologies for automation, and performed without human intervention.

In a number of practical problems, the exploitation of those pre-programmed sequences may identify bottlenecks that, when properly addressed, could lead to significant improvements on the production system, either in terms of process performance or quality of manufactured items. For that, nevertheless, one has to consider dealing with dynamic variables that appear along the process, such as temperature, pressure, flow and rates of resources to be consumed, etc. *Learning mechanisms* are alternatives to be combined to imperative programming in order to handle it. This approach allows to analyze industrial problems characterized by sequences of events which are unknown a priori and depend on the dynamics of the environment and on the availability of resources.

The ability for a system to *learn*, so performing complex tasks better than human specialists, is of great value for industry. Traditionally, such *learning* process has been hand-crafted, capturing from a human expert intuitions about the process, which requires a tedious and extensive human effort, while the results are imprecise, mixed and poor, in general.

In contrast, a successful learning machine is able to learn a given industrial task purely from computational effort, without the intellectual help of a human expert (even though he exists). In most cases and successful domains, such automatic learning techniques have performed significantly better than the best hand-crafted efforts (Andrieu et al., 2003).

In spite of the apparent advantages, few approaches have applied machine learning techniques to develop agent-based architectures to support the decision-making process in industry. The main reason why this approach does not reach industrial scale is that the choice for the appropriate learning method to be used depends on the application itself, and this decision may not be straightforward. What it is observed is that applying machine learning on large and complex problems implies to handle a large and intricate combination of variables and instances. Therefore it may not be trivial to extend the theory to practical problems (e.g., poultry farming), due to the inherent computational cost.

4 PROPOSED MODEL

An alternative to make machine learning practically feasible is to combine the approach to *Case-Based Reasoning* (CBR) models (Amores, 2013; Leake and McSherry, 2005). A *case* can be seen as a tuple of attributes of an instance, i.e. the records that compose an instance of the problem. The basic idea of the CBR method is to solve new instances of the problem according to solutions of previous ones (Aamodt and Plaza, 1994; Abdel-Aziz et al., 2014; McSherry, 2014; Jaidee et al., 2013), which had been stored in a knowledge database, in this paper denoted by *training set* ($\mathcal{TS}$). The update of $\mathcal{TS}$ is a 3-steps process, namely: (i) extract knowledge from previous situations; (ii) identify relevant characteristics on previous cases construct better solutions; and (iii) store solved problems as new learned cases (elements $t_i \in \mathcal{TS}$).

The quality of a CBR solution basically depends on the number of instances that define $\mathcal{TS}$. For each new instance to be solved, a comparison is conducted against instances in $\mathcal{TS}$, attempting to define whether or not it improves the solution for the problem (Aamodt and Plaza, 1994). This procedure is called *classification*. To classify new instances, we adopt in this paper a learning algorithm called *k-nn* (k-nearest neighbor)(Aha et al., 1991), which is appropriate to be used in conjunction to the CBR method.

The classification itself consists of finding a class for any new (*candidate*) instance t_c that arrives to be evaluated. Following the *k-nn* algorithm, t_c is firstly loaded to memory and it is compared to every $t_i \in \mathcal{TS}$. The element in $\mathcal{TS}$ that provides the shortest "distance" to t_c determines the class it actually belongs.

In this paper, instances are represented by data tuples and, so, we provide a model (see (1)) to implement the *k-nn* idea to classify them. We basically compare the j^{th} attribute of t_c to the j^{th} attribute of every $t_i \in \mathcal{TS}$. New instances are then derived based on the *distance similarity* between $\mathcal{TS}$ and t_c.

$$\sum_{i=1}^{n} \frac{\sum_{j=1}^{m}(t_i^j \cdot t_c^j)}{\sqrt{(\sum_{j=1}^{m}(t_i^j)^2) \cdot (\sum_{j=1}^{m}(t_c^j)^2)}} \tag{1}$$

The idea behind the model in (1) is as follows. Assume a training set $\mathcal{TS}$ such that each element $t_i \in \mathcal{TS}$, for $i = 1, \cdots, n$, is a m-tuple $\langle \iota_i, \tau_i, \mu_i, \nu_i, \gamma_i, \cdots m_i \rangle$, indexed by j_i, for $j = 1, \cdots, m$. We also assume that $t_c = \langle \iota_c, \tau_c, \mu_c, \nu_c, \gamma_c, \cdots m_i \rangle$ is a singe *candidate* tuple, which is expected to be estimate, from the training data, which class it belongs to. Thus, we associate and normalize the tuples from $\mathcal{TS}$ and t_c, obtaining as a result their similarity degree.

4.1 Example

Consider that $\mathcal{TS}$ and t_c are given as in Table 1.

Table 1: Parameters for the illustrative example.

$\mathcal{TS}$	ι_i	τ_i	μ_i	ν_i	γ_i
t_1	2	22	53	33	23
t_2	3	33	60	100	45
t_3	1	24	62	44	15
t_c	ι_c	τ_c	μ_c	ν_c	γ_c
	3	28	65	17	22

By applying (1) to the example, we obtain a similarity degree SD for t_c with respect to $i = 1, 2, 3$ respectively on the order of:

$$SD_1 = 0,96 \qquad SD_2 = 0,76 \qquad SD_3 = 0,94$$

Therefore, for this particular example, SD_1 and SD_3 clearly define the class t_c belongs to.

5 EXPERIMENTAL RESULTS

Now, we use a more realistic example to illustrates our approach. The broilers management process aims to improve the performance of a breeding (flock) in terms of feed conversion. Broiler production (broiler is a type of chicken raised specifically for meat production) is a sequential process where the ultimate performance is dependent on the successful completion of a set of steps. Each step must be toughly assessed and improvements are required for the maximum performance to be obtained. However, those steps are all interdependent, in such a way that if one of them is sub-optimal, then whole process performance suffers. The success of the poultry is directly related to environmental and feed control.

Data from the broilers management process can be formally described by 5-tuples $\langle \iota, \tau, \mu, \nu, \gamma \rangle$ where:

- $\iota = 1, 2, 3$ is the light density;
- τ, for $t \geq 18 \leq 33$, is the temperature value (C);
- μ, for $u \geq 50 \leq 70$, is the humidity value (%);
- $\nu \in \mathbb{N}$ is the spent time ventilating the structure;
- $\gamma \in \mathbb{N}$ is the amount of consumed nutrients (feed).

Temperature and humidity are collected from sensors. Ventilation time and light density can be obtained from poultry environmental controller. In order to measure the amount of consumed feed, we construct an automatic scale (see Fig. 1) able to register the total weight consumed per day.

Figure 1: Mechanism for weighing feed.

We automate the supply and transportation equipment, which has allowed us to measure flocks of feed arriving to be consumed. For the experiments, the scale has been adjusted to measure flocks of 50 *kg*, starting to operate whenever the supplier engine actuates. By reaching 50 *kg*, the supplier engine is switched off and the distribution engine starts to fill the feeders. When this step is over, the scale resets and the process restarts.

The weighing mechanism has been integrated to our learning model by the electrical device in Fig. 2 (a), which detects when the feed amount reaches the setting value (50 *kg*) and communicates this to a server (voltage levels of 0 and 5 volts (Fig. 2 (b))) through a parallel port. A monitoring software then records the action.

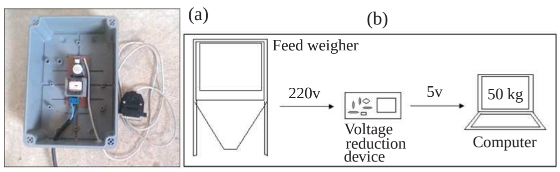

Figure 2: Device for voltage reduction.

For our experiment to be suitable for analysis by our learning model, the following modules are also integrated to the weighing mechanism, in order to properly compose instances: sensor, classifier, calculator, decision and actuator, whose interaction is depicted in Fig. 3.

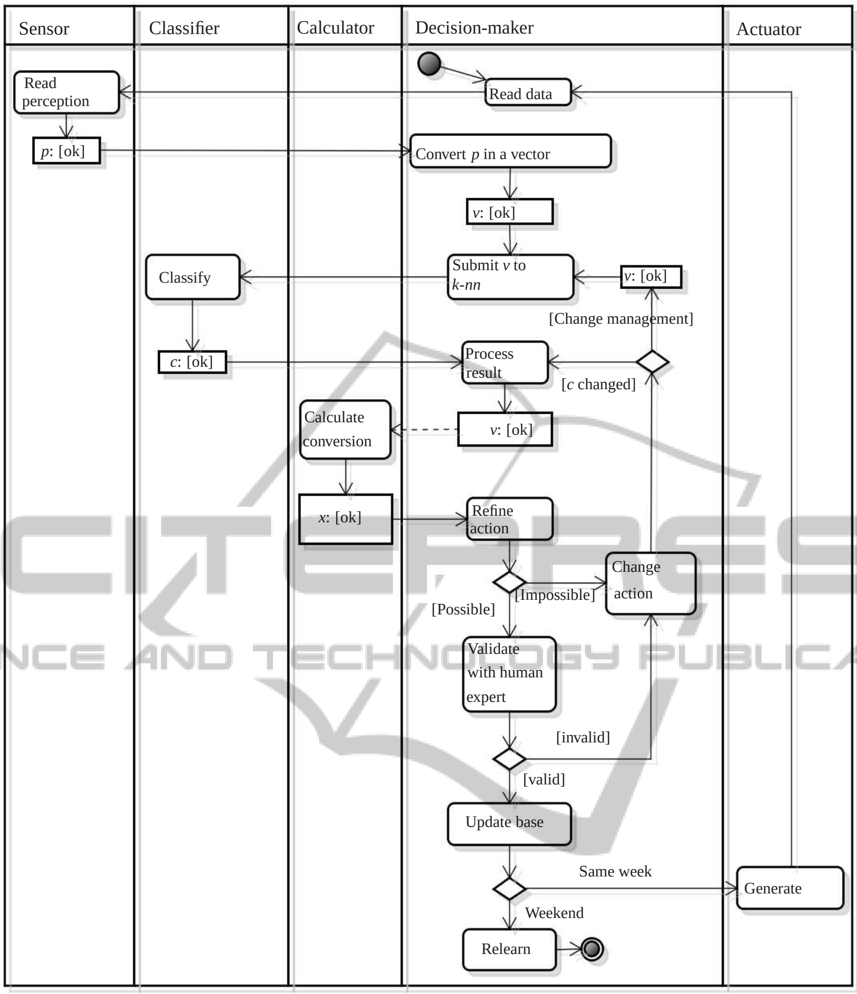

Figure 3: Learning model interaction.

The *sensor* captures different parameters from a flock, such as light density, temperature and humidity values, time ventilating, consumed feed supply. The *actuator* regulates (maintain, increases or decreases) the values of model parameters. The *calculator* module derives the value of the feed conversion (F_c), taking into account the quantity of consumed food (Q_f) and the weight of the broilers (W_b), according to the Equation (2).

$$F_c = \frac{Q_f}{W_b} \tag{2}$$

The *decision* module is responsible for the agent behavior. It receives data from sensors and generates a perception p. The values of p are then structured as a vector v in such a way that each position represents the i^{th} position of the 5-tuple that models an instance of the problem to be solved. The vector v (instance) is then submitted to the classifier, which returns an action c. Based on the value of c it has to be computed the values for the expected F_c and remaining elements in the tuple.

If the estimated value for the F_c is less than the reference value (from historical data), the state is recorded in a log file and estimated actions effected by the actuator. Otherwise, the amount of resources is increased. This happens until the F_c is smaller than the conversion generated from managements of previous flocks.

If it is not possible to increase the amount of resources of v, the previous management is maintained and the F_c is interactively recomputed until it finds a value of F_c able to optimize resources. The log generation allows to promote the process of re-learning, although this is considered beyond this paper.

The knowledge obtained from the application of machine learning can be represented by a set of rules, as illustrated next.

$$R_1: \quad (F_c < EXPECTED) \wedge (FEED\,CONSUMPTION > EXPECTED) \Rightarrow adjust\ \iota;$$

$$R_2: \quad (WEIGHT < EXPECTED) \wedge (FEED\,CONSUMPTION < EXPECTED) \wedge (LIGHT\ LEVEL \geq 2) \Rightarrow increase\ \tau;$$

...

R_1 is read as follows: "IF *a feed conversion is less than expected* and *feed intake is smaller than assumed* then *adjust the light level*". The values for the expected and estimated parameters are suggested by a human expert.

The rules presented above as well as the sequence diagram in Fig. 3 are used in conjunction to the model presented in Equation (1). An experiment is proposed to further validate the proposed learning model.

5.1 Practical Example

In the following experiments, the actions suggested by the proposed model are compared to the original management, empirically carried out by a human expert. Table 2 shows the structure and the configuration values for the experiments to be conducted.

Table 2: Structure and scenario configuration.

Parameters considered in our experiments	
Amount of broilers	25.000
Amount of flocks (historical bases)	30
Number of weeks per flock	6
Dimension of the environment (poultry)	2.100 m^2
Silo for feed	27.000
Box of water	10.000 liters
Automatic feeders	780 dishes
Automatic waterers	3.000 nozzles
Ventilation system	24 fans
Nebulization system	300 nozzles
Temperature control panel	1
Heating furnace	1

The agent behavior has been evaluated under two situations: i) based on the average weight of the broilers; and ii) on the weekly feed conversion. Both cases are discussed next.

5.1.1 Broilers Weight

An action policy is satisfactory when management employee increases the weight of the broilers and improves the feed conversion. Fig. 4 shows the average weight of broilers along six weeks (period of one flock).

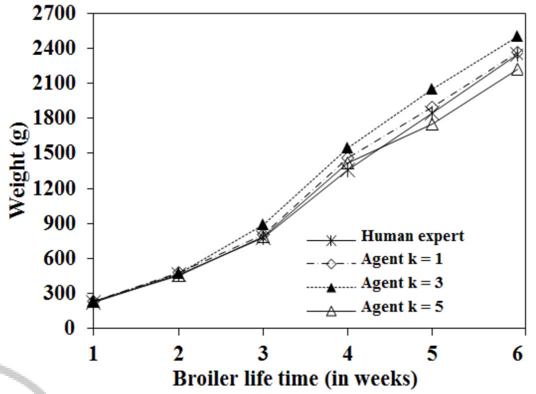

Figure 4: Broilers average weight: Agent × Human expert.

Is possible to observe that the broilers average weight is similar in the initial weeks. This occurs because during this period the growth process of broilers is influenced by the dose of certain supplements. From the third week is possible to notice that the management suggested by the agent obtains in general better efficiency in the average weight of the broilers. The best results were achieved with the agent using $k = 3$, which led to a classification with a higher degree of accuracy.

Remark also that the management suggested by the agent can increase or maintain the average weight of the broilers, because it uses historic data to generate combinatorial rules, a task that would be impracticable by human expert, given the their potential complexity. This complexity arises, for example, from the amount of management features and related combinatorial possibilities.

It is natural for the human expert to empirically select and apply resources, without considering factors such as temperature, humidity, light, broilers resting time, etc., nor the combination of these factors. In fact, the human expert merely observes and acts according to his perception and knowledge, having no mechanisms to improve the accuracy of such acts on the process. On the other hand, techniques using agents provide for the system a decision-making with minimal human intervention, in order to anticipate environmental changes and act accordingly. This occurs because during the learning procedure, an appropriate number of samples are created and, at each management, the agent seeks to specialize itself.

5.1.2 Feed Conversion

When a particular management is applied, feed conversion is modified by a number of factors, such as the environmental and structural conditions and daily activities. To be efficient in the management, the amount of feed should be constant and close enough to the maximum capacity of the reservoir, thus optimizing the time spent managing.

Usually, this is not trivial to be precisely established, though. The feed × time relationship, seeking for an efficient and profitable management, under different scenarios, can be complex even for a human expert. In this sense, an agent always attempts to maintain the amount of feed as close as possible to the maximum level. In Fig. 5, it can be noted that the feed conversion with the agent is more efficient when compared to equivalent procedure conducted by a human expert. This occurs because the agent tends to simultaneously increase the level of light, relative air humidity and temperature. On the other hand, the human expert tends to maintain such features below the expected value, attempting to achieve food conversion using few resources.

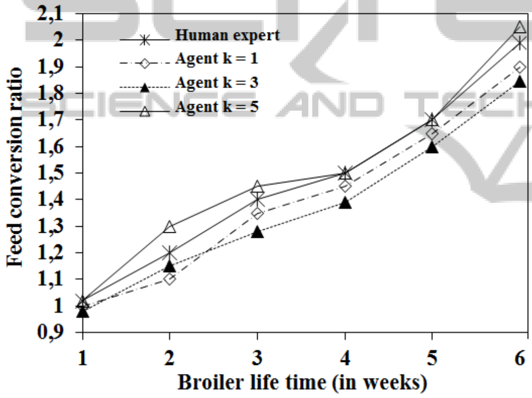

Figure 5: Feed conversion: Agent × Human expert.

Clearly, the human expert faces difficulties to predict the exact effect of actions, thus making complex the management planning throughout the broilers life cycle, indicating a feed conversion lower than expected. It has been observed that a proper (and complex) combination of different resources is more likely to lead to a higher average weight of broilers, contrasted with a lower feed intake. From the values of average broiler weight and feed conversion obtained from the use of the proposed learning model, we have noticed a substantial improvement on the broiler management process. Table 3 exemplifies the increase we have obtained on the average of weight and on the quality improvement of feed conversion, per week, on the simulated flock.

It can be observed that when previous experiences are recovered by the *k-nn* algorithm, the results are satisfactory, because the system can classify values from previous solutions, finding better results when compared to the human expert. Another advantage of the proposed model is that new processed cases lead to new solutions, which allows the agent learn and adapt its behaviors toward new situations.

Table 3: Best agent compared to the human expert.

Week	Weight (%)	Feed Conversion (%)
1	4.25	2.04
2	1.05	4.34
3	11.96	9.28
4	9.28	7.99
5	12.38	6.25
6	6.00	7.85
Average	7.48	6.29

6 CONCLUSIONS AND PERSPECTIVES

Broiler management is a complex task for humans due to the number of factors influencing on the development of broilers. In this paper, a learning model using intelligent agents has been introduced to support the automatic management of poultry farming. A learning agent controls the amount of feed, level of light, ventilation, temperature and relative humidity using the knowledge learned from previous cases (historical databases). An algorithm has been applied to classify patterns that improve feed conversion from previous data managements.

It has been shown that the proposed model substantially improves the poultry farming process. For the evaluated case, feed conversion improvements have been on the order of 6%, while the gain with broilers weight has increased in 7%. Despite promising preliminary results, additional research is yet required to complement the model and hopefully absorb the diversity of scenarios in which the human expert may be immersed.

Future research includes: i) evaluating the performance of the agent when handling specific management situations; (ii) checking the performance of the algorithm to process variations of scenario; iii) changing the set of attributes used to generate the rules, which can make them less susceptible to influence; iv) verifying the learning algorithm with other metrics distance. Such statements are objects of study for future research.

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