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# SCENARIO ANALYSIS INDICATES REVENUE INCREASE FOR GERMAN DAIRY FARMERS THROUGH SUPPLY CHAIN ENERGY MANAGEMENT

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## Highlights

- The research field of supply chain energy management (SCEM) is introduced and applied to the German dairy sector.
- Changes in farm revenues are quantified considering electricity sales and remuneration for energy data sharing.
- Results show that SCEM could become the most relevant driver for increasing energy-related revenues at dairy farms.

## Abstract.

Looking at the German food industry, its dairy sector plays an important role not only with regard to people nutrition, but also in terms of environmental responsibility. Analyzing the latter, one challenge is to bring the sector's sustainability efforts into balance with its profitability goals. In this context, especially farmers face the hurdle of operating profitably and are therefore highly interested in new, sustainable sources of income. One lever to establish such sustainable revenue streams for farms is energy management. However, energy management at dairy farms currently is mostly addressed only within a barn's boundaries, while profit-oriented collaboration on energy management along the German dairy supply chain has not yet been studied. This not only hinders a revenue increase for dairy farms in Germany, but also complicates the achievement of sustainability targets, hence, hampering a boost of the sector's public perception. To address this matter, we have applied supply chain energy management (SCEM) as a research field that is looking at energy-related interdependencies along the dairy supply chain. To quantify impact of SCEM, a scenario analysis was conducted assessing the future revenue change for German dairy farmers through application of SCEM. Results of this analysis indicate that SCEM has the potential to become the most relevant driver for increasing energy-related revenues at farms. For example, our studies on a sample farm with 56,950 kWh photovoltaic systems show that it will be able to increase its energy-related revenues by 170 % just by adapting its energy (data) distribution mode in the context of SCEM. Considering these findings, we recommend conducting further studies within the research field of SCEM which is the aim of the new initiative DairyChainEnergy.

*Keywords.* DairyChainEnergy, Electricity sales, Energy data sharing, Food industry, Income, Profitability, SCEM, Sustainability.

The food industry is causing 26 % of worldwide Greenhouse Gas (GHG) emissions, placing the sector in the focus of sustainability targets set by global organizations and governments (Poore et al., 2018; Gil et al., 2019). In order to fulfill this environmental responsibility while meeting global food demand, the aspired long-term goal is to achieve net-zero supply chains, i.e., to realize emission-neutral end-to-end food production (IPCC, 2018). However, handling this trade-off while running a profitable business in Germany poses a challenge—especially for dairy farmers. First, running a farm comes with high operating costs (e.g., for labor, feed, maintenance, fertilizers, contractors, and electricity) (Tauer, 2006; Hansen et al., 2019), a fact that has recently been exacerbated by the rise in euro inflation rates (Binder et al., 2022). Beyond that, dairy farmers have to deal with revenue shifts, e.g., due to volatile milk prices, resulting in planning uncertainty for the farmer (Tauer, 2006). However, despite this uncertainty, a dairy farm has to continuously invest (e.g., in new technology) in order to meet regulatory requirements and improve its environmental footprint (Dörr et al., 2022; Malliaroudaki et al., 2022). Against this backdrop, demand in the dairy sector is high for approaches that have a positive impact on both a dairy farm's profitability and its GHG balance. One such promising approach is energy management, comprising "the procurement, conversion, storage, distribution and utilization of energy" (VDI, 2018). This is because, for example, if a farm produces renewable energy, it will boost its revenues (e.g., via sales of electricity to the grid) and also mitigate its carbon footprint (Boadzo et al., 2011; Malliaroudaki et al., 2022).

However, looking at how energy management is currently conducted in the dairy sector, it is apparent that most effort focuses on the dairy farm itself: There is knowledge on how to reduce a farm's energy consumption and related costs (Boadzo et al., 2011; Shine et al., 2020; Mohsenimanesh et al., 2021), how to make a farm energy self-sufficient (Hijazi et al., 2020), how farmers should best invest in energy technology (Shine et al., 2019), and how to optimize on-farm GHG footprints (Fournel et al., 2019). In contrast, so far, only a small share of research is looking at energy management along the dairy supply chain (from farm to end consumer), e.g., end-to-end energy mitigation strategies (Malliaroudaki et al., 2022) or concepts on farm-grid interaction (Bernhardt et al., 2017).

Strikingly, this approach of managing energy along the supply chain, called supply chain energy management (SCEM), is already receiving much higher attention in other industries given its benefits of realizing GHG mitigation, cost reduction, and revenue increase (Smith et al., 2013; Yang et al., 2017; Yuyin et al., 2018). In this context, the field of SCEM comprises activities such as energy data sharing, knowledge distribution, application of a joined energy auditing approach, or mutual energy supply (Smith et al., 2013; Somjai et al., 2019). To translate these findings to the dairy sector and analyze how SCEM impacts farms' profitability, the target of this study is to quantify revenue changes for German dairy farmers through application of SCEM. To do so, we detailed and expanded the approach from Theunissen et al. (2022).

## **MATERIALS AND METHODS**

In order to achieve this paper's target, a research method needs to be selected that is able to quantify the impact of various influencing factors and uncertainties. This is because, for example, yield-effecting management decisions (e.g., herd size) and market conditions (e.g., market prices) are significantly impacting farms' revenues (Gerhardt,2022). To consider these dependencies, we decided to apply a scenario analysis, i.e., to quantify farm revenues under consideration of varying input assumptions. As methodology, we followed the approach from Kosow et al. (2008) as illustrated in Figure 1 comprising the following steps: identification of the scenario field, identification and analysis of key factors, and scenario generation and transfer. In the following sub-sections, it is outlined how this three-step approach has been applied in the context of this study.



Figure 1. Followed approach (scenario analysis) from Kosow et al. (2008) to quantify energy-related farm revenues IDENTIFICATION OF THE SCENARIO FIELD

The scenario field, i.e., the topic of our scenario analysis, is set equivalent to the target of this study. Hence, it is specified as quantifying revenue changes for a German dairy farm through application of SCEM, whereas energy-related revenues comprise income from both electricity sales and energy data sharing. While selling electricity is already an established revenue source for dairy farmers (Boadzo et al., 2011), remuneration for energy data sharing is a rather new concept in the dairy supply chain (Arla, 2022). However this data transparency is a prerequisite for the success of SCEM (Smith et al., 2013), and demand for this transparency is high: Retail stores intend to sell net-zero labeled food products to end consumers (Malliaroudaki et al., 2022), the public sector needs the transparency for well-informed political decisions (Worthy et al., 2022), contractors need data-driven insights to improve their products and maintenance services (Gerhardt, 2022), and regional grid operators can stabilize their power balance leveraging data on electricity generation and use (Bernhardt et al., 2017).

To quantify energy-related farm revenues and prove applicability of the approach, a scenario analysis was conducted for a German sample farm located in North Rhine-Westphalia. The purpose of this sample farm analysis was to provide valuable insights for the farm owner and to serve as a template for other farmers on how to conduct such a scenario analysis themselves. Moreover, to show how SCEM impacts revenues of German dairy farms overall, a generic sector scenario analysis was performed. However, given that there are more than 50 thousand dairy farms in Germany, all showing differences both in terms of animal and energy management (e.g., milk yield and electricity consumption) (FADN, 2023; Shine et al., 2020), a reasonable set of farm archetypes needs to be selected in order to represent the majority of German dairy farms while having a cognitively processable scenario output (Kosow et al., 2008). The definition of these farm archetypes is done as part of the key factor identification.

In addition to defining the scenario field, according to Kosow et al. (2008), the first step of a scenario analysis also includes a determination of out-of-scope limitations. In the context of this study, following such limitations are to be accepted: First, given that the pricing logic and regulatory framework in Germany differs across energy generation systems (Langniß et al., 2009), we limited our scenario field to one system which is very popular among German dairy farmers (Arla, 2022): electricity generation via roof photovoltaic systems. Furthermore, due to high uncertainty with regard to future political decisions (Isermeyer et al., 2019), we did not quantify the impact of SCEM on new or additional subsidy programs (e.g., monetization of carbon farming). Lastly, to reduce complexity of the scenario analyses, we did not model changes in a farm's total electricity generation volume over time (e.g., due to investments, outages, or changes in technical efficiency) and assumed to have only one roof photovoltaic system per farm archetype (instead of multiple systems with varying capacities and setup dates).

## **IDENTIFICATION AND ANALYSIS OF KEY FACTORS**

As the second step of Kosow et al.'s scenario analysis approach, key factors need to be identified and

analyzed, i.e., "variables, parameters, trends, developments, and events which receive central attention during the further course of the scenario process" (Kosow et al., 2008). Considering the identified scenario field, "change in energy-related farm revenues" is defined as the output variable looking at a 10-year period, comprising farm revenues from electricity sales and energy data sharing (Figure 2).

In the dairy sector, incentives for data sharing are typically provided in the form of a milk price surcharge (V<sub>3</sub>) (Arla, 2022), whereas a farm's total milk volume results from the average milk yield per cow (V<sub>1</sub>) and the herd size (V<sub>2</sub>)—with an observable trend in Germany that the average number of cows per barn is rising (T<sub>1</sub>) (Statista, 2022). Some dairy factories already pay up to four euro cent kg<sup>-1</sup> milk for shared GHG emission data (Arla, 2022), of which about one quarter is traceable to the farm's energy management (Thoma et al., 2013, Malliaroudaki et al., 2022), i.e., 1 cent kg<sup>-1</sup> of payment in the context of SCEM. The prerequisite for realizing such remunerations for a farm is the farmer's willingness to share the data (E<sub>2</sub>) (Arla, 2022).

To also achieve revenues from electricity sales, a farm has to generate electricity that is not fully consumed by the farm itself. When modeling this power consumption in state of the art, it is typically set in relation to the amount of milk produced ( $V_5$ ) and can be significantly impacted by a farm's future management decisions ( $T_2$ ), such as investments in automated systems and replacements of energy inefficient barn components (Shine et al., 2020). Furthermore, revenues from electricity sales are also highly dependent on the grid price (Boadzo et al., 2011). However, in Germany, providers of power generation systems can get support from the so-called renewable energy act (EEG levy -  $P_2$ ) that was introduced in 2000, i.e., at a time of low electricity market prices ( $P_3$ ) (Langniß et al., 2009). Yet, due to recent market changes, attractiveness of EEG levies has declined given that direct electricity sales prices are rising ( $T_4$ ) (Murphy et al., 2022). Nevertheless, the date at which a photovoltaic system was setup ( $V_4$ ) and the total amount of electricity produced ( $V_6$ ) have significant influence on what is the most profitable

type of electricity distribution  $(V_8)$ —EEG versus direct sales. This is because the EEG remuneration is fixed per setup date and electricity volume, and is paid only over a period of 20 years (P<sub>1</sub>) (Langniß et al., 2009). Hence, while there is a volume-dependent remuneration for EEG photovoltaic systems, the solar market value for direct electricity sales is applied as a volume-independent measure in our model (Netztransparenz, 2022). Moreover, low electricity sales prices and insecure energy supply can incite a farmer to work on the in-farm power utilization rate (V7), i.e., the share of generated electricity directly consumed at the barn (Bernhardt et al., 2017). In Germany, there are already prototypes tested that are able to influence this key figure by controlling a farm's electricity utilization curve (Bernhardt et al., 2017; Höhendinger et al., 2021). By applying such a farm-specific energy management and monitoring system (E<sub>1</sub>), a farm's in-house power utilization rate can be set to 100 %, if applicable: some farms generate more electricity than they are able to consume (Bernhardt et al., 2017). Lastly, if a dairy farmer decides to start collaborating in the context of SCEM (E<sub>2</sub>), the farm will expand its flexibility in distributing electricity. For example, next to EEG and direct sales to the grid, it could sell electricity directly at the barn (e.g., to business partners or service providers in the form of e-mobility contracts) (Riedner et al., 2019). Overall, as shown in Figure 2, three parameters, eight variables, four trends/developments, and two events are to be considered in the scope of the identified scenario field.



Figure 2. Illustration of key figures in scope of the identified scenario field based on Theunissen et al. (2022)

To conduct the scenario analyses with those key figures, data as shown in Figure 3 was selected: For quantifying revenues of the sample farm, data from 2020 was gathered. The farm is equipped with three roof photovoltaic systems (40/14/10 kWp systems, set up in 2013/2014/2015), whose generated electricity ( $V_6 = 56,950$  kWh) is consumed by the farm itself at a rate of 40 % ( $V_7$ ) or sold to the regional grid at EEG levies ( $V_8$ ). Compared to peers (FADN, 2023; Shine et al., 2020), the farm has an above-average milk yield per cow ( $V_1 = 11,167$  kg cow<sup>-1</sup>), but also a relatively high electricity consumption ( $V_5 = 0.078$  kWh kg<sup>-1</sup>). Considering findings from Shine et al. (2020) and Höhendinger et al. (2021), the latter can be explained by the barn's conventional milking system and other stable equipment such as climate conditioning and heating systems for the cows' drinking water. Furthermore, milk from the sample farm is sold to a dairy factory that remunerated the farm's sharing of energy data with 0.0003  $\notin$  kg<sup>-1</sup>. Looking at the future development of the sample farm, its owner stated to not intend changing the herd size ( $T_1$ ) or taking investments affecting the farm's future electricity consumption ( $T_2$ ) or its in-farm power utilization rate ( $T_3$ ). For the generic sector analysis, as defined in the scenario field, the data set was collected with the target of reflecting the range of dairy farm characteristics in Germany. According to the Farm

Accountancy Data Network (FADN) — a public database by the German Federal Ministry of Food and Agriculture (BMEL)—the average yearly milk yield per cow (V<sub>1</sub>) ranges from 7,257 to 9,526 kg cow<sup>-1</sup> across German states (FADN, 2023). Data on the herd size ( $V_2$ ) were also taken from FADN (2023). While Bavarian dairy farms are rather small with 42 livestock units, farms in Brandenburg have the largest average herd size with 387 cows per barn. On average, a German dairy farmer owns 74 cows (FADN, 2023), a figure that has increased by 3.5 % yearly since 2000 (Statista, 2022). Against this backdrop, we assumed scenarios where farms either grow at this rate or stay as is  $(T_1)$ . Moreover, electricity generation systems were considered in the generic sector analysis since the start of the EEG subsidy support in the year 2000 with distributed setup dates  $(V_4)$  and capacity  $(V_6)$  in order to be able to model the differences in EEG subsidies over time (Langniß et al., 2009). Furthermore, data on dairy farms' electricity consumption ( $V_5$ ) were taken from Shine et al. (2020) and, following insights from Linnemann (2021), the self-consumption from photovoltaic systems (V<sub>7</sub>) was expected to range from 20 to 60 %. Next, as is typical in Germany, electricity that is not consumed in-house is sold to the grid ( $V_8$ ) in the scope of EEG (Linnemann, 2021). On top of that, we considered two specifications for V<sub>3</sub>—farms which are already sharing their energy data (Arla, 2022) and farmers who do not. Furthermore, with regards to  $T_2$  and  $T_3$ . data points were defined based on observable margins in V<sub>5</sub> and V<sub>7</sub>. For both the sample farm and generic sector analysis, the future development of electricity sales market prices (T<sub>4</sub>) was modeled as staying either at a 2022 level or dropping back to magnitudes as seen in 2020 (Netztransparenz, 2022). Hence, no further inflationary effects on electricity market prices were included in our model due to recent efforts of the German government to limit energy consumer prices (BMWK, 2023). Lastly, values for the three parameters were received from publicly available knowledge: the duration of EEG support is paid for 20 years (Langniß et al., 2009), month- and capacity-specific EEG levies were taken from Netztransparenz (2022), and the German solar annual market values are accessible in Sonnenplaner (2022).

Sources: [0] Arta, 2022 [1] Langrils, et al., 2009 [2] Netzransparenz, 2022 [3] Shine, et al., 2020 [4] Linnemann, et al., 2021 [5] Dairy farmer [6] Statista, 2022 [7] Sonnerplaner, 2022 [8] FADN, 2020		SAMPLE FARM ANALYSIS (2020 → 2030)	GENERIC SECTOR ANALYSIS (2022 → 2032)					
Parameters	P <sub>1</sub> [a]	(20)[1]						
	P <sub>2</sub> [€ kWh <sup>-1</sup> ]	EEG levies (Date- and capacity-specific) [7]						
	P <sub>3</sub> [€ kWh <sup>-1</sup> ]	Solar annual market value 2020: {0.02458} [2]	Solar annual market value 2022: {0.22306} <sub>[2]</sub>					
Variables	V <sub>1</sub> [kg cow <sup>-1</sup> ]	{11,167} <sub>[5]</sub>	{7,257; 9,526} <sub>[8]</sub>					
	V <sub>2</sub> [cow]	{78.7} <sub>[5]</sub>	{42; 74; 387} <sub>[8]</sub>					
	V <sub>3</sub> [€ kg <sup>-1</sup> ]	{0.0003} <sup>*</sup> <sub>[5]</sub>	{0; 0.0025}					
	V <sub>4</sub>	{'Jun 2013'; 'Jul 2014'; 'Jul 2015') <sub>[5]</sub>	{'Jan 2000'; 'Jan 2005'; 'Jan 2010'; 'Jan 2015'; 'Jan 2020'}[1]					
	V <sub>5</sub> [kWh kg <sup>-1</sup> ]	{0.078} <sub>[5]</sub>	{0.03868; 0.04891; 0.073} <sub>[3]</sub>					
	V <sub>6</sub> [kWh]	{56,950} <sub>[5]</sub>	{20,000; 50,000; 150,000; 250,000} <sub>[1]</sub>					
	V <sub>7</sub> [%]	{40} <sub>[5]</sub>	{20; 60} <sub>[4]</sub>					
	V <sub>8</sub>	('EEG') <sub>[5]</sub>	{'EEG' <sub>[1]</sub>					
Trends	T <sub>1</sub> [%]	{0} <sub>[5]</sub>	{0; 3.5}					
	T <sub>2</sub> [%]	{0} <sub>[5]</sub>	{-7; 0; 7} <sub>[3]</sub>					
	T <sub>3</sub> [%]	{0} <sub>[5]</sub>	{-12; 0; 12} <sub>[4]</sub>					
	T <sub>4</sub> [%]	{0; 25} <sub>[2]</sub>	{-20; 0} <sub>[2]</sub>					
Events	E <sub>1</sub>	{'Yes'; 'No'}						
	E <sub>2</sub>	{'Yes'; 'No'}						
Receiption information from 2010								

## Figure 3. Data base for farm-specific and generic sector scenario analyses

## SCENARIO GENERATION AND TRANSFER

In order to generate scenarios and therefore quantify the output measure, mathematical correlations between key input figures need to be defined (Kosow et al., 2008). Following this approach and respecting predefined limitations of the analyses, Equation 1 shows the calculation logic for determining revenues changes (Equation 2) while considering the farm's energy-related revenues, the barn's electricity sales price (Equation 3) as well as the in-farm use of self-generated electricity (Equation 4).

$$RC = \frac{R_t - R_0}{R_0} * 100 \tag{1}$$

$$R_t = V_1 * V_2 * V_3 * (1 + T_1)^t + ESP_t * (V_6 - EUF_t)$$
(2)

$$ESP_t = \begin{cases} P_2, if V_8 = 'EEG' \\ P_3 * (1 + T_4)^t, otherwise \end{cases}$$
(3)

$$EUF_t = min\{V_1 * V_2 * V_5 * (1+T_1)^t * (1+T_2)^t; V_6 * min\{1; V_7 * (1+T_3)^t\}\},$$
(4)

where parameters (P), variables (V), trends (T), and time (t) are taken from Figure 2 and

RC = Energy-related revenue changes of a farm [%]

R = Energy-related revenues of a farm [€]

ESP = Electricity sales price of a farm [ $\notin$ /kWh]

*EUF* = In-farm utilization of self-generated electricity [kWh].

## **RESULTS AND DISCUSSION**

## SAMPLE FARM ANALYSIS

Applying Equations 2 to 4 with data from Figure 3, the sample farm's energy-related gross revenues in 2020 were quantified as  $\notin 5.829$ , of which 95.6 % came from EEG electricity sales to the regional grid at an average levy of 13.97 Cent kWh<sup>-1</sup> and the residual 4.4 % being related to energy data sharing with the farm's cooperating dairy factory (Figure 4). However, looking at the farm's total gross revenues in 2020, energy-related income was accountable only for 1 % (Figure 4). The majority of income was related to milk sales (62 %), followed by subsidies (15 %) and animal sales (11 %)—comparable orders of magnitude are known from the literature (Pelegrini et al., 2019). Nevertheless, when considering recent developments in the German electricity market (Figure 4), the farm's future income from electricity sales can be increased by considering a change in electricity distribution.



Figure 4. 2020 gross revenues of the sample farm and the development of electricity sales prices (EEG levy of sample farm vs. market values from Netztransparenz (2022))

This is also shown by results of the sample farm's scenario analysis (Figure 5), indicating a rise in energy-related net revenues when increasing flexibility in electricity distribution and enabling energy data sharing in the context of SCEM (E<sub>2</sub>). However, in relation to the farm's total revenues, the majority of scenarios indicate that energy-related revenues will not exceed the farm's core income streams such as milk sales or subsidies. This is due to assumptions made during the key factor analysis (scenarios 1 to 8) for the future development of electricity market prices (T<sub>4</sub>, Figure 3). In contrast, if electricity market prices kept rising (see additional approximation in Figure 5), as from January 2020 to December 2022 at a yearly average of 86 % (Netztransparenz, 2022), energy management would become the farm's most relevant source of income.



Figure 5. Results of the sample farm scenario analysis—change in energy-related net revenues

#### **GENERIC SECTOR ANALYSIS**

Using variables  $V_{1.8}$  (Figure 2) and data for the generic sector analysis from Figure 3, 1,356 farm archetypes were created to form a representative sample within the German dairy sector (Figure 6). To do so, all possible data combinations across variables  $V_{1.8}$  were permitted with the following exceptions: Not applicable combinations for farm archetypes with no electricity generation were excluded, i.e., if V<sub>6</sub> is "NA," V<sub>4/7/8</sub> had to be "NA" as well. Beyond that, given that a farm's electricity generation via roof photovoltaic systems is limited by the stable size, combination options of  $V_2$  and  $V_6$  were restricted considering a maximum electricity generation of 2.284,36 kWh cow<sup>-1</sup>. This threshold value was received using the space requirement for cows in a German organic barn (6 qm cow<sup>-1</sup>), utilizing a yield factor of 0.77 to reflect non-optimal orientations of stable roofs, assuming an average roof pitch of 40°, a 50 % share of slatted floor in total stable size, and an optimal yield of 183.33 kWh qm<sup>-1</sup> (Agriconcept, 2022; Solaranlagen-Portal, 2022; Ess-Kempfle, 2022). In addition to the determination of farm archetypes, 144 scenarios were defined based on data from Figure 3 for trends T<sub>1-4</sub> and binary occurrence of events E<sub>1-2</sub> (Figure 6).



#### Figure 6. Derivation of farm archetypes and scenarios for the generic sector analysis

Bringing these farm archetypes and scenarios together, the generic sector analysis comprises 195,264 return points in total (Figure 6). Looking at the output illustrated in Figure 7, in 41 % of the cases, energy-related revenues are expected to increase with the highest forecast of 6,956 % for farm archetype 847 (V<sub>1</sub> = 9,526 kg cow<sup>-1</sup>; V<sub>2</sub> = 387 cows; V<sub>3</sub> = 0  $\in$  kg<sup>-1</sup>; V<sub>4</sub> = 'Jan 2020'; V<sub>5</sub> = 0.03868 kWh kg<sup>-1</sup>; V<sub>6</sub> = 20.000 kWh; V<sub>7</sub> = 60 %; V<sub>8</sub> = 'EEG') and scenario 85 (T<sub>1</sub> = 3.5 %; T<sub>2</sub> = -7 %; T<sub>3</sub> = -12 %; T<sub>4</sub> = 0 %; E<sub>1</sub> = 'No'; E<sub>2</sub> = 'Yes') Furthermore, a minority of return points (3 %) show no revenue changes and 2,592 return points are incalculable when applying Equation 1 since energy-related revenues of related farm archetypes equal 0. The remaining 106,029 return points show a forecasted revenue decline, which can be attributed to increasing in-farm utilization, higher power consumption, ending EEG support, and/or declining electricity sales market prices. With -100 %, the highest revenue decline is shown for farm archetype 0 (V<sub>1</sub> = 7,257 kg cow<sup>-1</sup>; V<sub>2</sub> = 42 cows; V<sub>3</sub> = 0  $\in$  kg<sup>-1</sup>; V<sub>4</sub> = 'Jan 2000'; V<sub>5</sub> = 0.03868 kWh kg<sup>-1</sup>; V<sub>6</sub> = 20.000 kWh; V<sub>7</sub> = 60 %; V<sub>8</sub> = 'EEG') and scenario 130 (T<sub>1</sub> = 3.5 %; T<sub>2</sub> = 7 %; T<sub>3</sub> = 12 %; T<sub>4</sub> = -20 %; E<sub>1</sub> = 'Yes'; E<sub>2</sub> = 'No').



Figure 7. Results of generic sector scenario analysis-change in energy-related farm revenues

Finally, in order to analyze differences in influence of key figures on the scenario output, sensitivity of energy-related revenue changes was measured looking at all trends T<sub>1-4</sub> and events E<sub>1-2</sub>. Hence, it was detected how the output figure changed absolutely when considering a change of one key figure while keeping all other key figures as is. To do so, and to generate one sensitivity result for each trend and event, the average absolute difference in energy-related farm revenue changes was measured across all return points. With the help of such a sensitivity analysis, it was revealed that implementing SCEM (E<sub>2</sub>) has on average the highest positive impact on energy-related farm revenues (Figure 8). This is because E<sub>2</sub> is the only key figure that is impacting both income streams (energy data sharing and electricity sales) across all farm archetypes. Beyond that, a rise in number of cows per barn (T<sub>3</sub>) also has a positive impact on future energy-related farm revenues, mostly traceable to a higher total income from energy data sharing. Next to a bigger herd size, the recent trend of rising electricity market prices (T<sub>4</sub>) is also beneficial for farm incomes, but only for those farms with a direct electricity distribution in the context of SCEM. In contrast, an increase of in-farm power utilization rate  $(T_3)$ , or an application of farm-specific energy management and monitoring (E<sub>1</sub>) has a negative effect on energy-related farm revenues. However, this does not mean that increasing in-farm power utilization or applying an energy management and monitoring system should not be considered by a farmer given the benefit of cost reduction and self-sufficiency (Bernhardt et al., 2017; Höhendinger et al., 2021). Finally, even though a change in power consumption per kg of milk produced ( $T_2$ ) might be interesting for farmers given its effect of reducing costs (Shine et al., 2020),



our sensitivity analysis shows its negative effect on a farm's income.

#### Figure 8. Sensitivity of energy-related revenue changes for trends and events in percentage points

In the end, it is the farmer's decision on which strategic goal has highest priority for the farm: revenue increase vs. cost reduction vs. other targets (e.g., self-sufficiency). If priority is set on revenue increase, the benefits of SCEM can be best utilized at a German dairy farm by having a high energy generation capacity, a sufficient digital maturity to implement direct energy distribution and data sharing as well as an overall willingness to cooperate with other stakeholders along the dairy value chain.

For future studies looking at how SCEM impacts revenues of dairy farms outside of Germany, the overall structure of our scenario analysis can be taken as a starting point. However, a revision of the data input assumptions is required for non-German farms given country-specific differences in political frameworks, market conditions and infrastructure. For example, the concept of EEG levies is worldwide unique and electricity market prices significantly vary across countries (Langniß et al., 2009; ElectricRate, 2023). Furthermore, the predominance of photovoltaic systems for energy generation on dairy farms is much more profound in Germany than in other European countries (Arla, 2022). Nevertheless, SCEM is expected to be beneficial for revenues of dairy farms also outside of Germany, especially in countries with an existing infrastructure for electricity distribution and a strive for more sustainability in agriculture. Hence, dairy farmers in developed countries should be aware of SCEM as a lever for boosting energy-related farm revenues and hence should assess their options for electricity sales and energy data sharing .

By contrast, energy management in developing countries has to focus first on creating a functional energy infrastructure as a basis for enhancing the technical maturity of dairy farms before addressing benefits of SCEM (Sovacool, 2012).

## CONCLUSIONS

In this paper, considerable progress has been made in researching energy management as an instrument for dairy farmers to improve a farm's profitability. Novelty of our study is found in exploring the collaboration aspect of energy management along the supply chain and its effect on dairy farm revenues in Germany. Results of our scenario analyses show that impact of SCEM on dairy farms' future revenues is expected to be significant if a farm is willed to adjust its electricity distribution mode and is open to sharing data with other stakeholders along the supply chain. For example, our studies on a sample farm with 56,950 kWh photovoltaic systems show that it will be able to increase its energy-related revenues by 170 % just by adapting its energy (data) distribution mode in the context of SCEM. Results of a sensitivity analysis also show that SCEM has much higher positive effect on energy-related revenues compared to other key figures such as the recent rise in electricity market prices. However, to maximize energy-related revenues, farmers have to prioritize SCEM over other strategic goals such as energy self-sufficiency.

## REFERENCES

Agriconcept.(2022,September29).Retrievedfromhttps://www.agriconcept.de/dl/LAZBWrh\_Planungshilfen%20Rinder\_Stallbau.pdf

Arla. (2022). Data driven dairy: How climate checks are driving action to reduce emissions on Arla farms.

Bernhardt, H., Graeff, A., Woerz, S., Hoehendinger, M., Hoeld, M., & Stumpenhausen, J. (2017). Energy management of automatic dairy farms with integration in regional grids. ASABE Paper No. 1700262. MI: ASABE. Spokane.

Binder, C., & Kamdar, R. (2022). Expected and Realized Inflation in Historical Perspective. J. of Economic Perspectives, 36(3), 131–155. doi:10.1257/jep.36.3.131

BMWK. (2023, March 1). Retrieved from https://www.bmwienergiewende.de/EWD/Redaktion/Newsletter/2017/16/Meldung/direkt-erklaert.html

Boadzo, A., Chowdhury, S., & Chowdhury, S. P. (2011). Technical and Economic Assessment of Power Generation from Dairy Farm-based Biogas Plants in South Africa. *46<sup>th</sup> Int. Universities' Power Engineering*. Soest, Germany.

Dörr, J., & Nachtmann, M. (2022). Summary. In J. Dörr, & M. Nachtmann, *Handbook Digital Farming* (S. 385-397). Berlin, Heidelberg: Springer. doi:10.1007/978-3-662-64378-5

*Ess-Kempfle.* (2022, September 29). Retrieved from https://www.ess-kempfle.de/ratgeber/ertrag/pv-ertrag/

*ElectricRate*. (2023, March 1). Retrieved from https://www.electricrate.com/data-center/electricity-prices-by-country/

FADN. (27. January 2023). *EU Milk Specialised Farms*. Retrieved from Farm Accountancy Data Network: https://agridata.ec.europa.eu/extensions/DairyReport/DairyReport.html

Fournel, S., Charbonneau, E., Binggeli, S., Dion, J.-M., Pellerin, D., Chantigny, M. H., & Godbout, S. (2019). Optimal Housing and Manure Management Strategies to Favor Productive and Environment-Friendly Dairy Farms in Québec, Canada: Part II. Greenhouse Gas Mitigation Methods. *Trans. ASABE, 62*(4), 973–984. doi:10.13031/trans.13272

Gerhardt, C. B.-S. (2022). Framework for the Digital Transformation of the Agricultural Ecosystem. In J. Dörr, & M. Nachtmann, *Handbook Digital Farming* (S. 59-108). Berlin, Heidelberg: Springer. doi:10.1007/978-3-662-64378-5

Gil, J. D., Daioglou, V., van Ittersum, M., Reidsma, P., Doelman, J. C., van Middelaar, C. E., & van Vuuren, D. P. (2019). Reconciling global sustainability targets and local action for food production and climate change mitigation. *Global Environ. Change*. doi:10.1016/j.gloenvcha.2019.101983

Hansen, B. G., Herje, H. O., & Höva, J. (2019). Profitability on dairy farms with automatic milking systems compared to farms with conventional milking systems. *Int. Food and Agribusiness Manag. Rev.*, 22(2), 215-228. doi:10.22434/IFAMR2018.0028

Hijazi, O., Höhendinger, M., Stumpenhausen, J., & Bernhardt, H. (2020). Greenhouse gas emissions and energy balance in energy self-sufficient dairy cowsheds- CowEnergy. ASABE Paper No. 2000525. *MI: ASABE*. Omaha.

Höhendinger, M., Höld, M., Hijazi, O., Treiber, M., Bauerdick, J., Frech, L., . . . Bernhardt, H. (2021). Cowenergy—possibilities of energy management in energy self-sufficient dairy cowsheds. In D. Bochtis, *Bio-Economy and Agri-Prod. Concepts and Evidence* (S. 159–172). San Diego, CA, USA: Academic Press.

IPCC. (2018). Global Warming of 1.5°C.An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,. Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla.

Isermeyer, F., Heidecke, C., & Osterburg, B. (2019). *Integrating agriculture into carbon pricing*. Braunschweig/Germany. doi:10.22004/ag.econ.310017

Kosow, H., & Gaßner, R. (2008). *Methods of future and scenario analysis: Overview, assessment, and selection criteria*. Bonn: German Institute of Development and Sustainability gGmbH.

Langniß, O., Diekmann, J., & Lehr, U. (2009). Advanced mechanisms for the promotion of renewable energy—Models for the future evolution of the German Renewable Energy Act. *Energy Policy*, *37*(4),

1289-1297. doi:10.1016/j.enpol.2008.11.007

Linnemann, M. (2021). Post-EEG-Anlagen in der Energiewirtschaft. Praxishilfe für Energieversorgungsunternehmen und Anlagenbetreiber zum Umgang mit ausgeförderten Anlagen. Wiesbaden, Germany: Springer. doi:10.1007/978-3-658-35072-7

Malliaroudaki, M. I., Watson, N. J., Ferrari, R., Nchari, L. N., & Gomes, R. L. (2022). Energy management for a net zero dairy supply chain under climate change. *Trends in Food Sci. & Techn.* doi:10.1016/j.tifs.2022.01.015

Mohsenimanesh, A., LeRiche, E. L., Gordon, R., Clarke, S., MacDonald, R. D., MacKinnon, I., & VanderZaag, A. C. (2021). Review: Dairy Farm Electricity Use, Conservation, and Renewable Production—A Global Perspective. *Appl. Eng. Agric.*, *37*(5), 977–990.

Murphy, R. P., Yunis, J., & Aliakbari, E. (2022). *Can Canada avoid Europe's energy crisis?* Frasa Inst. *Netztransparenz.* (2022, January 28). Retrieved from https://www.netztransparenz.de/EEG/Marktpraemie/Marktwerte

Pelegrini, D. F., Lopes, M. A., Demeu, F. A., Rocha, Á. G., Bruhn, F. R., & Casas, P. S. (2019). Effect of socioeconomic factors on the yields of family-operated milk production systems. *Semina: Ciências Agrárias*, 1199-1213.

Poore, J., & Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. *Sci.*, 987–992.

Riedner, L., Mair, C., Zimek, M., Brudermann, T., & Stern, T. (2019). E-mobility in agriculture: differences in perception between experienced and non-experienced electric vehicle users. *Clean Technol. and Environ. Policy, 21*(1), 55–67. doi:10.1007/s10098-018-1615-2

Shine, P., Breen, M., Upton, J., O'Donovan, A., & Murphy, M. D. (2019). A decision support and optimization platform for energy technology investments on dairy farms. ASABE Paper No. 1901055.

MI: ASABE. Boston. doi:10.13031/aim.201901055

Shine, P., Upton, J., Sefeedpari, P., & Murphy, M. D. (2020). Energy Consumption on Dairy Farms: A Review of Monitoring, Prediction Modelling, and Analyses. *Energies*, *13*(5). doi:10.3390/en13051288

Smith, T. M., & Schmitt, J. (2013). Supply Chain Energy Efficiency: Engaging Small & Medium Entities in Global Production Systems. *Symp. on Supply Chain Coordination and Energy Efficiency*.

Solaranlagen-Portal. (2022, September 29). Retrieved from https://www.solaranlagen-portal.com/photovoltaik/voraussetzung/dachneigung

Somjai, S., Suksod, P., & Aeknarajindawat, N. (2019). Embedding Supply Chain Agility in Relationship between Energy Management Practices and Renewable Energy Supply Chain: An Empirical Investigation. *Int. J Sup. Chain. Mgt*, 8(5), 720-731.

Sonnenplaner.(2022,September29).Retrievedfromhttp://www.sonnenplaner.com/aktuelle\_einspeiseverguetung.html

Sovacool, B. K. (2012). The political economy of energy poverty: A review of key challenges. *Energy for Sustainable Development, 16*(3), 272–282. doi:10.1016/j.esd.2012.05.006

 Statista.
 (2022,
 September
 29).
 Retrieved
 from

 https://de.statista.com/statistik/daten/studie/28755/umfrage/anzahl-der-milchkuehe-je-halter-in deutschland-seit-1990/

Tauer, L. W. (2006). When to Get In and Out of Dairy Farming: A Real Option Analysis. *Agric.l and Resour. Economics Rev.*, 35(2), 339–347. doi:10.1017/S1068280500006778

Theunissen, T. C., & Bernhardt, H. (2022). Revenue increase for German dairy farmers through crossvalue chain energy management. ASABE Paper No. 2200711. *MI: ASABE*. Houston.

Thoma, G., Popp, J., Nutter, D., Shonnard, D., Ulrich, R., Matlock, M., ... Adom, F. (2013). Greenhouse gas emissions from milk production and consumption in the United States: A cradle-to-grave life cycle

assessment circa 2008. Int. Dairy J., 31. doi:10.1016/j.idairyj.2012.08.013

VDI. (2018). VDI 4602 Part 1 - Energy management - Fundamentals. Verein Deutscher Ingenieure.

Worthy, B., Morgan, C., & Langehennig, S. (2022). Is Data-Driven Politics Good for Democracy? *Political Insight*, 13(2), 22–25. doi:10.1177/20419058221108779

Yang, L., Zhang, Q., & Ji, J. (2017). Pricing and carbon emission reduction decisions in supply chains with vertical and horizontal cooperation. *Int. J. of Prod. Economics*, *191*, 286–297. doi:10.1016/j.ijpe.2017.06.021

Yuyin, Y., & Jinxi, L. (2018). Cost-Sharing Contracts for Energy Saving and Emissions Reduction of a Supply Chain under the Conditions of Government Subsidies and a Carbon Tax. *Sustainability*, *10*(3). doi:10.3390/su10030895

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