EU-PLF

Deliverable 4.2

Verified calculation models for socio-economic measures

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Introduction

Precision Livestock Farming (PLF) technology is an emerging research field that develops management tools aimed at (near) real-time automatic and continuous monitoring of animal production, growth, and animal health and welfare. By continuous monitoring, PLF wants to support farmers and their advisors in making better daily management decisions based on information from additional 'senses'. Moreover, PLF aims at making farmers less dependent on availability of human labour. The development of new PLF concepts (sensors and/or other hardware) that are potentially interesting for application on-farm are numerous: 126 peer-reviewed studies on 139 PLF technologies were published for the dairy cattle industry alone (Rutten et al., 2013) from January 2002 to June 2012. The emerging international conferences (e.g., Smart Agrimatics 2014, the European Conference on Precision Livestock Farming 2015, and the First International Conference on Precision Dairy Farming 2016) that focus on the collection, storage and use of sensor data confirm the growing need of improved management of animals using PLF technology.

Despite the growing demand for PLF technologies for decision support management, the uptake of most PLF concepts on commercial farms has been modest and slow. There are several explanations for these low adoption rates. The fact that PLF technologies generate substantial amounts of data without converting it into useful information for decision management was ranked in the top-three of explanations by dairy farmers (Russell and Bewley, 2013). This explanation may apply for PLF technologies developed for other livestock production systems too. Russell and Bewley (2013) also reported 'undesirable cost/benefit ratio' in the top-three and 'lack of perceived economic value' in the top-ten of explanations by dairy farmers for the modest uptake of PLF technologies.

The net economic benefit of PLF technology when applied on-farm is one of three key characteristics that determines the potential value of a PLF technology, in addition to 'development costs' and 'farmers' preferences' (Hogeveen and Steeneveld, 2013). At the same time, the absence of clear cost and even more so benefit data of PLF technologies is one of the most important limiting factors for commercialisation of PLF technologies (Banhazi et al., 2013). Economic analyses are, therefore, essential and logic thinking suggests that a PLF technology is likely to become more successful when information on the potential economic value is available. The economic value of a PLF technology depends on many different aspects of the PLF application (Hogeveen and Steeneveld, 2013). Many technologies aim at improving health statuses of animals (e.g., udder health in dairy cows, or respiratory diseases in broilers and fattening pigs). The costs of diseases are then an important element as these costs form the potential economic value of the PDF technology. But the improvement of animal health (and thus the reduction of costs made because of disease occurrence) are not the only element that PLF technology can influence: improved management and production efficiency and reduced labour are some other areas that can be affected.

Recently, several economic calculation tools for automated heat detection in dairy cattle have been developed that provide insight in the potential economic benefit of implementing these PLF technologies on-farm. These tools range from straightforward partial budgeting approaches (e.g., Jago et al., 2011), to bio-economic models such as those described by Bewley et al. (2010) and Rutten et al. (2014). It is of no surprise, really, why automated oestrus detection systems are one of the few PLF technologies for which such economic calculation tools are available: the technical performances of these systems are known and sufficient for field application, and the associated management action (inseminate this cow) is very clear. However, for PLF technologies that cannot be easily linked to a clear management action, or where there is little or no information on technical performances, estimating the economic benefit of implementing PLF technologies becomes more complicated. Finally, the available economic calculation tools do not acknowledge the potential social value of PLF technologies.

This deliverable will provide generic tools to assess the economic value of PLF technologies and to assess the preference for a number of social and economic indicators of PLF technologies. With these tools, suppliers and developers of PLF technologies can gain insight in the potential economic impact of PLF technologies, they can assess break-even points of investing in these technologies, and they can gain insight which social or economic aspects of PLF technologies are preferred by their potential buyers (farmers).

1. Levels of expressing value

The added value of PLF technologies can be of monetary (economic) value, but benefits can also be of social value. For some PLF technologies, e.g., automated heat detection in dairy cattle, estimating the potential economic benefit can be fairly straightforward. As long as technical performance of the PLF technology is known, and knowledge is available on area of farm management that is influenced and to what extent, the economic benefit can be estimated. In other words, the economic benefits of these PLF technologies are tangible. A clear example of such a PLF technology is the automated heat detection on dairy farms. However, there are PLF technologies where knowledge on technical performance is not (yet) available, or where it is not clear what management areas are affected to what extent. For other technologies it is unclear what management actions or interventions are associated with whatever the PLF technology is monitoring. Suppliers and developers of PLF technologies may have an idea of what management areas are affected, but the effects are not (yet) tangible. Such PLF technologies often monitor something and display the data graphically, but farmers still have to interpret the provided information and formulate appropriate decisions and management actions. Example of these PLF technologies with semi-tangible benefits are, e.g., systems that monitors broiler distribution or that monitor coughing sounds (e.g., for fattening pigs). Finally, the added value of PLF technologies can be of social value. These social values are often hard to measure and even harder to express in a monetary value. These PLF technologies have intangible benefits. Examples of these social benefits include social recognition, job satisfaction, and the easy of mind knowing that there are ‘ears and eyes’ working on your farm 24 hours, 7 days a week. But also labour conditions and the hours of labour are potential social benefits.

Since there are three levels to express benefit (value) of PLF technologies (tangible, semi-tangible, and intangible level), each of these three levels require their own tools to estimate the potential value of PLF technologies.

2. Estimating tangible effects

For the tangible PLF technologies, that can be linked to farm management areas and/or actions, a tool has been developed to estimate the economic benefits of implementing such a technology. This ‘Value Creation Tool’ works at farm level, and therefore, it’s inputs are parameters at farm level. Because dairy farms, fattening pig farms and broiler farms differ in many aspects (including labour, the value of buildings and inventory, and (volatile) market prices), one Value Creation Tool has been developed for each of these three groups. All three tools, however, use technical parameters (e.g., farm size, labour) and data on investments, costs and prices that are relatively easily accessible for farmers. The economic benefit of the PLF technology at farm level should, therefore, be associated with a change in these parameters. For example, the PLF technology can result in a decreased mortality rate in broilers, or an increased milk yield per dairy cow per year.

All three Value Creation Tools analyse two situations: a situation without PLF technology, and the alternative situation where PLF technology is implemented. The economic benefit of PLF technology is then assessed by comparing the output of these three tools for these two situations. All three Value Creation Tools generate two output parameters: the net farm income (NFI) and labour income (LI). The NFI is calculated by subtracting the total costs (TCO) from the total revenues (TRE):

(1) $NFI = TRE – TCO$

Labour income is then calculated by adjusting the NFI for the costs of own labour.

(2) $LI = NFI + Cost_{labour}$

Since the TRE and TCO are calculated differently for the three animal groups, the calculations to estimate these two outcome parameters are explained in more detail below for each of the three animal groups separately.

2.1 Estimating tangible effects on dairy farms

For dairy farms, the TRE consist of the revenues from milk production and the sales of animals or, e.g., roughage (for abbreviations see Table 1):

(3) $TRE = ((MP*PM) + LR + MR) * FS$

The TCO consist of costs for feed ($Cost_{feed}$), costs for buildings ($Cost_{buildings}$) and for machinery and equipment ($Cost_{mach\_equip}$), costs for land ($Cost_{land}$), costs of the interest rate of livestock ($Cost_{irl}$), costs for labour ($Cost_{labour}$), other costs ($Cost_{other}$), and in case of presence of PLF technology, the costs for PLF ($Cost_{PLF}$), so

(4) $TCO = Cost_{feed} + Cost_{buildings} + Cost_{mach\_equip} + Cost_{land} + Cost_{irl} + Cost_{other} + Cost_{labour} + Cost_{PLF}$

Where,

(5) $Cost_{feed}$ = (CMM+R)*FS

(6) $Cost_{buildings}$ = (RVB*DB)+(RVB*(NIR/2))+(RVB*MB)

(7) $Cost_{mach\_equip}$ = (RVME*DME)+(RVME*(NIR/2))+(RVME*MME)

(8) $Cost_{land}$ = (L*VL*IRL) + (FS*LL)

(9) $Cost_{irl}$ = NIR* ((FS*PDC)+(((RH*FS)-(MRH*RH*HS))*PH) +(FS*RH*PC))

(10) $Cost_{other}$ = ((CW+HCP+HCC+AIB+MC)*FS) + (FP*L)

(11) $Cost_{labour}$ = LP*LH * PL

(12) $Cost_{PLF}$ = (RVPLF*DPLF)+(RVPLF*(NIR/2))+(RVPLF*MPLF)+(VCPLF*FS)

2.2 Estimating tangible effects on fattening pig farms

For fattening pig farms, the TRE consist of the total delivered kg of meat times the price per kg. The total amount of produced meat consists of the total amount of purchased piglets minus those who died times the weight at delivery. This produced amount of meat has to be multiplied by the slaughter/live weight ratio to get to the total amount of delivered kg of meat. The TRE, therefore, is calculated as (for abbreviations see Table 2):

(13) TRE = DLpig*WPD*SLWR*PFP

The TCO consist of costs for purchased piglets ($Cost_{purchase}$), costs for feed ($Cost_{feed}$), costs for health care ($Cost_{health}$), costs of buildings ($Cost_{buildings}$), costs of the interest rate of livestock ($Cost_{irl}$), delivery costs ($Cost_{delivery}$), other costs ($Cost_{other}$), costs due to mortality ($Cost_{mort}$), costs for labour ($Cost_{labour}$), and in case of presence of PLF technology, the costs for PLF ($Cost_{PLF}$), so

(14) TCO = $Cost_{purchase}$ + $Cost_{feed}$ + $Cost_{health}$ + $Cost_{buildings}$ + $Cost_{irl}$ + $Cost_{delivery}$ + $Cost_{other}$ + $Cost_{mort}$ + $Cost_{labour}$ + $Cost_{PLF}$

Table 1: Input parameters, abbreviations (Abb) and Unit used to estimate economic impact of PLF technologies on dairy farms.

Input Parameters	Abb	Unit
Technical parameters		
Labour	LP	Full time equivalent
Labour hours	LH	Hours/year
Farm size	FS	Dairy cows
Replacement ratio heifers	RH	% of dairy cows
Mortality Replacement heifers	MRH	% of replacement heifers
Land	L	Ha
Milk production	MP	Kg milk/cow/year
Buildings, machinery and equipment (M&E)		
Value of Land	VL	€/ha
Interest rate Land	IRL	%
Nominal interest rate	NIR	%
Replacement value of buildings	RVB	€
Depreciation buildings	DB	% of total investment
Maintenance buildings	MB	% of total investment
Replacement value M&E	RVME	€
Depreciation M&E	DME	% of total investment
Maintenance M&E	MME	% of total investment
Replacement value PLF	RVPLF	€
Depreciation PLF	DPLF	% of total investment
Maintenance PLF	MPLF	% of total investment
Prices		
Dairy cow	PDC	€/dairy cow
Heifer (1-2 years)	PH	€/heifer
Calf	PC	€/calf
Milk	PM	€/kg milk
Labour	PL	€/hour
Other Revenues		
Livestock revenues	LR	€/dairy cow
Miscellaneous revenues	MR	€/dairy cow
Other Costs		
Rearing costs	RC	€/heifer
Concentrates, milk products, minerals	CMM	€/dairy cow
Roughage	R	€/dairy cow
Land leas	LL	€/dairy cow
Fertilizer and pesticides	FP	€/ha
Customer work	CW	€/dairy cow
Health care (preventive)	HCP	€/dairy cow
Health care (curative)	HCC	€/dairy cow
Artificial insemination and Breeding	AIB	€/dairy cow
Miscellaneous costs (water, electricity)	MC	€/dairy cow
Variable costs for PLF	VCPLF	€/dairy cow

Where,

(15) $Cost_{purchase}$ = DLpig*P

(16) $Cost_{feed}$ = (WPD-WPP)*FC*(PF/100)*DLpig

(17) $Cost_{health}$ = DLpig*HC

(18) $Cost_{building}$ = ((RVBI*FS)*DPB)+((RVBI*FS)*(NIR/2))+((RVBI*FS)*MB)

(19) $Cost_{irl}$ = AIP * NIRcor * DLpig

(20) $Cost_{delivery}$ = DLpig * DC

(21) $Cost_{other}$ = DLpig * MC

(22) $Cost_{mortality}$ = (DPig*P)+((($Cost_{feed}$+$Cost_{health}$+$Cost_{irl}$+$Cost_{other}$)/DLpig)/2)*DPig)))

(23) $Cost_{labour}$ = LP*LH*PL

(24) $Cost_{PLF}$ = (RVPLF*FS*DPLF)+(RVPLF*FS*(NIR/2))+(RVPLF*FS*MPLF)+(VCPLF*FS)

2.3 Estimating tangible effects on broiler farms

For broiler farms, the TRE are made-up of the total delivered kg of meat times the price per kg. The total amount of produced meat consists of the total amount of purchased broilers minus those who died times the weight at delivery. This produced amount of meat has to be multiplied by the slaughter/live weight ratio to get to the total amount of delivered meat. The TRE, therefore, is calculated as (for abbreviations see Table 3):

(25) TRE = DLbroiler*WD*SPB

The TCO are made-up of the costs for purchased broilers ($Cost_{purchase}$), costs for feed ($Cost_{feed}$), costs for health care ($Cost_{health}$), costs of buildings ($Cost_{buildings}$), costs of the interest rate of livestock ($Cost_{irl}$), delivery costs ($Cost_{delivery}$), miscellaneous costs for water, heating and electricity ($Cost_{mc}$), general costs and manure disposal ($Cost_{gm}$), costs for litter ($Cost_{litter}$), costs due to mortality ($Cost_{mort}$), costs for labour ($Cost_{labour}$), and in case of presence of PLF technology, the costs for PLF ($Cost_{PLF}$), so

(26) TCO = $Cost_{purchase}$ + $Cost_{feed}$ + $Cost_{health}$ + $Cost_{buildings}$ + $Cost_{irl}$ + $Cost_{delivery}$ + $Cost_{mc}$ + $Cost_{gm}$ + $Cost_{litter}$ + $Cost_{mort}$ + $Cost_{labour}$ + $Cost_{PLF}$

Where,

Table 2: Input parameters, abbreviations (Abb) and Unit used to estimate economic impact of PLF technologies on fattening pig farms.

Input Parameters	Abb	Unit (Notes)
Technical parameters		
Labour	LP	Full time equivalent
Labour hours	LH	Hours/year
Farm size	FS	Pig places
Length of fattening period	LFP	Days
Length of cleaning and disinfection	CLD	Days
Fattening rounds	FR	Rounds per year (=365/(LFP+CLD)
Weight piglet at purchase	WPP	Kg / piglet
Weight pig at delivery	WPD	Kg / fattening pig
Slaughtered / live weight ratio	SLWR	%
Feed conversion	FC	Kg feed / kg growth
Mortality rate	MR	%
Purchased piglets	PPig	Purchased piglets per year (=FS*FR)
Died piglets	DPig	Died piglets per year (=PPig*MR)
Delivered pigs	DLpig	Delivered pigs per year (=PPig-DPig)
Average Investment Pig	AIP	€/delivered pig (=P+(WPD*SLWR*PFP-DC)/2
Buildings, and inventory		
Nominal interest rate	NIR	%
Nominal interest rate corrected	NIR-cor	% (=NIR/(365/LFP)
Replacement value of buildings and inventory	RVBI	€/pig place
Depreciation buildings	DPB	% of total investment
Maintenance buildings	MB	% of total investment
Replacement value PLF	RVPLF	€/pig place
Depreciation PLF	DPLF	% of total investment
Maintenance PLF	MPLF	% of total investment
Prices		
Price piglet	P	€/piglet
Price fattening pig (slaughtered weight)	PFP	€/kg (corrected price if applicable)
Feed	PF	€/100kg
Labour	PL	€/hour
Other Costs		
Health care	HC	€/purchased piglet
Delivery costs	DC	€/delivered fattening pig
Miscellaneous costs (manure, electricity)	MC	€/delivered fattening pig
Other variable costs for PLF	VCPLF	€/pig place

(27) $Cost_{purchase}$ = DLbroiler*PPCostfeed = WD*FC*(PF/100)*DLbroiler

(28) $Cost_{health}$ = DLbroiler*HC

(29) Costbuilding = ((RVBI*FS/N/R)*DPB)+((RVBI*FS/N/R)*(NIR/2))+((RVBI*FS/N/R)*MB)

(30) $Cost_{irl}$ = NIRcor * AIB * DLBroiler

(31) $Cost_{delivery}$ = DLBroiler * DC

(32) $Cost_{mc}$ = DLBroiler * MC

(33) $Cost_{gm}$ = DLBroiler * GMC

(34) $Cost_{litter}$ = DLBroiler *L

(35) $Cost_{mortality}$ = (DBroiler*PP)+((($Cost_{feed}$+$Cost_{health}$+$Cost_{irl}$+$Cost_{mc}$+$Cost_{gm}$+$Cost_{litter}$)/DLbroiler)/2) *DBroiler)

(36) $Cost_{labour}$ = LP*LH*PL

(37) $Costs_{PLF}$ = ((RVPLF*FS/R)*DPLF)+((RVPLF*FS/R)*(NIR/2))+((RVPLF*FS/R) *MPLF)+(VCPLF*FS /R)

Table 3: Input parameters, abbreviations (Abb) and Unit used to estimate economic impact of PLF technologies on broiler farms.

Input Parameters	Abb	Unit (Notes)
Technical parameters		
Labour	LP	Full time equivalent
Labour hours	LH	Hours/year
Farm size	FS	Number of broilers
Length of growth period	LGP	Days
Length of cleaning and disinfection	CLD	Days
Rounds	R	Rounds per year (=365/(LGP+CLD)
Weight at delivery	WD	Kg / broiler
Number of animals / m^2	N	Broilers / m^2
Feed conversion	FC	Kg feed / kg growth
Mortality rate	MR	%
Purchased broilers	PBroiler	Purchased broilers per year (=FS*R)
Died broilers	DBroiler	Died broilers per year (=PBroiler*MR)
Delivered broilers	DLBroiler	Delivered broilers per year (=PBroiler - DBroiler)
Average Investment Broiler	AIB	€ /delivered broiler (=PP+((WD*SPB)-DC-$Cost_{building}$/DLBroiler))/2)
Buildings, and inventory		
Nominal interest rate	NIR	%
Nominal interest rate corrected	NIRcor	% (=NIR/(365/LGP)
Replacement value of buildings and inventory	RVBI	€/m^2
Depreciation buildings	DPB	% of total investment
Maintenance buildings	MB	% of total investment
Replacement value PLF	RVPLF	€/m^2
Depreciation PLF	DPLF	% of total investment
Maintenance PLF	MPLF	% of total investment
Prices		
Purchase price	PP	€/animal
Sales Price broiler (live weight)	SPB	€/kg of live weight
Price broiler	PB	€/broiler (=WD*SPB – DC)
Feed	PF	€/100kg
Labour	PL	€/hour
Other Costs		
Health care	HC	€/purchased broiler
Litter	L	€/purchased broiler
Delivery costs	DC	€/purchased broiler
General costs and manure disposal	GMC	€/purchased broiler
Miscellaneous costs (heating, water, electricity)	MC	€/purchased broiler
Other variable costs for PLF	VCPLF	€/purchased broiler

2.4 Baseline scenarios to assess the tangible effects

During a EU-PLF workshop organized in Unna in April 2014, it became clear that it was hard to retrieve information about the (range of) impact of PLF technologies on input parameters in the absence of a clear farm description on which the PLF technology would be implemented. To overcome this problem, for each animal group, four baseline scenarios for the Value Creation Tools were developed. These baseline scenarios are developed such that a wide range of different farm situations were covered. Two economically-based criteria were used to define these baseline scenarios: labour efficiency and capital intensity. For each baseline scenario, a region and country was selected in which farms were expected to meet the criteria. Figure 1 and 2 graphically demonstrate the baseline scenarios for dairy farms and for fattening pig or broiler farms, respectively. For each baseline scenario, values for the input parameters used in the Value Creation Tools were identified based on expert knowledge, or assessed from literature or national agricultural databases. Each baseline scenario, thus, represent a situation within the Value Creation Tools in which PLF technology is not implemented.

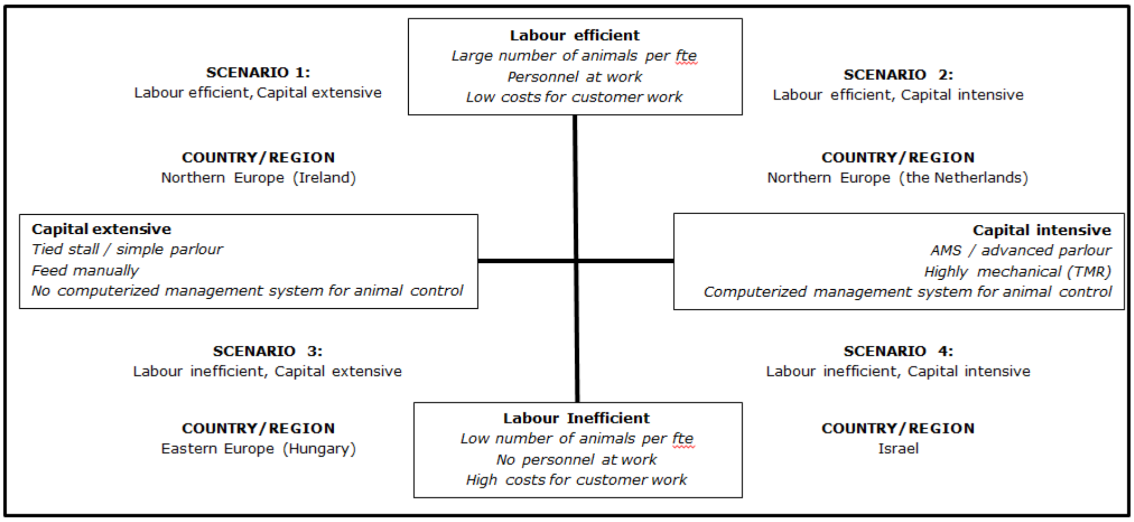

Figure 1. Baseline scenarios for dairy farms based on labour efficiency and capital intensity

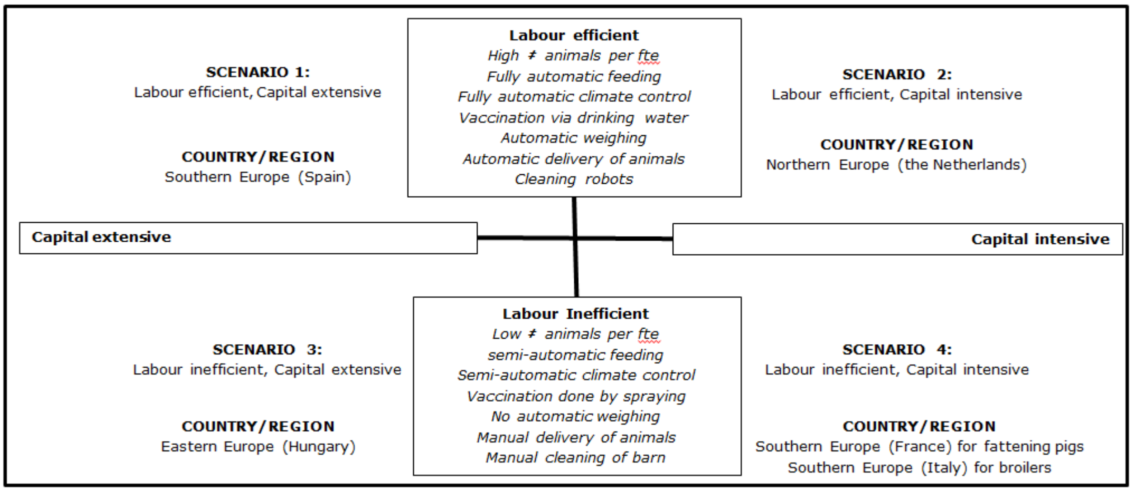

Figure 2. Baseline scenarios for fattening pig farms or broiler farms based on labour efficiency and capital intensity

2.5 Using the Value Creation Tool: the example of automated heat detection on dairy farms

Automated heat detection systems are becoming a mainstream PLF technology on dairy farms. It is estimated that approximately 20% of Dutch dairy farmers are using this system today (K. Huijps, CRV, Arnhem, the Netherlands, personal communication). These systems often monitor a cow's behaviour (e.g., activity, number of steps, number of lying bouts). Changes within this behaviour are then used as a proxy for a heat event. The systems generate a heat alert to farmers, and the associated management action by the farmer involves ordering semen and inseminating the cow. Implementation of automated heat detection on dairy farms is used as an example to illustrate how the Value Creation Tool works is used to gain insight in the potential economic benefit of PLF technologies.

As baseline scenario, the scenario of a labour efficient and capital intensive dairy farm is chosen (Scenario 2, Figure 1). Farms that meet the described criteria of this scenario can be found in, e.g., the Netherlands. Therefore, the Dutch agricultural national database (LEI, 2014) and literature are used to determine values for the input parameters used in the Value Creation Tool for dairy farms. These values are listed in Table 4 and define a situation in which no PLF technology is implemented. Using these values and the aforementioned formulas (formula 1 through 12), the Value Creation Tool estimates NFI at €11,933 and LI at €49,373. The alternative situation within the Value Creation Tool describes the same labour efficient and capital extensive farm but with implementation of automated heat detection (PLF; Table 4). Input parameters that are affected by implementing automated heat detection are changed accordingly (grey cells in Table 4). In addition to these effects on input parameters, investment and maintenance costs for automated heat detection systems are added. The investment costs were estimated at €10,000 with a depreciation period of 10 years and annual maintenance costs of 1% of the investment. Using these new values for input parameters, the Value Creation Tool estimates an NFI of €14,662 and an LI of €52,102 for the PLF situation. In other words, investing in automated heat detection has an estimated positive economic impact of €2,729 per annum for this labour efficient and capital intensive dairy farm.

Table 4: Input parameters and their units used to estimate the economic impact of PLF technologies on dairy farms. The values presented are for a labour and capital intensive dairy farm (LEI, 2014, unless otherwise stated) without PLF technology (no PLF) and for the same farm when automated heat detection (PLF) is implemented. Values for parameters that change due to the implementation of PLF are coloured grey

Input Parameters	Unit	No PLF	PLF
Technical parameters			
Labour	FTE	1	1
Labour hours	Hours/year	2,080	2,080
Farm size	Dairy cows	80	80
Replacement heifers	% of dairy cows	38	30
Mortality Replacement heifers	% of replacement heifers	10	10
Land	Ha	49	49
Milk production	Kg milk/cow/year	8,100	8,222
Buildings, machinery, and equipment			
Value of Land	€/ha	27,000	27,000
Interest rate Land	%	2	2
Nominal interest rate	%	5	5
Replacement value of buildings [1]	€[b]	800,000	800,000
Depreciation buildings	% of total investment	4	4
Maintenance buildings	% of total investment	1.5	1.5
Replacement value machinery and equipment	€	126,000	126,000
Depreciation machinery and equipment	% of total investment	10	10
Maintenance machinery and equipment	% of total investment	5	5
Replacement value PLF	€	-	10,000
Depreciation PLF	% of total investment	-	10
Maintenance PLF	% of total investment	-	1
Prices			
Dairy cow	€/dairy cow	1,200	1,200
Heifer (1-2 years)	€/heifer	835	835
Calf	€/calf[b]	100	100
Milk	€/kg milk	0.39	0.39
Labour	€/hour[a]	18	18
Other Revenues			
Livestock revenues	€/dairy cow	259	259
Miscellaneous revenues	€/dairy cow	166	166
Other Costs			
Concentrates, milk products, minerals	€/dairy cow	680	690
Roughage	€/dairy cow	121	121
Land lease	€/dairy cow	0	0
Fertilizer and pesticides	€/ha	87	87
Customer work	€/dairy cow[b]	200	200
Health care (preventive)	€/dairy cow[b]	50	50
Health care (curative)	€/dairy cow[b]	150	150
Artificial insemination and Breeding	€/dairy cow	80[b]	70
Miscellaneous costs	€/dairy cow[b]	200	200
Other variable costs for PLF	€/dairy cow	-	-

[1]incl. milking parlour; [a]Huijps *et al.*, 2008; [b]Expert knowledge; [d] based on Mohd Nor *et al.,* 2012

2.6 Using the Baseline Scenarios: the example of automatically weighing pigs

The different baseline scenarios can also be used to identify in which scenario PLF technologies are expected to have the biggest economic benefit or impact. On fattening pig farms, pigs are delivered to the slaughter house when they have reached a certain live-weight. In some countries, however, the price per delivered pig is reduced if there are too many pigs outside the expected pre-defined live-weight range. Automatic weighing of fattening pigs can help farmers to preselect pigs, to better estimate when the majority of the pigs are in the right live-weight range, and to adjust feed if necessary. Moreover, delivery costs and feeding costs can reduce as a result of this automatic weighing. All four baseline scenarios for fattening pig farms (Figure 2) are used to assess the potential economic benefit. For each baseline scenario, values for input parameters are found and these scenarios assume to represent farms without automatic weighing of pigs. Those input parameters affected by the pig weigh scale are adapted to estimate the economic situation for a farm with this PLF technology. The difference in NFI and LI between these two situations can be calculated with the Value Creation Tool for each baseline scenario. Figure 3 summarizes results for differences in LI. Implementing an automatic pig weight scale, in this example, has the largest effect on labour efficient and capital intensive fattening pig farms. Other baseline scenarios also demonstrate to have a positive economic effect on LI, but to a lesser extent. Within each of the analysed baseline scenarios, the automatic pig weight scale had the biggest effect on feed costs and delivery costs. The economic benefit for the labour efficient and capital intensive fattening pig farm is much larger, particularly because the automatic pig scale has a large impact on the price per delivered fattening pig by reducing the reduction of the delivery price by the slaughter house.

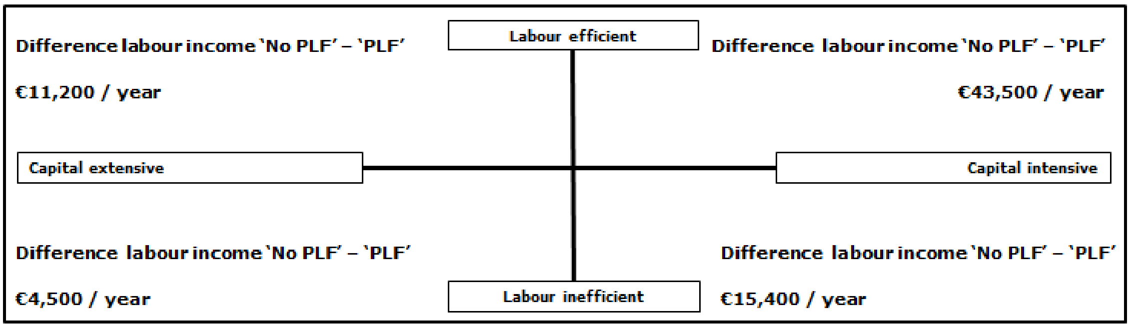

Figure 3. Difference in labour income between farms without PLF (No PLF) and those with an automatic pig weight scale (PLF) for four Baseline Scenarios for fattening pig farms. Differences are calculated using the Value Creation Tool for fattening pig farms, for all four Baseline Scenarios (see Figure 2).

3. Estimating semi-tangible effects

There are PLF technologies that are believed to have economic effects at farm level, but for which it is not possible (yet) to link the technology to clear areas of farm management and/or management actions. Examples of these PLF technologies with semi-tangible benefits involve, e.g., automatic weighing of dairy cows, or the monitoring of broiler distribution. Monitoring these aspects can be valuable for farmers and information may help farmers to note deviations from normal earlier than in a situation without these PLF technologies. Because farmers note these deviations earlier, this may lead to an earlier intervention, but farmers still have to interpret the information and think of potential causes and appropriate interventions (management actions). Estimating the economic benefit from these PLF technologies is much more difficult than for tangible PLF technologies. The Value Creation Tools as described in the previous chapter are, thus, not useful as there are too many unknown parameters. However, in most cases, the investment costs of these semi-tangible technologies are known. The Value Creation Tools can then be used to estimate how much, for example, milk production per cow per year has to increase to break-even with the investment of the semi-tangible PLF technology.

3.1 Estimating the break-even point of PLF technology.

For each of the three animal groups, a Break-Even Tool has been developed. Each Break-Even tool uses the associated Value Creation Tool to estimate NFI (as calculated using the formulas in the previous chapter) for a situation with and without PLF technology. The Break-even Tool then uses Solver (an add-in tool readily available within Microsoft Office Excel), to estimate the required change within one input parameter of the Value Creation Tool to ensure that the NFI in both situations are the same. In doing so, the break-even point with the investment of PLF technology is calculated. The Break-even Tools, thus, uses the following formula:

$$NFI_{no\ plf} = NFI_{plf} \mid X$$

Where X can be any singular input parameter of the Value Creation Tool and which is the parameter the Break-even Tool is allowed to adjust such that NFI in both situations is equal.

3.2 Using the Break-even Tool: the example of monitoring weight of cows on dairy farms.

Suppose, there is a PLF technology that monitors a cow’s weight each time she is milked (usually twice a day). The cow’s individual weight is displayed graphically to the farmer and the famer uses this information to assess whether the cow is not losing too much weight during early lactation. If it appears that she is in a negative energy balance for too long, the farmer may decide to increase the amount of concentrate or decides to change to another type of concentrate that better fits the cow’s need. Suppose, farmers have to invest €10,000 in this this PLF technology, and that the supplier uses a depreciation period of 15 years and estimates maintenance costs per year to be 1% of the investment costs. There are no additional variable costs associated with this PLF technology. This information can be used as input for the PLF situation in the Value Creation Tool for dairy farms. For example, this PLF technology is implemented on a labour efficient and capital intensive dairy farm (Baseline Scenario 2; Figure 1). The Value Creation Tool estimates the NFI for this type of farm (using the default values for this scenario as input parameters) at €11,933 for the situation without PLF. The tool estimates NFI at €10,916 after investing in this PLF technology. This NFI is lower because the Value Creation Tool adjusts for the costs of this PLF technology, but no other input parameter has been changed since it is unknown what parameters are expected to change and to what extent. So, the difference in NFI is €1,017. In theory, the PLF technology should have an economic benefit of at least this same amount of money to break-even with the investment costs. The Break-even Tool is allowed to change one parameter within the Value Creation Tool to reduce this difference to zero. The Break-even Tool can change any input parameter of the Value Creation Tool, but intuitively the parameter to be changed should be one that the supplier or farmer believes is affected as a consequence of implementing the PLF technology. Suppose, the supplier thinks that milk production per cow per year may increase as a result from using automatic weighing of cows (since farmers are able to reduce the length and intensity of the negative energy balance). The Break-even Tool estimates to what extent the milk production per cow per year should increase to ensure that NFI is the same for the situation with and without PLF. Table 5 demonstrates how the outcome of the Break-even Tool may look like. In case the automatic weighing would only affect milk production, then milk production has to increase with 32.6 kg per cow per year to break-even with the investment. In case the automatic weighing would only affect the amount of concentrates fed to cows, the costs of concentrates should reduce with €12.71 per cow per year to break-even with the investment (Table 5). Table 5 also summarizes how much the amount of working hours per year should reduce (75h per year) to break-even with the investment, but it is not likely that automatic weighing reduces the amount of hours farmers work.

Table 5. Example of using Solver to estimate the break-even point of investing in semi-tangible PLF technologies. In this example, parameter values for Default Scenario 2 (labour efficient and capital intensive dairy farm; Figure 1) are used as input for the Value Creation Tool for dairy farms. Input parameters that the Solver can change are milk production, costs of concentrates, and the number of working hours per year

Input investment costs PLF technology		*Output Value Creation Tool using Default Scenario 2 (€)*	
Investment (€)	10,000	$NFI_{no\ pl}$	11,933
Depreciation (years)	15	NFI_{plf}	10,916
Maintenance (% investment)	1	Difference	1,017
Variable costs (€)	--		

Input parameters	*No PLF*	*PLF*	*Solver solution to break-even ($NFI_{no\ plf} = NFI_{plf}$)*
Milk production	8,100	8,132.6	+ 32.6 kg of milk per cow per year
Costs of concentrates	680	667.29	- €12.71 per cow per year
Hours per year	2,080	2,005	- 75 hours per year

4. Estimating intangible effects

The potential value of PLF technologies is not always (semi-)tangible, and farmers do not always invest in PLF technology because of (perceived) economic benefit. There are social factors that influence farmers' decisions to invest in PLF technologies. Examples of social value include social recognition, job satisfaction, the easy of mind knowing that there are 'ears and eyes' working on your farm 24 hours, 7 days a week. But also labour conditions and the hours of labour are potential social benefits. These social factors are hard to estimate and even harder to express in a monetary value, but these factors should not be underestimated for their influence in making a PLF technology successful. A clear example of the strength of social benefits are automated milking systems (AMS). With over 10,000 farms worldwide using AMS (Rodenburg, 2013), this technology is likely to be one of the most well-adopted PLF technologies at present. This may be surprising, since several studies concluded that AMS negatively affect economic performance at farm level when compared with milking in a conventional milking parlour (Hogeveen and Steeneveld, 2013). However, the two most important motivators for farmers to invest in AMS were (1) a reduction in heavy labour, and (2) flexibility of working hours (Hogeveen et al., 2004). Both motivators are strongly linked with social factors, and thus social benefits in this particular example are preferred over economic benefits. Insight in the preference of potential buyers (farmers) for social and economic benefits of PLF technology is of value for suppliers as insight in these aspects can support with the development of PLF technologies such that the preferences are met as much as possible. Disregarding preferences of (groups of) farmers will probably lead to an unsatisfactory adoption rate of PLF technologies. Preferences of social and economic benefits of potential buyers of PLF technologies can be assessed using an Adaptive Conjoint Analysis (ACA).

Conjoint analysis is a questionnaire-based method for market research and used to determine desirable features (and prices) of defined products based on different attributes and levels of these attributes (Huijps et al., 2009; Mollenhorst et al., 2012). The term 'adaptive' refers to the fact that the computerized-administered questionnaire is customized for each respondent: at each step, previous answers are used to decide which question is asked next to obtain the most information about respondent's preferences (Sawtooth Software, 2007). An ACA is a multivariate model that assumes that consumers buy products (e.g., a car), which have a number of characteristics (attributes in ACA terminology) each with its own levels. So, the product 'car' has ' colour' as an attribute. This attribute has 'black', 'white', or 'red' as its levels. Each attribute of a product, a, has two or more levels, i.

An ACA consists of four distinct sections in which information is derived from the respondents' preferences for the different levels of each attribute of a product (Sawtooth Software, 2007). After and during each section, derived information is updated and used as input for the next section. The derived information are called part-worth utilities, which are always zero-centred. Part-worth utilities comprise information on the relative preference for attributes. More importantly, these part-worth utilities contain vector information on which level is preferred over another. Part-worth utilities are refined through a series of graded paired comparisons using a hierarchical Bayesian updating sense (where the respondents' previous answers are used at each step to select the next paired combination question to collect as much information as possible). The final part-worth utilities are estimated for each level of an attribute. The difference between the most and the least preferred level within an attribute result in the relative preference or utility scores for each attribute (μ(ai)). A respondent's utility U for a multi-attributed product, can be expressed in a simple way as the sum of utilities for its attributes μ(ai):

(1) $U = \mu(a_1) + \mu(a_2) + \ldots + \mu(a_n)$

The sum of the importance of all attributes per individual's response always equals 100%. A crucial assumption of conducting an ACA survey is that attributes are not mutually exclusive. Huijps et al. (2009) provides an excellent detailed appendix on ACA. Van Soest (2015) provides a clear description how part-worth utilities are computed and used by ACA.

4.1 Estimating preferences for social and economic benefits

The ACA Tool developed can be used to assess the preference of farmers for social and economic factors of PLF technologies. For each type of farmers (dairy, fattening pigs, or broilers) a separate ACA has been developed using Sawtooth software (Orem, USA). Within each of these ACA surveys, PLF technologies are the 'product', and social and economic benefits are the different characteristics or 'attributes' describing this product. Lokhorst et al. (2013) identified social and economic key indicators of PLF technologies. The top five social key indicators were 'labour conditions', 'number of labour hours', 'pride and motivation to talk about and demonstrate animal production and facilities', 'availability of advisory systems', and 'successor of farm business'. The top five economic key indicators included 'feed conversion', 'growth', 'health costs', 'delivery weight', and 'energy costs'. These key indicators were as basis to define attributes to be used in each ACA tool.

Each ACA Tool starts with a questionnaire to assess general information of respondents (e.g., age, gender, successor, whether they have a specific technology in mind when they think of PLF, and if so to specify this PLF technology). This is followed by a number of statements to assess reference values for the respondent's perception of their current situation. General information and answers on provided statements can be used to define groups of farmers and to analyse whether certain groups have different preferences for social and economic benefits than other groups of farmers. For example, farmers with young families can perceive the hours they work as far more important than older farmers that consider farm performance to be more important to secure a successor to take over the family-farm. The ACA survey that follows after these two sections uses six attributes to describe potential social and economic benefits or changes of PLF technology (Table 6). Each attribute has two or three levels describing how these changes may look like (Table 6). Since the EU-PLF project aims at a wide range of PLF technologies (existing or still to be developed), the description of levels within each attribute are relatively imprecise. However, providing more detailed levels would introduce the difficulty that some details would be correct for some PLF technologies, whereas these details would not apply for others. Moreover, respondents are asked to indicate whether or not they think of a specific technology when talking about PLF. Having a specific PLF technology in mind will help them interpret the questions, attributes, and levels used in the ACA survey.

In the first section of the ACA survey, farmers will be asked about their preference for their selected PLF technology when this technology leads to certain benefits or changes within each attribute. Farmers are asked to fill in the ACA survey using the assumption that there are no practical or monetary issues associated with the PLF technology they have in mind. Each question (one for each attribute) are posed on a rating task using a 7-point scale ranging from 'not preferable' to 'extremely preferable'. For each attribute-level combination, the ACA will elicit preferences, resulting in a total of 14 crude part-worth utilities. An example of how a question in this first section of ACA looks like is provided in Figure 4.

Table 6. Description of attributes and levels to describe Precision Livestock Farming (PLF) technologies. Attributes identified with an ‘S’ refer to social key indicators, those with an ‘E’ to economic key indicators as indicated by Lokhorst et al. (2013)

Attribute (n = 6)	**Description of the attribute**	**Levels within each attribute (n = 14)**
Labour conditions (S)	PLF technology has the potential to affect the daily working conditions. Working conditions refer to the environment in which you work and whether this work is physically and/or mentally hard.	Working conditions 1. stay the same 2. improve
Work load (S)	PLF technology has the potential to affect the work load. Work load refers to the number of hours you work during a day or a week.	Work load 1. reduces 2. stays the same 3. increases
Farmers’ image (S)	Adoption of PLF technologies can affect the image of farmers	Image can be that of 1. an innovator 2. no innovator
Farm performance (E)	PLF technology has the potential to impact farm performance (milk production, feed conversion, length of growth period, labour income)	Farm performance 1. stays the same 2. improves
Energy requirements (E)	PLF technology has the potential to affect energy requirements on your farm.	Energy requirements 1. reduce 2. stay the same 3. increase
Animal health (E)	PLF technology has the potential to change animal health and welfare levels on your farm.	Levels of animal health 1. stay the same 2. improve

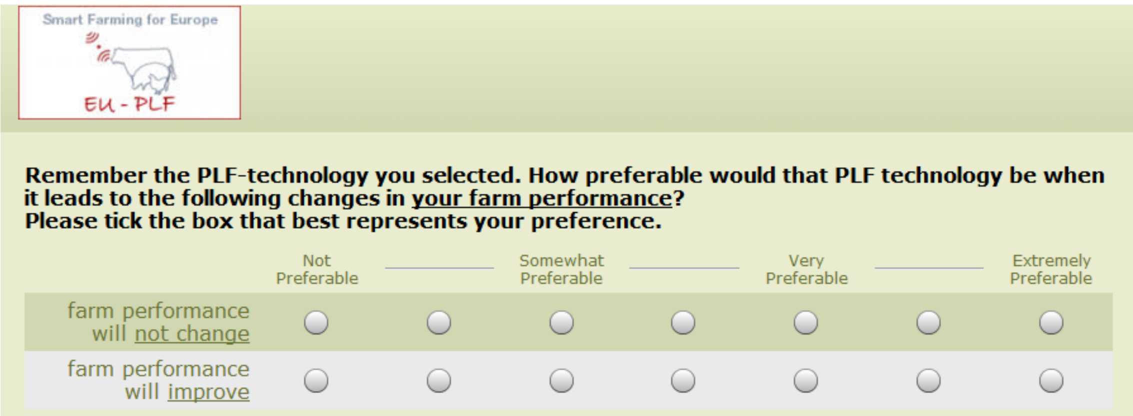

Figure 4. Example of a Section 1 question for the attribute ‘farm performance’ (Table 5)

The second section of the ACA survey uses the crude part-worth utilities from the first section to ask respondents how important the difference is in levels within attributes. They are asked to imagine two suppliers that sell their selected PLF technology and to indicate the importance if the PLF technology sold by the two suppliers would differ in one level of social or economic benefit or change. For example, a respondent has automated heat detection as selected PLF technology and indicated that the least preferred level for the attribute ‘Work load’ would be ‘increases’, and the most preferred level would be ‘reduces’ (Table 6). The ACA assesses the importance of the difference between two heat detection systems that are similar in all other aspects, accept these two levels. An example of this question is provided in Figure 5. The importance of the difference in levels will be done for each attribute, and the crude part-worth utilities from the first section are update with the new derived information from the second section, to prior part-worth utilities.

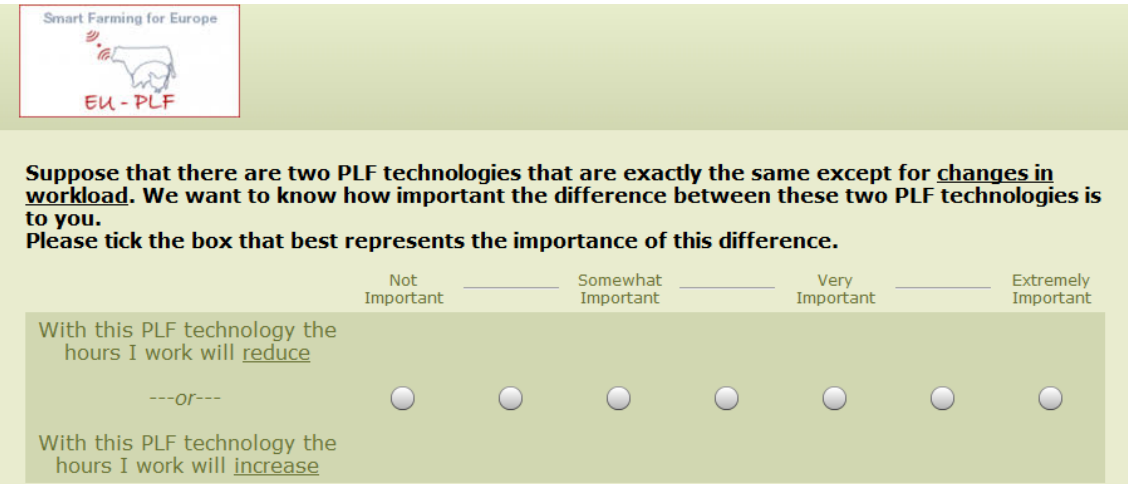

Figure 5. Example of a Section 2 question where the importance of differences in levels within the attribute ‘Work load’ are compared.

The third section asks respondents to make paired comparisons between multiple levels of different attributes, where the prior part-worth utilities are used to compose two social or economic key indicators that were nearly balanced in preference based on answers provided in the first two sections. Since there are 14 attribute-level combinations, the number of paired comparisons is limited to 7, determined by the following formula (Huijps et al., 2009):

(1) Number of paired comparison questions = 3(N-n-1) – N

Where,

N = the number of levels (14)

n = the number of attributes (6)

An example of a section 3 question is provided in Figure 6. The respondents' answer at each paired comparison question will be used to select the next paired comparison question by updating the estimates of the respondent's part-worth utilities after each paired comparison.

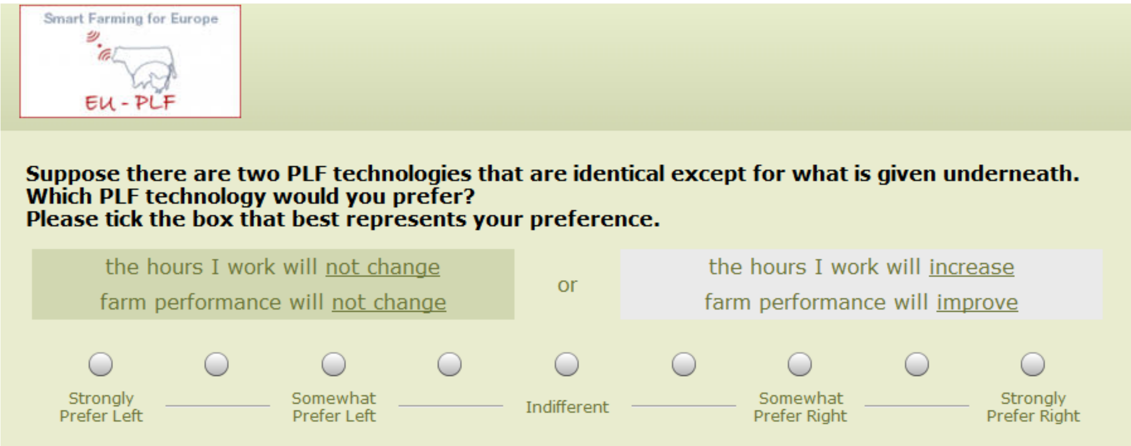

Figure 6. Example of a Section 3 question where different levels of two attributes 'Labour' and 'Farm performance are combined

The fourth and final section serves as consistency check in which respondents are presented four different packages of PLF technologies, each with three social or economic key indicators and are asked how preferable that technology would be for implementation on their farm by rating the PLF technology a value between 0 and 100 (an example is provided in Figure 7). Each respondent is first shown with what would be the least attractive concept, followed by the most attractive concept, as determined from previous answers. The third and fourth remaining concept are of intermediate attractiveness.

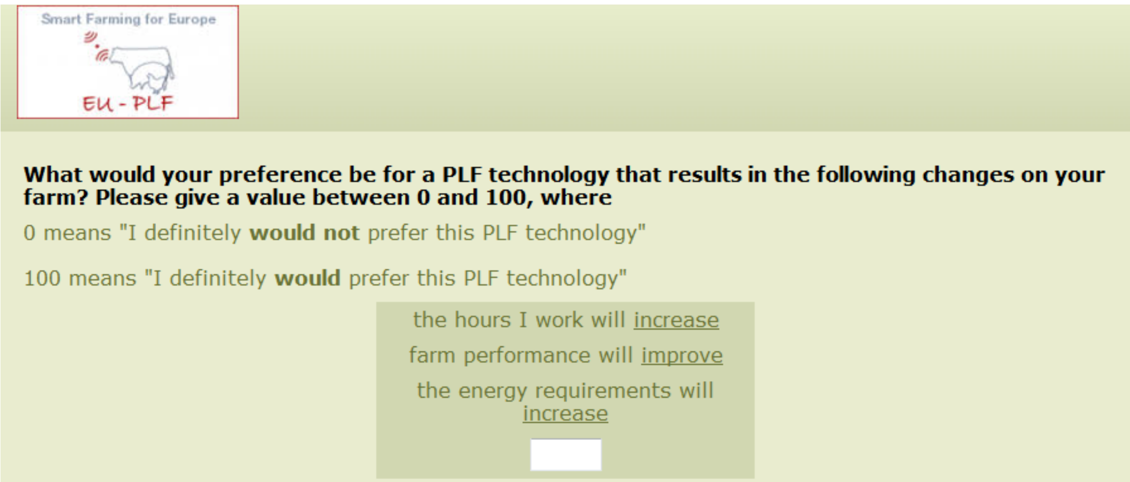

Figure 7. Example of a Section 4 question where a PLF technology with a package of levels of different attributes is presented that respondents have to rate with a value between 0 and 100.

4.2 Using ACA: the example of mastitis detection systems on dairy farms

Adaptive Conjoint Analysis has been used previously by Mollenhorst et al. (2012) to assess Dutch dairy farmers' preferences concerning alerts from automated mastitis detection systems. Six attributes were developed to describe characteristics of such a detection system (Table 7). In case dairy farmers would be indifferent for these defined attributes, the ACA would result in utility scores of 16.7% for each attribute. In that case, farmers would think all six characteristics of a mastitis detection system to be equally (un)important; they would not prefer one characteristic or attribute above another. In case the ACA would result in different utility scores for each attribute, information would be gained what characteristics of a mastitis detection system are preferred over other characteristics.

The ACA was completed by 139 Dutch dairy farmers and the analyses demonstrated that the surveyed farmers considered the attributes 'Time After', 'False Alerts', and 'Severity missed' to be more important than the other three attributes (Figure 8). Within these attributes, the levels '0 hours after', '1 false alert per day', and 'not sick', respectively, retrieved the highest part-worth utilities. So, on average, Dutch dairy farmers prefer a mastitis detection system that produces a low number of false alerts and provides alerts for the more severe cases and in good time (not too late for effective measures to be taken). The analysis also showed a large variability per attribute between farmers (Figure 8), denoting that farmers' preferences differ considerably.

Table 7. Description of attributes and levels to define automated mastitis detection systems (From: Mollenhorst et al., 2012)

Attribute	Description (Levels)
Time After	First alert is given at most this amount of time after the cow actually has clinical mastitis (0, 24, 48 hours)
Time Before	First alert is given at most this amount of time before the cow actually has clinical mastitis (0, 24, 48 hours)
Costs	Variable costs of detection per year (€300, €600, €1200)
False alerts	Number of false alerts per day (1, 3, 5, 10)
Number missed	Number of cows with clinical mastitis missed per year (2, 4, 6)
Severity missed	Health status of most severely affected missed cow (not sick (only flakes in milk, sick, severely sick)

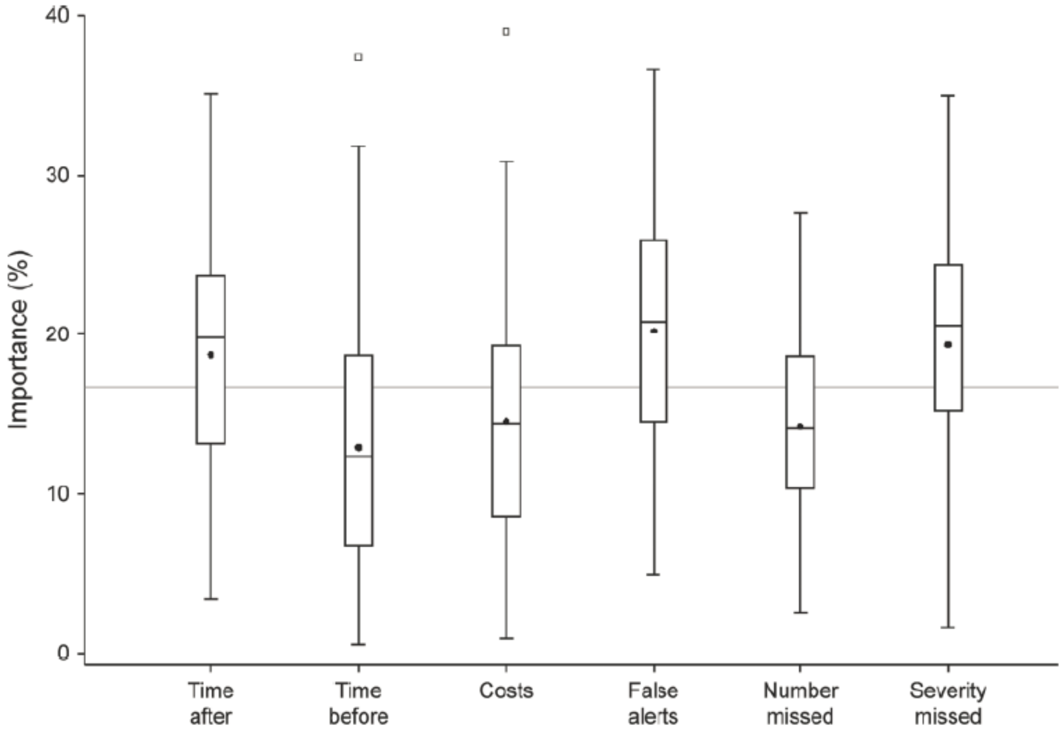

Figure 8. Box-and-whiskers plots of the importance (%) of the attributes with a reference line at 16.7%, representing equal importance. The dots represent the mean, the boxes represent the lower and upper quartiles and the medians, the serifs of the whiskers represent the minimum and maximum values within 1.5 times the interquartile range of the quartiles, and squares represent the observations outside the 1.5 times the interquartile range of the quartiles (From: Mollenhorst et al., 2012).

Conclusions

This Deliverable provides three tools for each of three animal groups to estimate the economic benefit or to assess preferences for social or economic benefits of PLF technologies. Economic benefit can be estimated for tangible PLF technologies using the Value Creation Tools and the associated Baseline Scenarios. Economic benefit of semi-tangible PLF technologies can be assessed using the Break-even Tools. The Adaptive Conjoint Analysis Tools, finally, can be used to assess the preferences. Each tool is basic and generic. This is done deliberately since the term PLF technology is a very broad definition. However, each tool can be easily adapted by suppliers or farmers to make it more technology and/or farm specific. Each tool is ready to be used, but it is strongly adviced to make each tool as specific as possible to gain the most information from them.

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