POLITECHNIKA
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im. Jana i Jędrzeja Śniadeckich

ROZPRAWA DOKTORSKA

DYSCYPLINA: ZOOTECHNIKA I RYBACTWO

mgr inż. Joanna Aerts

Czynniki warunkujące wydajność stada krów w oborach wyposażonych w automatyczny system doju

Factors of cow heard performance in barns equipped with automatic milking system

PROMOTOR
Prof. dr hab. Dariusz Piwczyński
Politechnika Bydgoska im. J.J. Śniadeckich

PROMOTOR POMOCNICZY
Dr hab. inż. Beata Sitkowska, Prof. PBŚ
Politechnika Bydgoska im. J.J. Śniadeckich

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SPIS TREŚCI

1. WSTĘP

Pierwsze prototypy robotów udojowych pojawiły się w latach osiemdziesiątych ubiegłego wieku, a pierwszego produkcyjnego robota zainstalowano w 1992 r. w Holandii (de Koning i Rodenburg, 2004), jednak przełom w technologii automatycznego doju nastąpił na przełomie XX i XXI wieku. W roku 2002 liczba robotów na świecie osiągnęła 1745 szt. (de Koning i Van der Vorst, 2002). Dwadzieścia lat później szacunkowa liczba pracujących robotów na świecie samej tylko firmy Lely wyniosła 42 500 szt., w tym 600 szt. w Polsce (Lely, informacja ustna). Obecnie automatyczny system doju (AMS) zyskuje coraz większą popularność na całym świecie (Piwczyński i in., 2020b). Rozwiązanie to jest innowacją w gospodarstwach mlecznych, których celem jest m.in. zastąpienie pracy człowieka w przygotowaniu wymienia, zakładaniu kubków udojowych i dezynfekcji strzyków po każdym doju. Zaletą AMS jest też możliwość zwiększenia częstotliwości doju w ciągu doby, gdyż krowy mają dostęp do robota udojowego niezależnie od obecności pracownika. Dzięki połączeniu zarzadzania częstotliwością doju i m.in. kontrolą ruchu zwierząt można uzyskać maksymalne efekty produkcyjne dla każdego zwierzęcia. Należy podkreślić, że instalacja AMS w gospodarstwie wymaga znacznej modernizacji istniejących budynków, a najlepsze efekty w zakresie produkcji mleka i dobrostanu krów są rejestrowane, gdy system ten wdrażany jest w nowym budynku zaprojektowanym w kierunku doju automatycznego (Piwczyński i in., 2018).

Wyniki kompleksowych badań przeprowadzonych przez zespół naukowców z Politechniki Bydgoskiej im. J.J. Śniadeckich (Sitkowska i in., 2015; Brzozowski i in., 2020, Piwczyński i in., 2020a; Kolenda i in., 2021) świadczą o korzystnym wpływie automatyzacji doju na najważniejsze cechy produkcyjne i funkcjonalne, m.in. wydajność mleczną krów w pierwszej i drugiej laktacji pełnej, zawartość komórek somatycznych w próbach mleka, indeks inseminacyjny pierwiastek. Powyższe fakty pozwalają sugerować, że dalsze wdrażanie AMS w wysoko wydajnych stadach krów rasy PHF jest w pełni uzasadnione. Ten korzystny aspekt zmiany systemu doju z konwencjonalnego na automatyczny udokumentowało również wielu autorów krajowych (Bogucki i in., 2014; Sitkowska i in., 2015) i zagranicznych (Österman i in., 2005; Svennersten-Sjaunja i Pettersson, 2008). Stosunkowo nieliczne są badania związane z wpływem automatyzacji doju na długowieczność krów. Dotychczasowe, wstępne wyniki badań Piwczyńskiego i in. (2021b) wskazują, że w większości wziętych pod uwagę stad, automatyzacja doju wiązała się wręcz z pogorszeniem przeżywalności krów do drugiej i trzeciej laktacji.

Obory wyposażone w AMS dostarczają ogromnej ilości danych związanych z procesem doju, aktywnością krów, m.in. czasem podłączenia kubków udojowych do strzyków, czasem i szybkością doju, czasem pobytu krowy w boksie udojowym, przewodnością elektryczną mleka, pobraniem paszy treściwej czy czasem przeżuwania, które mogą być wykorzystane do poprawy poziomu produkcji mleka w stadzie, ale także statusu dobrostanu zwierząt (Svennersten-Sjaunja i Pettersson, 2008; de Koning, 2010; Shevchenko i Aliev, 2013). Podkreślenia wymaga, że badania w zakresie szacowania parametrów genetycznych cech rejestrowanych przez AMS są stosunkowo nieliczne (Nixon in., 2009; Pitkänen i in., 2018; Aerts i in., 2021; Piwczyński i in., 2021c). Wynika to z utrudnionej dostępności do tego typu danych, ale również wielkości przetwarzanych baz danych – w porównaniu ze zbiorami pochodzącymi z comiesięcznych dojów próbnych liczba rekordów jest co najmniej 30 razy większa.

W gospodarstwie mleczarskim wykorzystującym konwencjonalny system doju (CMS) najważniejszą cechą z ekonomicznego punktu widzenia jest dobowy uzysk mleka od krowy. Z kolei w gospodarstwie z AMS ważniejszą rolę w tym zakresie odgrywa efektywność doju. Cecha ta charakteryzuje indywidualną przydatność krowy do doju automatycznego. Efektywność doju najczęściej opisywana jest jako wydajność mleka na minutę czasu przebywania krowy w boksie udojowym (Løvendahl i in., 2014). Najwyższą efektywność doju uzyskuje się zatem przy najlepszym stosunku między wysoką wydajnością mleka od krowy a szybkość oddawania mleka (Odorčić i in., 2019). Na efektywność doju mogą wpływać różne czynniki, w tym: częstotliwość doju (mniejsza przyczynia się do niższej wydajności), liczba krów przypadająca na robota udojowego (duża liczba zwierząt może zwiększać konkurencję w dostępie do robota i negatywnie wpływać na ich wydajność mleczną) czy rodzaj obory, w której zwierzęta są dojone (nowe obory budowane i przystosowane do doju zrobotyzowanego pozwalają krowom efektywniej wykorzystywać AMS, zwiększając ich wydajność mleczną) (Rotz i in., 2003; Gygax i in., 2007; André i in., 2010; Castro i in., 2012; Tremblay i in., 2016). Heringstad i Bugten (2014) zauważyli, że efektywność doju zmienia się wraz z liczbą dni laktacji: najniższa jest we wczesnej laktacji, a najwyższa w połowie laktacji, po czym ponownie maleje, jest to zgodne z przebiegiem krzywej laktacji u krów.

Instalacja, a następnie eksploatacja AMS jest dla każdego hodowcy dużym wyzwaniem finansowym. Z tego względu głównym celem hodowców w zrobotyzowanych gospodarstwach utrzymujących krowy mleczne jest maksymalizacja produkcji mleka uzyskanego z robota w ustalonej jednostce czasu, np. na dobę. Efekt ten możliwy jest do osiągnięcia wtedy, gdy robot doi maksymalnie dużą liczbę wysoko wydajnych, szybko dojących się krów. tj. charakteryzujących się wysoką efektywnością doju. Kluczowym dylematem pozostającym do rozstrzygnięcia jest ustalenie optymalnej obsady krów na robot oraz wolnego czasu robota w ciągu doby. Jak wskazują badania Sobczyńskiego i in. (2018) określając obsadę krów na robot konieczne jest uwzględnienie m.in. czynnika rasowego.

Zarówno efektywność doju jak i dobowy uzysk mleka z robota uwarunkowane są licznymi czynnikami genetycznymi i pozagenetycznymi (Castro i in., 2012; Jacobs i Siegford, 2012; Siewert i in., 2018; Piwczyński i in., 2021a). Z tego względu ustalenie optymalnego poziomu czynników potencjalnie warunkujących te cechy jest niezmiernie trudne i wymaga zastosowania zaawansowanych metod statystycznych analizy danych. Jedną z polecanych metod może być technika drzew decyzyjnych (Piwczyński i in., 2020c; Ghiasi in., 2015). W dostępnej literaturze naukowej powszechne są przykłady zastosowania tej metody w modelowaniu statystycznym cech produkcyjnych i funkcjonalnych bydła (Piwczyński i Sitkowska, 2012; Piwczyński i in., 2013). Technika drzew decyzyjnych pozwala wizualizować uzyskane wyniki analiz w prosty graficzny, przypominający drzewo sposób. Algorytm drzewa decyzyjnego tworzy struktury przypominające pień, gałęzie i liście. Podział zbioru danych rozpoczyna się od węzła głównego, który jest dalej dzielony na mniejsze węzły które mogą dzielić się dalej, aż do momentu, gdy nie można już dokonać dalszego podziału, tworząc liść. Po końcowym skonstruowaniu drzewo składa się z podzbiorów maksymalnie jednorodnych pod względem wartości badanych cech.

2. WYKAZ ARTYKUŁÓW NAUKOWYCH STANOWIĄCYCH CYKL PUBLIKACJI ROZPRAWY DOKTORSKIEJ

A1. Aerts J., Kolenda M., Piwczyński D., Sitkowska B., Önder H., 2022a. Forecasting Milking Efficiency of Dairy Cows Milked in an Automatic Milking System Using the Decision Tree Technique. Animals 12(8), 1040; https://doi.org/10.3390/ani12081040

pkt. MEiN – 100, Impact Factor = 3,231.

A2. Aerts J., Sitkowska B., Piwczyński D., Kolenda M., Önder H., 2022b. The optimal level of factors for high daily milk yield in automatic milking system. Livestock Science 264, 105035; https://doi.org/10.1016/j.livsci.2022.105035

pkt. MEiN – 140, Impact Factor = 1,929.

A3. Aerts J., Piwczyński D., Ghiasi H., Sitkowska B., Kolenda M., Önder H., 2021. Genetic Parameters Estimation of Milking Traits in Polish Holstein-Friesians Based on Automatic Milking System Data. Animals 11(7), 1943; https://doi.org/10.3390/ani11071943

pkt. MEiN – 100, Impact Factor = 2,752.

Podsumowanie wskaźników cyklu publikacji:
Sumaryczna liczba punktów MEiN = 340 pkt.
Sumaryczny Impact Factor = 7,912.

3. UZASADNIENIE SPÓJNOŚCI TEMATYCZNEJ CYKLU PUBLIKACJI ROZPRAWY DOKTORSKIEJ

Podczas kilku ostatnich dekad, wprowadzone zostały nowe systemy doju krów, spośród których AMS, stanowi osiągniecie przełomowe. Automatyczny system doju oferuje możliwość częstszego dojenia krów - dostosowanego do fazy laktacji. Zapewnia on spójne procedury doju, łącznie z procedurami dla stymulacji wymienia oraz karmienia podczas udoju skutkując uwolnieniem odpowiedniej ilości oksytocyny oraz wydzielaniem mleka. Dobrze funkcjonujący wolny ruch krów stanowi warunek dla sprawnego funkcjonowania AMS i uzyskania optymalnej liczby wizyt. W konsekwencji prowadzi to do uzyskania wysokiej ilości mleka otrzymanego z robota przy minimalnej obsadzie krów na niego przypadającej. Automatyczny system doju dostarcza hodowcy ogromną ilość informacji, które pozwalają na sprawne zarządzenie stadem, a tym samym poprawę opłacalności produkcji.

Tematyka publikacji naukowych wskazanych jako osiągnięcie dotyczy możliwości prognozowania wysokiej efektywność doju oraz dobowego uzysku mleka z robota na podstawie informacji rejestrowanych przez AMS. Podkreślenia wymaga, że efektywność doju oraz dobowy uzysk mleka z robota udojowego to kluczowe czynniki decydujące o opłacalności produkcji w zrobotyzowanym gospodarstwie mlecznym. Cały cykl badań przeprowadzono w gospodarstwach z zainstalowanym AMS utrzymujących krowy rasy polskiej holsztyńsko-fryzyjskiej w systemie wolnostanowiskowym. W badaniach związanych z prognozowaniem efektywności doju oraz dobowego uzysku mleka z robota AMS ustalono, że najsilniej są one warunkowane wydajnością mleka, szybkością oddawania mleka, w związku z tym w kolejnym opracowaniu oszacowano odziedziczalność oraz korelacje genetyczne między tymi cechami.

3.1. WYKAZ SKRÓTÓW

AMS – automatyczny system doju - automatic milking system
CMS – konwencjonalny system doju - conventional milking system
ME – efektywność doju - milking efficiency
PHF – rasa polska holsztyńsko-fryzyjska – Polish Holstein-Friesian breed
RY – dobowy uzysk mleka z robota – daily milk yield from the robot

3.2. HIPOTEZA BADAWCZA, CEL I ZAKRES BADAŃ

Hipoteza badawcza: Istnieje możliwość prognozowania wysokiej efektywność doju krów w stadzie, jak i efektywnego wykorzystanie robota udojowego (dobowego uzysku mleka z robota) na podstawie parametrów doju rejestrowanych przez AMS przy wykorzystaniu techniki drzew decyzyjnych.

Cel: Zasadniczym celem przeprowadzonych badań było ustalenie czynników odpowiedzialnych za zmienność ważnych z ekonomicznego punktu widzenia cech, tj.: efektywności doju i dobowego uzysku mleka z robota udojowego, a w szczególności ustalenie za pomocą techniki drzew decyzyjnych takiej kombinacji czynników i ich poziomów, które gwarantują wysoki poziom tych cech. Dodatkowym celem badań było oszacowanie wskaźników odziedziczalności i korelacji genetycznych między cechami (wydajność mleka, szybkość doju, częstotliwość doju), które w największym stopniu wpływają na efektywność doju i dobowy uzysk mleka z robota udojowego.

Zakres: Badania zostały przeprowadzone w 21 stadach bydła mlecznego zlokalizowanych na terenie Polski utrzymujących krowy rasy PHF. Powyższa grupa stad została wyselekcjonowana na podstawie wyników przeprowadzonej ankiety wśród polskich hodowców (56 stad) wykorzystujących w doju AMS firmy Lely. Kryterium niezbędnym do objęcia badaniami stada były: co najmniej 3 letni okres użytkowania AMS oraz zgoda hodowcy na analizę danych z ich stad. Łącznie badaniami objęto 4 985 sztuk krów dojonych w latach 2011-2015. Źródłem informacji do prowadzonych badań były dane pozyskane z systemu SYMLEK oraz z systemu rejestracji danych T4C firmy Lely. Z powyższych baz danych do prognozowania efektywności doju oraz dobowego uzysku z robota wykorzystano informacje dotyczące kilkudziesięciu parametrów rejestrowanych przez AMS oraz informacje związane z warunkami utrzymania krów pozyskane z ankiet przeprowadzonych wśród hodowców. Zgromadzony materiał liczbowy opracowano statystycznie za pomocą: analizy wariancji oraz techniki drzew decyzyjnych. W oszacowaniu parametrów genetycznych wydajności mleka, częstotliwości doju wykorzystano metodę AIREML-AM.

3.3. MATERIAŁY I METODY BADAŃ

Badania zrealizowano w 21 stadach zlokalizowanych na terenie całej Polski, w których w latach 2010-2013 tradycyjny system doju zastąpiono systemem automatycznym – roboty udojowe Astronaut A4 (Lely Industries N.V., Cornelis van der Lelylaan 1, Maassluis, The Netherlands). W stadach użytkowano krowy rasy polskiej holsztyńsko-fryzyjskiej, które utrzymywano w systemie wolnostanowiskowym i żywiono w systemie PMR (partial mix ration - częściowo wymieszana dawka). Łącznie badaniami objęto 4 985 krowy. Dane dotyczące użytkowości krów pochodziły z systemu SYMLEK oraz systemu zarządzania i rejestracji danych T4C firmy Lely.

Badanie 1 (A1, Aerts i in., 2022a**)**

W badaniach uwzględniono dane z zakresu użytkowości mlecznej 1 823 krów znajdujących się od 1 do 3 laktacji, utrzymywanych w 20 stadach na terenie całej Polski. Analizie poddano następujące cechy rejestrowano przez AMS: dzień doju, częstotliwość doju (n/24h), czas podłączenia (czas podłączenia kubka udojowego do pojedynczego strzyka, s), czas w boksie udojowym (czas spędzony przez krowę w boksie udojowym, min/24h), szybkość doju (przeciętny przepływ mleka w ciągu doby, kg/min), wydajność mleka (kg/24h), udział mleka z ćwiartek tylnych (%), efektywność doju (ME, uzysk mleka w przeliczeniu na czas spędzony przez krowę w boksie udojowym, kg/min). W pierwszym etapie przeprowadzonej analizy statystycznej przy zastosowaniu wieloczynnikowej analizy wariancji i modelu mieszanego zmienność wszystkich wymienionych cech warunkowano, m.in. kolejnym rokiem od instalacji AMS w gospodarstwie, typem obory (nowa, zmodernizowana ze względu na potrzeby związane z instalacją AMS), obsadą krów na robot, sezonem wycielenia, kolejną laktacją, wiekiem krów w dniu pierwszego wycielenia, dniem laktacji). W kolejnym etapie analizy podjęto się modelowania statystycznego ME przy zastosowaniu techniki drzew decyzyjnych stosując różne kryteria podziału zbioru danych: redukcji wariancji, statystyki F. W celu zapobieżenia przetrenowania modelu założono, że minimalna wielość ostatecznego podzbioru wynosi co najmniej 5000. Maksymalną głębokość drzewa ustalono na 5 poziomów. Jakość prognostyczną porównywanych modeli oceniano za pomocą średniego błędu kwadratowego. Ostateczny model drzewa decyzyjnego skonstruowano przy użyciu algorytmu CART (Classification And Regression Trees). W celu uszeregowania czynników w zakresie ich znaczenia w budowie drzewa decyzyjnego obliczono miarę „Importance".

Badanie 2 (A2, Aerts i in., 2022b**)**

W badaniach nad dobowym uzyskiem mleka z robota udojowego (RY, kg/robot/24h) wzięto pod uwagę wyniki produkcyjne pochodzące od 4 854 krów utrzymywanych w 20 stadach w okresie 3 lat od instalacji AMS. Analizę statystyczną danych liczbowych przeprowadzono równolegle za pomocą dwóch metod, tj. wieloczynnikowej analizy wariancji oraz techniki drzew decyzyjnych. Zmienność RY analizowano w zależności od (wartości uśrednione dla wszystkich krów korzystające z robota udojowego w danym dniu): wysokości w krzyżu dojonych krów (cm), szybkości doju (kg/min), dobowego uzysku mleka od krowy (kg/24h), obsady krów na robot udojowy (n/robot), dnia laktacji (dni), czasu spędzonego w boksie udojowym przez krowę związanego z czynnościami poprzedzającymi i kończącymi dój (%/24h), czasu wolnego robota udojowego (%/24h), udziału w genotypie krów rasy PHF (%), wieku krów w dniu pierwszego wycielenia (dni), częstotliwości doju (n/24h), czasu spędzonego w boksie udojowym (s/24h), czasu trwania doju (s/24h), uzysku mleka od krowy w przeliczeniu na dój (kg/dój), czasu przeżuwania (min/24h), udziału dojących się wieloródek (%/robot/24h), liczby wszystkich dojów podjętych przez robot udojowy (n/robot/24h), liczby dojów nieudanych (n/robot/24h), liczby dojów zakończonych sukcesem (n/robot/24h), liczby dojów odrzuconych (n/robot/24h), udziału dojów odrzuconych (%/robot). W modelowaniu RY techniką drzew decyzyjnych zastosowano algorytm CART wykorzystujący miarę redukcji wariancji jako kryterium podziału danych. Przed rozpoczęciem konstruowania drzewa założono, że minimalna wielkość podzbioru w wyniku podziału wynosić będzie co najmniej 100, zaś głębokość drzewa ustalono na 5 poziomów. W celu uszeregowania rankingu zmiennych w budowie drzewa decyzyjnego zastosowano miarę „Importance”.

Badanie 3 (A3, Aerts i in., 2021**)**

Badaniami objęto 1 713 szt. krów pierwiastek użytkowanych w 21 stadach, z kompletnymi danymi rodowodowymi, które były córkami 702 buhajów oraz 1 562 matek. Zbiór rodowodowy stanowiło łącznie 4 231 szt. zwierząt. W badaniach dla każdego dnia doju oszacowano wskaźniki odziedziczalności oraz korelacje genetyczne między: wydajnością mleka (kg/24h), częstotliwością doju (n/24h) i szybkością doju (kg/min). W tym celu zastosowano dwucechowy model zwierzęcia z regresjami losowymi. Krzywe regresji modelowano za pomocą wielomianów Legendre'a stopnia 2. Podkreślenia wymaga, że rozważane były również wielomiany do 5 stopnia, z założeniem homo- jak heterogeniczności wariancji kontrolowanych cech. Do oszacowania komponentów (ko-) wariancji wykorzystano metodę AIREML-AM. Ostateczne modele użyte do oszacowania parametrów genetycznych wyselekcjonowano na podstawie następujących kryteriów jakości modelu: logarytm wiarygodności (logL), bayesowskie kryterium informacyjne (BIC) oraz kryterium informacyjne Akaike'a (AIC).

3.4. WYNIKI

Badanie 1 (A1, Aerts i in., 2022a**)**

Posługując się analizą wariancji wykazano, że zmienność ME, częstotliwości doju, czasu podłączenia strzyka, czasu spędzonego przez krowę w boksie udojowym, szybkości doju były wysoko istotnie uwarunkowane wpływem: czasu (liczby lat), który minął od instalacji AMS, obsady krów na robot udojowy, kolejnej laktacji, sezonu wycielenia, wieku krów w dniu pierwszego wycielenia, dnia laktacji, udziału mleka pozyskanego z ćwiartek tylnych i interakcji między kolejną laktacją a sezonem wycielenia. Na podstawie wyznaczonych średnich najmniejszych kwadratów zauważono, że ME krów była najwyższa: w pierwszych dwóch latach po instalacji robotów udojowych – 1,71 kg/min, przy obsadzie krów na robot wynoszącej między 61 a 75 sztuk – 1,76 kg/min, wśród wieloródek – 1,79 kg/min, wśród krów wycielonych wiosną – 1,74 kg/min, w grupie jałówek wycielonych powyżej 36 miesiąca życia – 1,80 kg/min, od 151 do 250 dnia laktacji – 1,73 kg/min, i wreszcie, gdy udział mleka z ćwiartek tylnych wahał się od 51 do 60% –1,73% (A1, Aerts i in., 2022a, tab. 3).

Z kolei modelując statystycznie ME przy zastosowaniu drzew decyzyjnych wykazano, że zgodnie z miarą „Importance" największy na nią wpływ, w kolejności malejącego znaczenia miały: wydajność mleka, częstotliwość doju, czas podłączenia strzyka, dzień laktacji, kolejna laktacja i obsada krów na robot (A1, Aerts i in., 2022a, tab. 5). Algorytm budujący drzewo decyzyjne utworzył diagram (A1, Aerts i in., 2022a, ryc. 2-6) składający się z 59 podzbiorów, spośród których 29 stanowiły liście. Analizując strukturę drzewa ustalono, że liściem (podzbiorem danych) o najwyższej ME, wynoszącą 2,01 kg/min był węzeł 50 (A1, Aerts i in., 2022a, ryc. 5). Liść ten powstał w wyniku podziału wejściowego zbioru danych według następujących kryteriów: wydajność mleka ≥ 45 kg/24h, częstotliwość doju < 4 n/24h, czas podłączenia strzyka < 7,65 s, obsada krów na robot < 56 szt. (A1, Aerts i in., 2022a, ryc. 2, 5). Z kolei najniższej ME (1,25 kg/min) (węzeł 41) (A1, Aerts i in., 2022a, ryc. 4) należy oczekiwać przy zachowaniu następujących kryteriów: wydajność mleka < 30 kg, częstotliwość doju ≥ 3 n/24h, czas podłączenia strzyka ≥ 8,79 s.

Badanie 2 (A2, Aerts i in., 2022b**)**

Przeprowadzona analiza wariancji wykazała wysoko istotny wpływ na dobowy uzysk mleka z robota (RY) większości czynników uwzględnionych w modelu klasyfikacyjnym, z wyjątkiem efektu opalania wymion (A2, Aerts i in., 2022b, tab. 3). Analizując obliczone średnie najmniejszych kwadratów zaobserwowano, że z każdym kolejnym półroczem upływającym od instalacji AMS w oborze RY wzrastała o około 8%. Biorąc pod uwagę szybkość doju, to najwyższą RY (1794,34 kg/24h) obserwowano dla udojów, w których średnia szybkość doju wahała się w granicach 2,6-2,8 kg/min (A2, Aerts i in., 2022b, tab. 3). Zaobserwowano również tendencję do wzrostu RY wraz ze skracaniem się czasu wolnego robota (różnica między skrajnymi grupami przekroczyła 35% – 1857,83 vs 1372,41 kg) oraz czasu przeznaczonego na czynności poprzedzające i kończące dój: od 1750,95 kg/24h (=< 30% czasu w boksie) do 1414,21 kg/24h (> 38% czasu w boksie udojowym). Wraz ze wzrostem obsady krów przypadających na AMS obserwowano wzrost RY od 1497,52 (=< 55 krów/robot) do 1792,62 kg/24h (> 65 krów/robot). Wyższą RY (1707,31 kg/24h) odnotowano w stadach o największym odsetku krów wieloródek (> 65%). Stwierdzono, że RY zmniejszała się wraz ze wzrostem wieku pierwszego wycielenia od 1678,14 kg/24h (=< 820 dni) do 1575,47 kg/24h (> 950 dni), podobnie jak z zaawansowaniem laktacji: od 1735,26 kg/24h (=< 160 dnia) do 1504,60 kg/24h (> 200 dni). W badaniach wykazano, że RY wzrastała wraz ze wzrostem indywidualnej wydajności krów od 1314,64 kg/24h (=< 24 kg) do 1898,76 kg/24h (> 30 kg), jak również częstotliwości doju - różnica między skrajnymi grupami wyniosła ponad 5,5%: 1560,11 kg/24h vs 1654,30 kg/24h. Ustalono, że optymalny udział odmów doju w ciągu doby z punktu widzenia wysokiego RY (1801,43 kg/24h) winien wahać się w przedziale od 20 do 30% (najniższą RY 1537,02 kg/24h zanotowano, gdy udział odrzuconych dojów w ciągu doby przekraczał 40%). Zaobserwowano, że wraz z wysokością w krzyżu dojonych krów RY zwiększała się od 1572,14 kg/24h (=<141 cm) do 1798,52 kg/24h (>145 cm).

Podobnie, dłuższy czas przeżuwania dojonych krów sprzyjał wysokiemu RY, od 1550,25 kg/24 (=< 420 min) do 1677,28 kg/24h (> 460 min). Analogiczną tendencję zanotowano w przypadku udziału rasy PHF w genotypie krów: RY rosła od 1589,38 kg/24h (PHF =< 75%) do 1795,81 kg/24h (PHF > 90%), ale także z częstotliwością korekcji racic w ciągu roku: od 1623,76 kg/24h (1/rok) do 1732,04 kg/24h (3/rok). Ponadto zanotowano, że RY była wyższa o 3,5% w okresie dojów wiosennych i letnich (1661,98 kg/24h) niż jesiennych i zimowych (1605,86 kg/24h). Analiza statystyczna wykazała, że RY była wyższa w stadach z jednym robotem (1648,83 kg/24h), w nowych oborach (1657,13 kg/24h) z podłożem betonowym w części spacerowej obory (1646,18 kg/24h) niż w oborach zmodernizowanych (1609,92 kg/24h), z wieloma robotami (1584,81 kg/24h), z podłożem rusztowym w części spacerowej (1604,18 kg/24h).

Na podstawie analizy statystycznej techniką drzew decyzyjnych wykazano, że największy wpływ na RY, zgodnie z miarą „Importance" i malejącym znaczeniem miały: wydajność mleka dojonych krów, obsada krów na robot, czas wolny robota, szybkość doju, faza laktacji, czas w boksie poświęcony na czynności poprzedzające i kończące dój, udział dojów odrzuconych i wysokość krów w krzyżu (A2, Aerts i in., 2022b, tab. 4). Zastosowany algorytm CART umożliwił skonstruowanie drzewa decyzyjnego zawierający 61 liści i głęboki na 5 poziomów (A2, Aerts i in., 2022b, ryc. 2-6). Przy tworzeniu drzewa największa liczba podziałów powstała w oparciu o obsadę krów na robot (11 podziałów), czas wolny robota (5 podziałów), wydajność mleka od krów i szybkość doju (po 4 podziały). Wygenerowany diagram drzewa decyzyjnego pozwala przewidywać, że najwyższej (2095 kg/24h) RY należy spodziewać się wśród krów produkujących średnio ponad 30 kg mleka dziennie, o szybkości doju powyżej 2,4 kg/min, w dniach pracy robota, w których czas wolny nie przekraczał 10% (A2, ryc. 5, węzeł 52). Z kolei najniższego (1051 kg/24 h) RY należy oczekiwać od krów dających średnio maksymalnie 24 kg mleka dziennie, o szybkości doju mniejszej lub równej 2,4 kg/min, dla których czynności poprzedzające i kończące dój zajmują co najmniej 38% czasu pobytu w boksie, zaś czas wolny robota jest dłuższy niż 25% (z uwzględnieniem czasu mycia robota) (A2, Aerts i in., 2022b, ryc. 3, węzeł 37).

Badanie 3 (A3, Aerts i in., 2021**)**

W rezultacie przeprowadzonych badań stwierdzenie, że krzywa obrazująca wartości dziennych wskaźników odziedziczalności wydajności mleka od 5 (0,133) do 21 dnia laktacji (0,131) wykazywała łagodną tendencję spadkową, a następnie rosnącą do 160 dnia, tj. do osiągnięcia wartości maksymalnej odziedziczalności – 0.345 (wartość ta nie zmieniała się do 169 dnia laktacji) (A3, Aerts i in., 2021, ryc. 3). Od 169 dnia laktacji wykazano systematyczny spadek wskaźnika odziedziczalności wydajności mleka (do poziomu 0,212) trwający już do końca laktacji. W badaniach wykazano, że odziedziczalność częstotliwości doju była najwyższa w początkowej fazie laktacji – 0,322 (A3, Aerts i in., 2021, ryc. 3). W kolejnych 50 dniach laktacji (do 55 dnia) obserwowano spadek wskaźnika odziedziczalności (0,225), a następnie jego wzrost do poziomu 0,227 w 156 dniu laktacji. Od 166 dnia laktacji krzywa charakteryzowała się tendencją spadkową już do końca laktacji. Biorąc pod uwagę dzienną odziedziczalność szybkości doju stwierdzono jednolitą, rosnącą tendencję w całym okresie trwania laktacji – od wartości 0,336 do 0,493 (A3, Aerts i in., 2021, ryc. 3). W badaniach wykazano, że najwyższym, uśrednionym wskaźnikiem odziedziczalności (średnia arytmetyczna z oszacowań dziennych) charakteryzowała się szybkość doju – 0,420, następnie wydajność mleka – 0,257 i częstotliwość doju – 0,230 (A3, Aerts i in., 2021, tab. 2).

W badaniach stwierdzono, że oszacowane wartości korelacji genetycznych między dzienną częstotliwością doju a wydajnościami mleka rejestrowanymi w tych samych dniach wahały się w przedziale od 0,561 do 0,929 (A3, Aerts i in., 2021, tab. 7), zaś krzywa prezentująca wskaźniki korelacji genetycznych wykazywała tendencję do przyjmowania wyraźnie wyższych wartości w końcowej fazie laktacji (A3, Aerts i in., 2021, ryc. 5). Wskaźnik korelacji obliczony na podstawie wyników dziennych wyniósł 0,705. Krzywa prezentująca dzienne wskaźniki korelacji między częstotliwością doju a szybkością oddawania mleka zmierzonymi w tych samym dniach laktacji charakteryzowała się od początku do około 180 dnia laktacji tendencją wzrostową, a następnie spadkową (A3, Aerts i in., 2021, ryc. 5). Wartości oszacowanych wskaźników korelacji wahały się w przedziale od -0,255 do 0,090 – przeciętnie -0,054 (A3, Aerts i in., 2021, tab. 7). Dodatnie zależności między częstotliwością i szybkością doju zarejestrowane w tych samych dniach laktacji obserwowano w środkowej fazie laktacji, tj. od 123 do 228 dnia (A3, Aerts i in., 2021, ryc. 3). Analizując współczynniki dziennych korelacji genetycznych między szybkością doju a wydajnością mleka z tych samych dni laktacji wykazano, że wahały się one w wąskim przedziale od -0,174 do 0,020 – przeciętnie -0,057 (A3, Aerts i in., 2021, tab. 7). Krzywa prezentująca wartości korelacji do 142 dnia laktacji wykazywała łagodną tendencję rosnącą, a następnie malejącą (A3, Aerts i in., 2021, ryc. 3). Dodatnie wartości współczynników korelacji otrzymano między szybkością doju i wydajnością mleka rejestrowanymi od 104 do 172 dnia laktacji (A3, Aerts i in., 2021, ryc. 3).

3.5. DYSKUSJA

Zasadniczym celem przeprowadzonych badań było prognozowanie ME i RY – kluczowych cech z ekonomicznego punktu widzenia w gospodarstwach wyposażonych w AMS. Pierwsza z cech jest wskaźnikiem przydatności krowy, z kolei druga przydatności całego stada do doju automatycznego (A1, Aerts i in., 2022a, A2, Aerts i in., 2022b).

Løvendahl i in. (2014) stwierdzili, że w gospodarstwach zrobotyzowanych krowa, która daje najwięcej mleka w ciągu jednej minuty czasu przebywania w boksie (ME), powinna być nazywana "krową wydajną w AMS". Vosman i in. (2014) w badaniach na krowach rasy holsztyńsko-fryzyjskiej uzyskali ME na poziomie 1,61 kg/min. Piwczyński i in. (2021a) ustalili, że ME może być warunkowana krajem, w którym dojone są krowy, i tak na Łotwie wyniosła ona 1,44 kg/min, na Litwie 1,45 kg/min, w Czechach i Holandii 1,55 kg/min, w Niemczech, Francji i Polsce 1,61 kg/min, zaś we Włoszech 1,75 kg/min. Konfrontując stwierdzoną w badaniach własnych ME (1,67 kg/min) z zanotowaną przez Vosman i in. (2014) i Piwczyńskiego i in. (2021a) należy uznać ją za relatywnie wysoką, co mogło być spowodowane faktem, iż krowy wybrane do badań pochodziły z wysoko wydajnych stad.

W oborach z AMS dzienna wydajność mleka na robota może być uważana za kluczowy czynnik opłacalności produkcji (Salfer i in., 2017). Piwczyński i in. (2022) analizowali przeciętny RY w 8 krajach UE i USA. Autorzy wykazali, że w zależności od kraju RY wahała się od 1294 (Litwa) do 1862 kg (USA), przy obsadzie krów na robot wynoszącej od 53,06 (Holandia) do 58,95 szt. (Niemcy). W badaniach własnych (A2, Aerts i in., 2022b) RY wyniosła 1634,56 kg przy wyraźnie wyższej obsadzie krów na robot wynoszącej średnio 60,48 szt. Podkreślenia wymaga, że uzyskany wynik był lepszy aniżeli raportowany w odniesieniu do wszystkich 8 krajów przynależących do UE (Piwczyński i in., 2022). Jednocześnie należy zaznaczyć, że potencjalne możliwości poprawy RY są jeszcze bardzo duże. Piwczyński i in. (2022) podają, że przeciętna RY dla 200 najlepszych na świecie gospodarstw utrzymujących bydło mleczne za rok 2021 wyniosła 2665 kg.

W badaniu 1 (A1, Aerts i in., 2021a) analizowano wpływ 9 czynników/zmiennych na ME przy użyciu metody analizy wariancji oraz techniki drzew decyzyjnych. Rezultatem pierwszej z metod było wykazanie statystycznego wpływu większości, poza typem obory, uwzględnionych w modelu liniowym czynników na ME. Z kolei druga z metod, oprócz uszeregowania znaczenia czynników w kształtowaniu zmienności ME, umożliwiała wskazanie najlepszej/najgorszej kombinacji poziomów czynników gwarantującej najwyższą/najniższą ME. W modelowaniu tym jako zmiennej objaśniającej nie uwzględniono szybkości doju, gdyż przeprowadzona wcześniej analiza korelacyjna wykazała wysoko istotną zależność (współczynnik korelacji równy 0,879) między nią a ME. Uznano tym samym, że szybkość doju winna być uznana za podstawowe kryterium selekcyjne w doskonaleniu ME. Zastosowana technika drzew decyzyjnych wykazała, że spośród pozostałych zmiennych (8) największy wpływ na ME („Importance” > 0,5) wywarły: wydajność mleka, częstotliwość doju, czas podłączenia strzyka, dzień laktacji, kolejna laktacja i obsada krów na robot. Fakt bezpośredniego związku między wydajnością mleka krowy i ME został odnotowany przez Piwczyńskiego i in. (2021a). Cytowani autorzy zanotowali, że w krajach (Włochy, USA), w których krowy reprezentują wysoką indywidualną mleczność rejestrowana jest wysoka ME.

Statystycznego znaczenia częstotliwości doju w kształtowaniu zmienności wydajności mleka, a w konsekwencji ME dowodzą wyniki badań Bach i Busto (2005), Gygax i in. (2007), Løvendahl i in. (2014). Løvendahl i Chagunda (2011) wykazali, że krowy o wyższej częstotliwości mleka dawały o 20% więcej mleka niż krowy o częstotliwości niższej. W przeprowadzonych badaniach własnych (A1, Aerts i in., 2021a) wykazano, że wielkość wpływu częstotliwości doju na ME była dodatkowo warunkowana wydajnością mleka dojonych krów. W przypadku krów o wydajności mleka poniżej 35 kg na dobę najwyższą ME obserwowano wtedy, gdy częstotliwość doju wynosiła 2 razy na dobę, zaś od 35 kg konieczne były 3 doje na dobę. Podkreślenia wymaga, że zwiększenie częstotliwości doju wśród krów z wydajnością mleka powyżej 35 kg do co najmniej 4 razy na dobę pogarszało ME.

W badaniach wykazano, że skracanie się czasu podłączenia strzyka do kubka udojowego zawsze sprzyjało wysokiej ME. Pozwala to wnioskować, że w doskonaląc ME konieczne jest prowadzenie selekcji krów na prawidłową budowę wymienia, tj. dostosowaną do AMS. Uzyskane wyniki w tym zakresie są zgodne z zaprezentowanymi przez Bach i Busto (2005), którzy wykazali, że niepowodzenia w zakładaniu kubków udojowych mają duży wpływ na ogólną wydajność mleka. Piwczyński i in. (2021c) sugerują, że krótki czas podłączenia strzyka może poprawić opłacalność automatycznego doju, gdyż krowa szybciej zwalnia miejsce w robocie dla kolejnego zwierzęcia, co pozwala na zwiększenie liczby krów korzystających z jednego robota.

Na podstawie diagramu drzewa zaobserwowano, że krowy dojące się do 150 dnia laktacji charakteryzowały się z niższą ME, niż dojone w drugiej jej połowie, co jest zgodne z wynikami Heringstad i Bugten (2014). Wykazano również, że wyższą ME charakteryzowały się wieloródki niż pierwiastki, co z kolei koresponduje z wynikami badań Vosman i in. (2014).

W literaturze przedmiotu brakuje informacji na temat zależności pomiędzy obsadą krów na robot a ME. Dostępne są zaś opracowania dotyczące wpływu obsady krów na robot na MY, choć nie zawsze jest to wpływ statystyczny (Siewert i in., 2018; Tse i in., 2018). Lee i in. (2019) stwierdzili, zwiększanie się MY wraz ze wzrostem obsady krów na robot do 60 szt. W badaniach własnych, w budowie drzewa decyzyjnego obsada krów na robot została uwzględniona jednokrotnie. Z powstałego podziału drzewa można wnioskować, że lepszej ME należy oczekiwać wtedy, gdy obsada krów nie przekracza 56 krów na robot. Pozostaje to w sprzeczności z wynikami wcześniej przeprowadzonej analizy wariancji. Uzasadnieniem tej rozbieżności może być fakt, że w przypadku analizy wariancji, w odróżnieniu do techniki drzew decyzyjnych nie badano interakcji między czynnikami głównymi.

W Badaniu 2 (A2, Aerts i in., 2021b) analiza wariancji wskazała aż 18 zmiennych statystycznie związanych z RY. Z kolei algorytm CART drzewa decyzyjnego skonstruował diagram drzewa w oparciu o tylko 8 zmiennych. Zaznaczania wymaga, że były to zmienne, poza wysokością w krzyżu, wskazane również przez analizę wariancji jako źródło zmienności RY. Z tego względu dyskusję wyników ograniczono do wspólnej grupy 7 zmiennych wskazanych przez obydwie metody.

Zastosowane w Badaniu 2 (A2, Aerts i in., 2021b) analiza wariancji i technika drzew decyzyjnych wykazały, że RY wzrastała wraz ze wzrostem wydajności mleka, co jest to zgodne z wynikami badań Piwczyńskiego i in. (2021a) oraz Castro i in. (2012). W badaniach własnych najwyższą RY obserwowano przy wydajności mleka od krowy powyżej 30 kg na dobę.

W objętych badaniami stadach przeciętna obsada krów na robot wynosiła 60,48 szt., co odpowiada wynikowi podanemu przez Pezzuolo i in. (2017) – 60,8. Zdaniem Rodenburga (2017) maksymalne obłożenie nie powinno przekraczać 60 krów na jednego robota udojowego. W przeprowadzonych badaniach (A2, Aerts i in., 2021b) dowiedziono, że możliwe jest zwiększenie obsady krów nawet do powyżej 65 szt., co skutkowało najkorzystniejszymi wartościami RY, tym samym umożliwia to wcześniejszy zwrot kosztów instalacji AMS w oborze. Na sformułowanie podobnego wniosku pozwalają wyniki zaprezentowane przez Castro i in. (2012). W cytowanych badaniach obsada krów na robot wyniosła 68 szt., dzięki temu zwiększyła się statystycznie roczną wydajność mleka na robota (185460 ± 137460 kg

W badanych stadach czas wolny robota przeciętnie wyniósł 17,77% doby, co jest okresem krótszym niż podany przez Tse i in. (2018) – 23% i Castro i in. (2012) – 28%, czy też Piwczyńskiego i in. (2021a) dla krów dojonych w wybranych krajach UE, od 19,91% (Polska) do 27,24% (Czechy). Z analizy obliczonych średnich najmniejszych kwadratów, jak również powstałych reguł podziału drzewa decyzyjnego wynika, że dążąc do maksymalizacji RY możliwe jest skrócenie czasu wolnego robota udojowego nawet poniżej 10%.

W badaniach własnych (A2, Aerts i in., 2022b) średnia szybkość doju kontrolowanych krów wyniosła 2,49 kg/min, podobnie jak w badaniach Lee i Choudhary (2006) oraz Sitkowskiej i in. (2018). Piwczyński i in. (2020b) wykazali, że szybkość doju była istotnie zróżnicowana krajem, w którym dojone są krowy: wahała się między 2,10 kg/min (Litwa) a 2,79 kg/min (we Włochy). W badaniach własnych wykazano tendencję do wzrostu RY wraz z szybkością doju, co czyni zasadnym wybór do dalszej hodowli szybko dojących się krów. Jednak należy również zwrócić uwagę na fakt, że zbyt szybki dój może prowadzić do uszkodzenia strzyków i może być przyczyną stanów zapalnych wymienia *mastitis* (Lee i Choudhary, 2006; Sitkowska i in., 2017; Piwczyńskiego i in., 2021c).

W badaniach (A2, Aerts i in., 2022b) stosując równolegle analizę wariancji i technikę drzew decyzyjnych wykazano, że RY malało wraz z fazą zaawansowania laktacji. Oznacza to, że z punktu widzenia wysokiej RY, a tym samym opłacalności produkcji zalecane są krótkie laktacje. Praktycznym ustaleniem przeprowadzonych badań było również wykazanie, że długi czas poświęcony na czynności poprzedzające oraz kończące dój, powyżej 30% czasu spędzonego przez krowę w boksie udojowym obniżał RY o ponad 300 kg/dobę. Jest to zrozumiałe, gdyż czas spędzony przez krowę w robocie, który nie jest wykorzystywany do doju, jest nieproduktywny i powoduje straty ekonomiczne. Ponadto ogranicza dostęp do robota innym krowom, szczególnie znajdujących się w niższej hierarchii w stadzie oraz zazwyczaj krowom tuż po wycieleniu.

Zgodnie z zaleceniami producentów AMS liczba dojów odrzuconych powinna wahać się w przedziale 1,5 do 2,5 (odpowiedź ustna: Lely indastry). W badaniach przeprowadzonych przez Piwczyńskiego i in. (2021a) na podstawie danych z systemu rejestracji danych firmy Lely wykazano, że przeciętna liczba dobowa liczba dojów odrzuconych w zależności od kraju i roku rejestracji wahała się o 1,51 do 3,78. Podkreślenia wymaga, że spośród objętych badaniami krajów na Litwie, w której zarejestrowano największą dobową liczbę dojów odrzuconych 3,33-3,78, pozyskiwano najmniejszą ilość mleka z robota udojowego – od 1277 do 1411 kg/24h. Na podstawie analizy struktury drzewa decyzyjnego oraz obliczonych średnich (analiza wariancji) (A2, Aerts i in., 2022b) wynika, że wysoki udział dojów nieudanych (w szczególności powyżej 40%) negatywnie wpływa na RY.

W Badaniach 1 i 2 (A1, Aerts i in., 2022a, A2, Aerts i in., 2022b) dotyczących prognozowania ME i RY wykazano, że były one najsilniej uwarunkowane wydajnością i szybkością oddawania mleka, a także częstotliwością doju (dotyczy ME). W związku z tym za zasadne uznano oszacowanie odziedziczalności, a także korelacji genetycznych między tymi trzema cechami. Źródłem danych do przeprowadzonego Badania 3 (A3, Aerts i in., 2021) były dzienne wydajności pierwiastek zarejestrowane przez AMS. Podkreślenia wymaga, że w literaturze przedmiotu znajduje się niewiele prac z tego zakresu (Nixon i in., 2009). Badania z udziałem bydła rasy PHF i danych pozyskanych z AMS były prowadzone jedynie przez Piwczyńskiego i in. (2021c), a ich podstawą były wyniki zarejestrowane przez AMS w odstępach miesięcznych. W związku z powyższym podjęte badania należy traktować jako pionierskie.

Uzyskana w badaniach własnych krzywa opisująca przebieg dziennych odziedziczalności wydajności mleka w czasie laktacji posiadała kształt odwróconej paraboli, co jest zbieżne z wynikami m.in. Sasaki i in. (2017), Costa i in. (2008), Piwczyński i in. (2021c). Wartości oszacowanych wskaźników odziedziczalności dla dziennych wydajności mleka wahały się z przedziale od 0,131 do 0,345, co jest przedziałem zbliżonym do uzyskanego na podstawie wyników dojów próbnych przez Cobuci i in. (2005) (0,15-0,31), Biassus i in. (2011) i Piwczyńskiego i in. (2021c). Z kolei odmienny zakres wartości podają Costa i in. (2008) (0,27-0,42), Naderi (2016) (0,45-0,60) oraz Moretii i in. (2018) (0,14-0,53). W badaniach przeprowadzonych przez Nixona i in. (2009) z wykorzystaniem danych z AMS zakres dziennych odziedziczalności był węższy niż w badaniach własnych, wahał się od 0,14 do 0,20. Uśredniona wartość dziennych odziedziczalności wydajności mleka, obliczona na podstawie 300 dziennych wskaźników – 0,257, znajdowała się w zakresie wyników prezentowanych przez innych autorów: 0,12-0,34 (Gray, 2011; Nixon i in., 2009; Sasaki i in., 2017; Kirsanova i in., 2019; Kheirabadi, 2019).

Badania Brzozowskiego i in. (2020) i Piwczyńskiego i in. (2020a) wykazały, że zamiana systemu doju z CMS na AMS korzystnie wpływa na wzrost wydajności mleka, co jak sugerują de Koning i in. (2004), Österman i in. (2005), Tse i in. (2018) oraz Santos i in. (2018) jest efektem zwiększonej frekwencji dojów w ciągu doby. Z tego względu ważne jest ustalenie genetycznego uwarunkowania tej cechy, zwłaszcza, że prace z tego zakresu są stosunkowo nieliczne (König i in., 2006; Nixon i in., 2009; Calström i in., 2013; Santos i in., 2018; Piwczyński i in., 2021c). Nixon i in. (2009) oszacowali odziedziczalności częstotliwości doju w oparciu o wskaźniki dobowe pozyskane z AMS. Wyznaczona na ich podstawie krzywa wykazywała początkowo tendencję spadkową, później rosnącą, po połowie laktacji ponownie spadkową, a w ostatnim jej miesiącu – rosnącą, co w pewnej mierze jest zbieżne z uzyskaną w badaniach własnych. Różnica polega na znacznie niższym zakresie wartości oszacowanych dziennych odziedziczalności w badaniach Nixona in. (2009) niż obecnie prezentowanych, odp.: 0,02-0,08 vs. 0,153-0,322. Szerszy zakres wartości dziennych odziedziczalności częstotliwości doju niż w obecnie prezentowanych, stwierdzono w badaniach Piwczyńskiego i in. (2021c). W badaniach własnych (A3, Aerts i in., 2021) stwierdzono relatywnie wysoką odziedziczalność częstotliwości doju w początkowej fazie laktacji, co bezpośrednio wpłynęło na duży zakres zmienności tego wskaźnika w czasie trwania laktacji. W przeprowadzonych badaniach uśredniony wskaźnik odziedziczalności obliczony na podstawie wartości dziennych wyniósł 0,230, tym samym wyraźnie przekracza uzyskany przez Calström i in. (2013) na podstawie wyników 1, oraz dla łącznie 2 i 3 laktacji (0,02- 0,07) oraz König i in. (2006) dla kolejnych 100. dniowych okresów laktacji, odp.: 0,16, 0,19, 0,22. Przeprowadzone badania pozwalają zatem wnioskować, że możliwa jest skuteczna selekcja krów pierwiastek na zwiększoną frekwencję doju.

Z punktu widzenia opłacalności produkcji w oborach z AMS kluczowym czynnikiem jest wysoki uzysk mleka z robota udojowego w jednostce czasu. Z tego względu w oborach tych szczególnie pożądane są szybko dojące się krowy. Badania przeprowadzone przez Gäde i in. (2006, 2007), Carlström i in. (2013), Santos i in. (2018) oraz Wethal i Heringstad (2019), na podstawie wydajności dobowych oraz dojów próbnych z obór wyposażonych w AMS, wykazały że oszacowana z zastosowaniem regresji losowych odziedziczalność szybkości doju wahała się od 0,25 do 0,55. W badaniach Piwczyńskiego i in. (2021c), w których również zastosowano regresje losowe, dzienna odziedziczalność szybkości doju wahała się w przedziale 0,252 do 0,665, zaś oszacowany wskaźnik odziedziczalności dla 305. dniowej laktacji wyniósł 0,431. Podkreślenia wymaga, że krzywa opisująca zmiany dziennych odziedziczalności w tych badaniach przyjęła stosunkowo wysokie wartości w pierwszym i ostatnim miesiącu laktacji. W pozostałym okresie krzywa wykazywała tendencję do wzrostu do 170-180 dnia laktacji, a następnie do spadku do 250 dnia. W aktualnie przeprowadzonych badaniach uzyskano wyniki świadczące o umiarkowanej odziedziczalności szybkości doju (od 0,336-0,493) dającej podstawę do prowadzenia efektywnej selekcji na tę cechę, a tym samym zwiększenia opłacalności produkcji w gospodarstwie. Uzyskany w badaniach własnych (A3, Aerts i in., 2021) uśredniony wskaźnik odziedziczalności szybkości doju dla wydajności dziennych (0,420) był dwukrotnie wyższy niż oszacowany przez Berry i in. (2013) przy wykorzystaniu wyników dojów próbnych wynoszący (0,210).

W badaniach (A3, Aerts i in., 2021) stwierdzano dodatnie, umiarkowane, a nawet wysokie genetyczne zależności między częstotliwością doju i wydajnością mleka mierzonymi w tych samych dniach laktacji: 0,561-0,929. Poparciem uzyskanych wyników są rezultaty badań König i in. (2006), którzy oszacowali wskaźniki korelacji genetycznych między częstotliwości doju i wydajności mleka dla kolejnych 100. dniowych okresów laktacji, wynoszące odpowiednio: 0,47-0,57, 0,46-0,48, 0,49-0,53. Zbieżne z wynikami badań własnych są też wartości dziennych współczynników korelacji genetycznych zaprezentowane przez Nixon i in. (2009): od 0,27 do 0,80. Podkreślenia wymaga, że najsilniejsze genetyczne zależności między częstotliwością doju i wydajnością mleka cytowani autorzy zaobserwowali w końcowej fazie laktacji, co ściśle koresponduje z prezentowanymi wynikami.

Wethel i Heringstad (2019) analizowali zależność między częstotliwością doju i szybkością doju na podstawie dziennych wydajności rejestrowanych w AMS. Uzyskany przez nich wskaźnik korelacji genetycznej (0,14), podobnie jak w badaniach własnych (-0,054) świadczy o słabej zależności między tymi cechami. Jednak w przeprowadzonych badaniach oszacowane wskaźniki przyjmowały na ogół wartości ujemne, co sugeruje, że selekcja na zwiększoną częstotliwość doju może w niewielkim stopniu negatywnie wpłynąć na szybkość doju – w szczególności w okresie do 60 dnia laktacji (wsp. korelacji genetycznej < –0,138). Prawdopodobną różnicą między oszacowaniami własnymi oraz Wethel i Heringstad (2019) może być zastosowany odmienny model statystyczny. W badaniach własnych (A3, Aerts i in., 2021) zastosowano model z regresjami losowymi wraz z wielomianami Legendre'a, podczas gdy cytowani autorzy efekt dnia doju oraz łączony stado- kalendarzowy dzień doju włączyli do modelu jako efekt stały.

Oszacowane w badaniach (A3, Aerts i in., 2021) wskaźniki korelacji genetycznych między wydajnością mleka i szybkością doju mierzonych w tych samych dniach laktacji, świadczą o słabych, w większości przypadków ujemnych zależnościach między tymi cechami. Z kolei, uśredniony wskaźnik korelacji genetycznej, na podstawie dziennych oszacowań z całej laktacji –0,057 wskazuje na brak zależności między wydajnością mleka i szybkością doju. Uzyskane w badaniach własnych wyniki w zakresie korelacji genetycznych między wydajnością mleka i szybkością doju pozostają w sprzeczności z prezentowanymi przez innych autorów: Gäde i in. (2006): 0,51; Amin (2007): od 0,83 do 0,93, Berry i in. (2013): 0,69, Santos i in. (2018): 0,40,. Prawdopodobnym źródłem tych rozbieżności było pochodzenie danych (wydajności dzienne, doje próbne, laktacyjne), metoda i model szacowania parametrów.

3.6. PODSUMOWANIE

Analiza statystyczna wykonana techniką drzew decyzyjnych wykazała, że największy wpływ na efektywność doju oraz uzysk mleka z robota udojowego miała indywidualna wydajność mleka od krowy. Dodatkowo efektywność doju warunkowana była szybkością i częstotliwością doju, czasem podłączenia kubka udojowego do strzyka, dniem laktacji, kolejną laktacja i obsadą krów na robot, udziałem mleka pozyskanego z ćwiartek tylnych, wiekiem w dniu pierwszego wycielenia i sezonem wycielenia. Dobowy uzysk mleka z robota udojowego zależał od: obsady krów na robot, czasu wolnego robota, szybkości doju, fazy laktacji, czasu w boksie poświęconemu na czynności poprzedzające i kończące dój, udziału dojów odrzuconych i wysokości w krzyżu dojonych krów.

Zastosowanie w analizie statystycznej techniki drzew decyzyjnych pozwoliło na wyłonienie i wskazanie optymalnej kombinacji poziomów kontrolowanych czynników gwarantującej wysoką efektywność doju oraz wysoki uzysk mlek z robota udojowego. Wykazano, że najwyższej efektywności doju należy oczekiwać wśród krów produkujących powyżej 35 kg mleka dziennie, dojonych w robotach o obłożeniu mniejszym niż 56 krów oraz utrzymywanych w nowych oborach, w których system AMS wykorzystywany był od co najmniej 3 lat. Z kolei najwyższego uzysku mleka z robota należy się spodziewać w oborach, gdy wolny czas robota nie przekracza 10%, dobowy uzysk mleka od krowy wynosi powyżej 30 kg, zaś szybkość doju jest wyższa niż 2,4 kg/min.

Przeprowadzone badania jednoznacznie wykazały, że istnieje możliwość prowadzenia skutecznej selekcji na szybkość oddawania mleka, wydajność mleka i częstotliwość doju, co sprzyjać powinno wysokiej efektywności doju krów, wysokiemu dobowemu uzyskowi mleka z robota udojowego, a tym samym zwiększeniu opłacalności produkcji w stadzie. Biorąc pod uwagę wysoką, dodatnią korelację genetyczną między częstotliwością doju a wydajnością mleka, należy sugerować preferowanie w hodowli krów z naturalną skłonnością do odbywania częstych wizyt w robocie udojowym, co winno pośrednio doskonalić równocześnie założenia genetyczne wydajności mleka.

3.7. LITERATURA

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4. STRESZCZENIE

Czynniki warunkujące wydajność stada krów w oborach wyposażonych w automatyczny system doju

mgr inż. Joanna Aerts

Słowa kluczowe: automatyczny system doju, efektywność doju, parametry doju, parametry genetyczne, prognozowanie

Automatyczny system doju dostarcza hodowcy ogromną ilość informacji, które pozwalają na sprawne zarządzenie stadem, a tym samym poprawę opłacalności produkcji. Efektywność doju oraz dobowy uzysk mleka z robota udojowego to kluczowe czynniki decydujące o opłacalności produkcji w gospodarstwie mleczarskim. Z tego względu podjęto badania, których celem było ustalenie czynników odpowiedzialnych za zmienność efektywności doju i dobowy uzysk mleka z robota udojowego, a w szczególności ustalenie za pomocą techniki drzew decyzyjnych takiej kombinacji czynników i ich poziomów, które gwarantują wysoki poziom tych cech. Dodatkowym celem badań było oszacowanie odziedziczalności i korelacji genetycznych między cechami (wydajność mleka, szybkość doju, częstotliwość doju) krów pierwiastek, które w największym stopniu wpływają na efektywność doju i dobowy uzysk mleka z robota udojowego. Podkreślenia wymaga, że do tej pory tak kompleksowe badania w powyższym zakresie na bydle rasy polskiej holsztyńsko-fryzyjskiej nie były prowadzone. Badania zrealizowano w 21 stadach zlokalizowanych na terenie całej Polski, w których w latach 2010-2013 tradycyjny system doju zastąpiono systemem automatycznym – roboty udojowe Astronaut A4. W stadach użytkowano krowy rasy polskiej holsztyńsko-fryzyjskiej, które utrzymywano w systemie wolnostanowiskowym i żywiono w systemie PMR (częściowo wymieszana dawka). Łącznie badaniami objęto 4985 krowy. Dane dotyczące użytkowości krów pochodziły z systemu zarządzania i rejestracji danych T4C firmy Lely. Analiza statystyczna wykonana techniką drzew decyzyjnych wykazała, że największy wpływ na efektywność doju oraz uzysk mleka z robota udojowego miała indywidualna wydajność mleka od krowy. Dodatkowo efektywność doju warunkowana była szybkością i częstotliwością doju, czasem podłączenia strzyka, dniem laktacji, kolejną laktacja i obsadą krów na robot, udziałem mleka pozyskane z ćwiartek tylnych, wieku w dni pierwszego wycielenia i sezonu wycielenia. Dobowy uzysk mleka z robota zależała od: obsady krów na robot, czasu wolnego robota, szybkości doju, fazy laktacji, czasu w boksie poświęconemu na czynności poprzedzające i kończące dój, udziału dojów odrzuconych i wysokości w krzyżu krów. Przeprowadzona analiza statystyczna techniką drzew decyzyjnych pozwoliła na wyłonienie i wskazanie optymalnej kombinacji poziomów kontrolowanych czynników gwarantującej wysoką efektywność doju i dobowy uzysk mleka z robota udojowego. Wykazano, że najwyższą efektywność doju (2,01 kg) charakteryzowały się krowy, które produkowały więcej niż 35 kg mleka dziennie, były dojone w robotach o obłożeniu mniejszym niż 56 krów a utrzymywane były w nowych oborach, w których system AMS wykorzystywany był od co najmniej 3 lata. Z kolei najwyższego dobowego uzysku mleka z robota udojowego (2096 kg) należy oczekiwać w oborach, w których wolny czas robota nie przekraczał 10%, dobowy uzysk od krowy wynosił powyżej 30 kg, zaś szybkość doju była wyższa niż 2,4 kg/min. Oszacowane w badaniach wskaźniki odziedziczalności (uśrednione wartości wskaźników odziedziczalności dziennej dla całej laktacji) pozwalają wnioskować, że istnieje możliwość prowadzenia skutecznej selekcji na szybkość oddawania mleka (0,420), wydajność mleka (0,257) i częstotliwość doju (0,230), co sprzyjać powinno wysokiej efektywności doju krów, wysokiemu dobowemu uzyskowi mleka z robota udojowego, a tym samym zwiększeniu opłacalności produkcji w stadzie. Biorąc pod uwagę wysokie, dodatnie wartości korelacji genetycznych między dzienną frekwencją dojów a wydajnością mleka (0,561-0,929), należy preferować w hodowli krowy z naturalną skłonnością do odbywania częstych wizyt w robocie udojowym, co winno pośrednio doskonalić założenia genetyczne wydajności mleka.

5. ABSTRACT

Factors of cow herd performance in barns equipped with automatic milking systems

Joanna Aerts, M.Sc.

Key words: automatic milking system, milking efficiency, milking parameters, genetic parameters,forecasting

An automated milking system provides the dairy farmer with a huge amount of information to manage the herd efficiently, thereby improving production profitability. Milking efficiency and milk yield from the milking robot are key factors in determining the profitability of production on a dairy farm. Therefore, a study was undertaken to identify the factors responsible for the variability in milking efficiency and milk yield from a milking robot and to determine, using the decision tree technique, the combination of factors and their levels that guarantee a high level of these traits. An additional aim of the study was to estimate the heritability and genetic correlations between the traits (milk yield, milking speed, milking frequency) of primiparous cows that most influence milking efficiency and milk yield from the milking robot. It should be emphasized that so far, such comprehensive research in the above-mentioned scope on Polish Holstein-Friesian cattle has not been conducted. The research was conducted in 21 herds located all over Poland, in which in the years 2010-2013 the traditional milking system was replaced by an automatic system - milking robots Astronaut A4. The herds used Polish Holstein-Friesian cows, which were kept in the free-stall system and fed in the PMR (partial mix ration) system. A total of 4985 cows were included in the study. Cow performance data were obtained from Lely's T4C data management and recording system. Statistical analysis using the decision tree technique showed that individual milk yield per cow had the greatest influence on milking efficiency and milk yield from the milking robot. In addition, milking efficiency was determined by milking rate and frequency, teat connection time, day of lactation, subsequent lactation and cow density per robot, proportion of milk obtained from hind quarters, age on days of first calving and calving season. Daily milk yield from the robot depended on cow stocking density per robot, free time of the robot, milking rate, lactation stage, time in stall devoted to pre- and post-milking activities, proportion of rejected milkings and height in cow cross. The statistical analysis carried out using the decision tree technique allowed for the identification and identification of the optimal combination of levels of controlled factors guaranteeing high milking efficiency and milk yield from the milking robot. It was shown that the highest milking efficiency (2.01 kg) was found in cows that produced more than 35 kg of milk per day, were milked in robots with an occupancy of less than 56 cows and were kept in new barns where the AMS system had been used for at least three years. On the other hand, the highest milk yields from the milking robot (2096 kg) are to be expected in barns where the free time of the robot did not exceed 10%, the daily yield per cow was above 30 kg and the milking rate was higher than 2.4 kg/min. The heritability indices estimated in the study (averaged values of daily heritability indices for the whole lactation) allow us to conclude that it is possible to conduct effective selection for milking rate (0.420), milk yield (0.257) and milking frequency (0.230), which should favour high milking efficiency of cows, high daily milk yield from the milking robot, and thus increase the profitability of production in the herd. Given the high, positive values of the genetic correlations between daily milking frequency and milk yield (0.561-

0.929), cows with a natural tendency to make frequent visits to the milking robot should be preferred in breeding, which should indirectly improve the genetic assumptions of milk yield.

6. ZAŁĄCZNIKI

6.1. KOPIE ARTYKUŁÓW NAUKOWYCH STANOWIĄCYCH CYKL PUBLIKACJI ROZPRAWY DOKTORSKIEJ

animals

MDPI

Article

Forecasting Milking Efficiency of Dairy Cows Milked in an Automatic Milking System Using the Decision Tree Technique

Joanna Aerts [1], Magdalena Kolenda [2,*], Dariusz Piwczyński [2], Beata Sitkowska [2] and Hasan Önder [3]

[1] Lely Services B.V., Cornelis van der Lelylaan 1, 3147 PB Maassluis, The Netherlands; jaerts@lely.com
[2] Department of Animal Biotechnology and Genetics, Faculty of Animal Breeding and Biology, Bydgoszcz University of Science and Technology, 85-084 Bydgoszcz, Poland; darekp@pbs.edu.pl (D.P.); beatas@pbs.edu.pl (B.S.)
[3] Department of Animal Science, Ondokuz Mayis University, Samsun 55139, Turkey; honder@omu.edu.tr
* Correspondence: kolenda@pbs.edu.pl

Simple Summary: Automatic milking systems are gaining popularity worldwide as they help in monitoring milk production traits, inter alia, milking efficiency defined as milk yield divided by box time. In our study we used a statistical method called the decision tree technique, which allows us to study the impact of specific factors on milking efficiency and display them as a simple graphical model. By studying the tree a farmer might identify the factors most affecting milking efficiency.

Abstract: In barns equipped with an automatic milking system, the profitability of production depends primarily on the milking efficiency of a cow (ME; kg/min) defined as cow milk yield per minute of box time. This study was carried out on 1823 Polish Holstein–Friesian cows milked by the automatic milking system (AMS) in 20 herds. Selected milking parameters recorded by the AMS were analyzed in the research. The aim of the study was to forecast ME using two statistical techniques (analysis of variance and decision trees). The results of the analysis of variance showed that the average ME was 1.67 kg/min. ME was associated with: year of AMS operation (being the highest in the first year), number of cows per robot (the highest in robots with 61–75 cows), lactation number (highest for multiparas), season of calving (the highest in spring), age at first calving (>36 months), days in milk (151–250 days) and finally, rear quarter to total milk yield ratio (the highest between 51% and 55%). The decision tree predicted that the highest ME (2.01 kg/min) corresponded with cows that produced more than 45 kg of milk per day, were milked less than four times/day, had a short teatcup attachment time (<7.65 s) and were milked in robots that had an occupancy lower than 56 cows.

Keywords: milking efficiency; automatic milking system; decision trees; dairy cattle

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1. Introduction

During recent decades milk production has changed greatly, due, among other reasons, to the implementation of new milking systems including the automatic milking system (AMS). Automatization in dairy farms has been introduced, for instance, in the form of milking robots, automated milking parlours and rotary milking parlours. The AMS is gaining in popularity in Europe [1,2] due to the possibility of reducing manual labour on dairy farms as the AMS aids farmers with teat-cleaning, attaching teat cups and disinfecting teats after each milking. One of the advantages of the AMS is that the milking frequency per day may increase as cows have access to the AMS regardless of farm employee presence and may use it when needed. This may result in higher milk yield [3–5]. It is well known that the profitability of milk production depends heavily on the milking efficiency of a cow. Milking efficiency may be affected by different factors, including: milking frequency (lower contributes to a lower yield), number of cows per robot (a high number of animals may increase competition in the herd and negatively affect yield) or type of barn in which the animals are milked (new barns built specifically for AMS use may be better adjusted to this purpose and therefore allow cows to use the AMS more efficiently, increasing yield) [6–10]. In the AMS milking efficiency is mostly described as milk yield per minute of box time [11]. The highest milking efficiency is obtained with the best ratio between high milk yield from a cow and the short time spent by said cow in a robot [12]. Heringstad and Bugten [13] noted that ME changes with days in milk (DIM). ME is the lowest during early lactation and highest in mid-lactation, after which it decreases. It is also worth noting that ME is affected by inter alia, the herd, season, milk yield, milking frequency and milking speed.

Many authors have pointed out that milking performance of cows is a complex issue affected by many factors such as number of cows per robot, robots per barn, box time, number of connection attempts or type of traffic (free/forced) [9,10]. ME is an important factor that affects profitability of production and therefore, studies aiming at forecasting ME using prediction models may be beneficial. One of the statistical methods used to forecast the milking efficiency is a decision tree technique, which helps visualise data in a simple tree-like graphical way. This technique creates structures that resemble trunk, branches and leaves. Division of the datasets starts with a root node that is further divided into child nodes, which may divide subsequently until no further division can be made thus creating a leaf. Once the tree is developed it consists of subsets that are maximally homogeneous in terms of the value of the tested traits. Such tree allows one to identify the factors and their levels that contribute to the highest and the lowest values of the tested trait [14]. The authors of the present study have shown that the decision tree technique may be an alternative to analysis of variance or multiple linear regression [15,16].

The aim of this study was to forecast the milking efficiency of Polish Holstein–Friesian cows using the decision tree technique, and at the same time to determine the sources of variability of milk speed and yield, milking frequency, attachment time and box time in automatic milking systems.

2. Material and Methods

2.1. Animals

The study included a total of 1823 Polish Holstein–Friesian cows kept in 20 dairy farms located in Poland (Table 1). Cows were milked using an automatic milking system (AMS; Astronaut A4 by Lely Industries N.V.: Cornelis van der Lelylaan 1, Maassluis, The Netherlands) and were fed a partial mixed ration (PMR), with concentrate feed that was given to animals individually in the milking box depending on their milk yields. Data were collected from dairy cows in their first to third lactation. Data on milking performance of cows milked in AMS were obtained from the T4 C management and data registration system by Lely East. A total of 713,206 records were obtained. The following milking performance variables were tested in this study:

- Days in milk (days, DIM)—average number of milking days;
- Milking frequency (number/day, MF)—number of milkings per cow milked by AMS per day;
- Attachment time per milking (s, AT)—the average time per milking per cow that it took the robot to attach the teatcup;
- Box time (min/day, BT)—the total time spent by a cow in the milking box during a day;
- Milk speed (kg/min, MS)—average milk flow rate per cow per day of robot operation;
- Milk yield (kg/day, MY)—total daily milk yield of a cow per day;
- Ratio of rear quarter MY to total (front and rear quarter) MY (%, RTR),
- Milking efficiency (ME, kg/min)—milk yield per day divided by box time.

Table 1. Characteristics of studied dairy herds milked with automatic milking system.

Her	Number of Robots per Herd	Mean No. of Cows per Robot	Laying Area	Walking Area
A	1	54	Mats	Grates
B	1	59	Mats	Grates
C	1	66	Mats	Grates
D	2	53	Straw	Grates
E	1	55	Straw	Concrete
F	2	51	Mats	Grates
G	1	56	Mats	Concrete
H	1	65	Mats	Concrete
I	1	59	Mats	Grates
J	3	44	Straw	Grates
K	1	55	Mats	Concrete
L	1	63	Mats	Grates
M	1	58	Mats	Grates
N	5	50	Straw	Concrete
O	1	58	Mats	Grates
P	2	53	Mats	Concrete
R	1	59	Mats	Grates
S	3	52	Mats	Grates
T	1	56	Mats	Grates
W	1	62	Mats	Grates

2.2. Statistical Analysis

Other variables that may affect milking efficiency were taken into consideration: year of AMS operation (yAMS: 1, 2 or 3 years), number of cows per one robot (noC: 45–50; 51–55; 56–60 or 61–75 cows), lactation number (noL: 1 or higher (2 or 3)), season of calving (SC: autumn, spring, summer or winter) and age at 1st calving (AFC). For the purposes of statistical analyses, the above-mentioned variables were categorized as follows: DIM: <50, 51–100, 101–150, 151–200, 201–250 and 251–305 days; MF: 1, 2, 3, 4 and ≥5); MY: <25, 25–30, 31–35 and 35–45 kg; RTR: 34–50%; 51–55%; 56–60% and 61–73%.

The statistical analysis of the collected data was performed in three stages. First, using the mixed model repeated measures analysis of variance (procedure mixed SAS) the analysis of milk yield variability and recorded milking parameters was performed [17]. For this purpose, the following mixed model was used (1):

$$y_{ijklmnoprs} = \mu + yAMS_i + Barn_j + noC_k + nL_l + SC_m + AFC_n + DIM_o + RTR_p + (nL \times SC)_{lm} + a_r + e_{ijklmnoprs} \quad (1)$$

where:

$y_{ijklmnopqrs}$—the phenotype value of the trait (ME, MF, AT, BT, MS, MY),
μ—a general average,
$yAMS_i$—the fixed effect of the *i*th yAMS class,
$Barn_j$—the fixed effect of the *j*th barn type,
noC_k—the fixed effect of the *k*th class of noC,
nL_l—the fixed effect of the *l*th noL,
SC_m—the fixed effect of the *m*th SC,
AFC_n—the fixed effect of the *n*th AFC class,
DIM_o—the fixed effect of the *o*th DIM class,
RTR_p—the fixed effect of the *p*th RTR class,
$(nL \times SC)_{lm}$—interaction nL × SC,
a_r—the random effect of *r*th cows,
$e_{ijklmnoprs}$—random error.

The significance differences between the selected groups were established using the Scheffe test (SAS).

In the next step of the statistical procedure, the Pearson correlation coefficients between ME and MF, AT, BT, MS and MY were calculated. The aim of this task was to reduce the number of variables used in the next stage of analysis for prediction of ME.

Then, in the third stage of statistical analysis—the main stage of research—attempts were made to forecast ME using the decision tree technique [17]. All variables were taken into consideration; however, MS was excluded from the model as a high correlation (0.998) between ME and MS was noted.

In ME forecasting the CART (classification and regression trees) algorithm was ultimately used. This algorithm uses variance reduction as a tree division criterion. Due to the continuous nature of the tested variable (ME), two different division criteria were taken into consideration while creating the decision tree—F test statistic and variance reduction [18]. Subsequently trees constructed based on these criteria were compared in terms of the quality of forecasting of ME based on the average squared error. It is worth mentioning that the decreasing value of the average squared error indicated a higher quality of the model. During construction, mean square error was used as a measure to select the best tree based on validation data. Data were divided into training and validation sets. The "training set", which was used to preliminarily fit the model, was constituted from 60% of all observations, while the "validation set" (the set that prevented modelling from overfitting, that is, it prevented an excessive fit of the tree model to the data on the basis of which it was created) was constituted from 40% of all observations. Cows were assigned to the training or validation sets by the random sampling method. It was assumed that the minimum size of a leaf should not be less than 5000 observations, and the maximum depth of a tree (number of branches) should not be deeper than 5.

Each node of the created tree was composed of the following data: node ID (1); milking efficiency (2); and number of observations in a given node or a leaf (3) (Figure 1). An "Importance" measure was used to create a ranking of different variables in terms of their importance in splitting the dataset [17,19]. The "Importance" measure and the way in which it was calculated are provided in the paper by Grochowska et al. [19]. The "Importance" measure takes values between 0 and 1, and a higher value indicates a greater importance during tree construction. This ranking also provides the data on the number of node divisions that were performed based on respective variables [16–19].

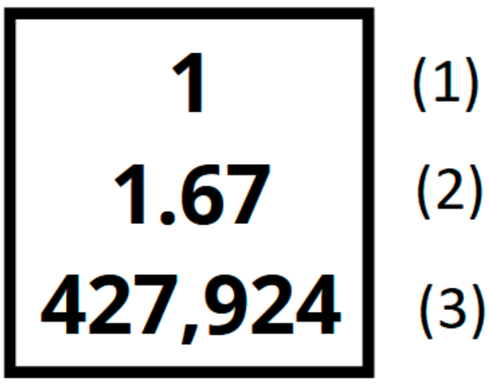

Figure 1. The description of the root node, including the node ID (1), milking efficiency (2) and number of observations in a node or a leaf (3).

3. Results

3.1. Analysis of Milk Yield Variability and Recorded Milking Parameters with the Use of Multivariate Analysis of Variance

Descriptive statistics of analysed traits are presented in Table 2. Cows produced on average of 29 kg of milk per day. While the average box time per milking was 18.41 min, cows spent approximately 6.03 min attached to a robot and milked on the average 2.83 times a day. Results showed that 54.5% of the milk produced by the cows was collected from rear quarters. The results showed that the average milking efficiency in the analyzed population of cows was 1.67 kg/min (Table 2).

Table 2. Descriptive statistics of tested traits.

Variable	N	Mean	SD	CV (%)
Number of cows per robot (n)	713,206	55.37	8.36	15.09
Age at 1st calving (days)	713,206	907.30	237.26	26.15
Days in milk (days)	713,206	149.65	84.22	56.28
Milking frequency (n/day)	713,206	2.83	0.91	31.95
Attachment time (s)	713,206	6.03	3.92	65.05
Box time (min/day)	713,206	18.41	7.57	41.12
Milk speed (kg/min)	713,206	2.59	0.91	34.93
Milk yield (kg/day)	713,206	29.03	9.92	34.17
Rear quarter to total quarter MY ratio (%)	658,159	54.49	7.02	12.88
Milking efficiency (kg/min)	713,206	1.67	0.46	27.33

SD—standard deviation, CV—coefficient of variation.

The analysis of variance showed a highly significant influence of yAMS, noC, noL, SC, AFC, DIM, RTR and noLx SC on ME, MF, AT, BT, MS and MY. Barn type was not significantly associated with ME, MF, MS or MY.

From the mixed-model analysis it was noted that ME was affected by the following factors: yAMS (being the highest in the first years), noC (the highest in robots with 61–75 cows), noL (highest for multiparas), SC (spring), AFC (>36 month), DIM (201–305 days) and finally by RTR (the highest between 51 and 55). It was also noted that the interaction between noL and SC affected ME (Table 3).

Table 3. Impact of selected factors on tested traits (least square means).

Factor	Level	ME	MF	AT	BT	MS	MY
Year of AMS operation	1	1.71 ^{A}	2.93 ^{A}	5.91 ^{A}	18.74 ^{A}	2.67 ^{A}	30.30 ^{A}
	2	1.71 ^{B}	2.88 ^{AB}	6.08 ^{AB}	18.65 ^{AB}	2.65 ^{AB}	30.29 ^{B}
	3	1.69 ^{AB}	2.77 ^{AB}	6.00 ^{AB}	18.36 ^{AB}	2.59 ^{AB}	29.56 ^{AB}
Barn type	Adapted	1.69	2.88	6.15 ^{A}	18.98 ^{A}	2.63	30.34
	New	1.72	2.84	5.82 ^{A}	18.19 ^{A}	2.65	29.76
Number of cows per robot	45–50	1.65 ^{A}	2.89 ^{A}	5.95 ^{Aa}	18.62 ^{A}	2.59 ^{A}	29.26 ^{A}
	51–55	1.69 ^{AB}	2.91 ^{AB}	5.93 ^{B}	18.73 ^{AB}	2.63 ^{AB}	30.08 ^{AB}
	56–60	1.71 ^{ABC}	2.88 ^{ABC}	6.00 ^{BCa}	18.66 ^{BC}	2.64 ^{ABC}	30.26 ^{ABC}
	61–75	1.76 ^{ABC}	2.76 ^{ABC}	6.12 ^{ABC}	18.32 ^{ABC}	2.70 ^{ABC}	30.61 ^{ABC}
Lactation number	1	1.61 ^{A}	2.83 ^{A}	6.12 ^{A}	18.49 ^{A}	2.52 ^{A}	28.17 ^{A}
	2 or 3	1.79 ^{A}	2.88 ^{A}	5.88 ^{A}	18.68 ^{A}	2.76 ^{A}	31.93 ^{A}
Season of calving	Autumn	1.70 ^{A}	2.90 ^{A}	5.99	18.91 ^{A}	2.63 ^{A}	30.49 ^{A}
	Spring	1.74 ^{AB}	2.77 ^{AB}	6.06 ^{A}	18.11 ^{AB}	2.69 ^{AB}	29.76 ^{AB}
	Summer	1.68 ^{ABC}	2.85 ^{BC}	5.99	18.57 ^{ABC}	2.60 ^{ABC}	29.47 ^{ABC}
	Winter	1.70 ^{BC}	2.91 ^{BC}	5.97 ^{A}	18.74 ^{BC}	2.63 ^{BC}	30.49 ^{BC}
Age at first calving (months)	$\leq$24	1.67 ^{Aa}	2.76 ^{A}	5.65 ^{A}	18.43 ^{A}	2.61 ^{Aa}	28.03 ^{A}
	[24–25)	1.59 ^{Ba}	2.66 ^{B}	6.33 ^{A}	15.92 ^{AB}	2.38 ^{B}	25.42 ^{AB}
	[25–26)	1.71 ^{Bb}	2.90 ^{ABC}	5.89	18.86 ^{BC}	2.64 ^{BCa}	30.73 ^{ABC}
	[26–36)	1.76 ^{AB}	3.08 ^{ABCD}	5.95	21.61 ^{ABCD}	2.75 ^{AB}	34.92 ^{ABCD}
	$\geq$36	1.80 ^{ABb}	2.88 ^{ABD}	6.17 ^{A}	18.09 ^{BD}	2.82 ^{ABC}	31.15 ^{ABD}

Table 3. *Cont.*

Factor	Level	ME	MF	AT	BT	MS	MY
Days in milk (days)	50	1.64 ^{A}	3.00 ^{A}	6.25 ^{Aa}	21.25 ^{A}	2.47 ^{A}	32.63 ^{A}
	51–100	1.70 ^{AB}	3.06 ^{AB}	6.30 ^{Ba}	21.51 ^{AB}	2.55 ^{AB}	34.24 ^{AB}
	101–150	1.72 ^{ABC}	2.97 ^{ABC}	6.05 ^{ABC}	19.47 ^{ABC}	2.65 ^{ABC}	31.74 ^{ABC}
	151–200	1.73 ^{ABCD}	2.87 ^{BCD}	5.83 ^{ABCD}	17.91 ^{ABCD}	2.71 ^{ABCD}	29.63 ^{ABCD}
	201–250	1.73 ^{ABCE}	2.74 ^{ABCDE}	5.77 ^{ABCD}	16.53 ^{ABCDE}	2.73 ^{ABCDa}	27.49 ^{ABCDE}
	251–305	1.71 ^{ABCDE}	2.51 ^{ABCDE}	5.79 ^{ABC}	14.83 ^{ABCDE}	2.72 ^{ABCDa}	24.58 ^{ABCDE}
Rear quarter to total quarter MY ratio (%)	34–50	1.67 ^{A}	2.76 ^{A}	5.98 ^{A}	18.03 ^{A}	2.61 ^{A}	28.57 ^{A}
	51–55	1.73 ^{AB}	2.87 ^{AB}	5.92 ^{AB}	18.44 ^{AB}	2.70 ^{AB}	30.49 ^{AB}
	56–60	1.73 ^{AC}	2.91 ^{ABC}	5.94 ^{C}	18.76 ^{ABC}	2.68 ^{ABC}	30.89 ^{ABC}
	61–73	1.67 ^{BC}	2.89 ^{ABC}	6.15 ^{ABC}	19.11 ^{ABC}	2.57 ^{ABC}	30.26 ^{ABC}

ME—milking efficiency (kg/min); MF—milking frequency (n); AT—attachment time (s); BT—box time (min); MS—milk speed (kg/min); MY—milk yield (kg); A-E—in columns, separately for each effect, values marked with the same letters vary significantly at $p \leq 0.01$; a, b—in columns, separately for each effect, values marked with the same letters vary significantly at $p \leq 0.05$.

Higher levels of MF, AT, BT and MY were noted in barns that were adapted to AMS use although only for AT and BT were the differences in the levels of features between new and adapted barns significant. The highest MF and the longest BT were found in herds with 51 to 55 cows per robot. The longest AT and highest MS, MY, and ME were recorded in the herds with the highest density (over 60 cows per milking robot). The lowest MY, MS and ME were recorded in the herds with the lowest density per robot (fewer than 51 cows).

Lactations 2 and 3 were associated with higher ME, MF, BT, MS, and MY, and lower AT. Differences between lactations were statistically significant (Table 3).

Cows calving in the autumn and winter were characterized by significantly higher levels of MF, BT and MY compared to summer and spring. The highest values of AT, MS and ME were found in the spring. The lowest levels of MS, MY and ME were observed in summer.

Age at first calving significantly differentiated the level of the examined traits. MF, BT and MY were significantly higher with an AFC of 26–36 months and ME and MS with an AFC of more than 36 months. AT was significantly higher with an AFC of 24–25 months.

When analyzing days in milk, the highest levels of MF, AT, BT and MY were recorded up to the 100th day of lactation, and in subsequent stages the levels decreased. On the other hand, higher levels were noted later in lactation for ME (151–250 days) and MS (201–250 days). It was observed that the higher the share of rear quarter to total quarter MY ratio, the higher the levels of MF, AT, BT, MY and ME. The highest MS was found for milkings whose rear quarter to total quarter MY ratio was between 51 and 55% (Table 3).

Correlation between milking efficiency and other tested traits that characterized milking processes were investigated (Table 4). The results showed the high correlation between ME and MS (0.879), therefore MS was not included in the algorithm creating decision tree model.

Table 4. Pearson's linear correlation between milking efficiency and number of cows per one robot, age at 1st calving, milking frequency, attachment time, box time, milk speed, milk yield and rear quarter to total quarter MY ratio.

Trait	Milking Efficiency	*p*-Value
No. of cows per robot (n)	−0.043	<0.0001
Age at 1st calving (days)	0.081	<0.0001
Milking frequency (n/day)	−0.079	0.5544
Attachment time (s)	−0.161	<0.0001
Box time (min/day)	−0.483	<0.0001
Milk speed (kg/min)	0.879	<0.0001
Milk yield (kg/day)	0.229	<0.0001
Rear quarter to total quarter MY ratio (%)	−0.020	<0.0001

3.2. Forecasting ME

The study found that the decision tree models built on the basis of the alternative two division criteria—F test statistic and variance reduction—had the same prognostic ability, as evidenced by the same mean standard error (0.18).

A decision tree method is of particular value to people who, not familiar with statistical analysis, would like to verify the influence of various factors on a tested trait solely on the basis of the graphical model [20]. Such people, following the graphical presentation of splits, may identify the factors and their levels that may contribute to improvement of the investigated trait.

The Importance measure, calculated on the basis of the validation set, indicated that the greatest impact on ME in the order of decreasing importance was MY, MF, AT, DIM, noL and noC (Table 5). One of the most important variables, with an Importance measure of 1 was MY, although it contributed only to 4 splits. The graphical representation of the decision tree (Figures 1–6) showed that cows that were characterised by a higher MY also had a higher ME. The variable that caused the tree to split the most was the AT (10 splits) and DIM (5 splits).

Table 5. Number of division rules and importance of tested variables in tree creation based on Importance measure.

Variable	Number of Splits	Importance	Importance of Validation
Milk yield	4	1.000	1.000
Milking frequency	2	0.984	0.982
Attachment time	10	0.917	0.921
Days in milk	5	0.678	0.679
Lactation number	2	0.550	0.547
Number of cows per robot	1	0.531	0.529
Rear quarter to total quarter MY ratio	3	0.259	0.265
Age at 1st calving	1	0.131	0.125
Season of calving	1	0.104	0.102

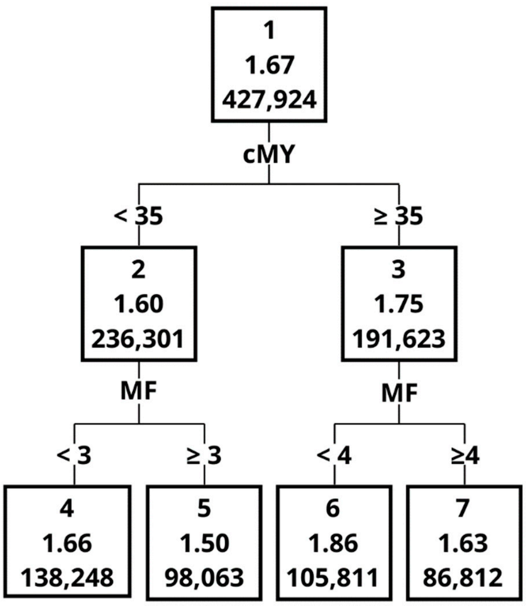

Figure 2. The graphical model of the decision tree—part 1. Abbreviations used in Figures 2–6: cMY—milk yield; MF—milking frequency; AT—attachment time; DIM—days in milk; noL—lactation number; noC—number of cows per robot; RTR—rear quarter to total quarter MY ratio; AFC—age at 1st calving; SC—season of calving.

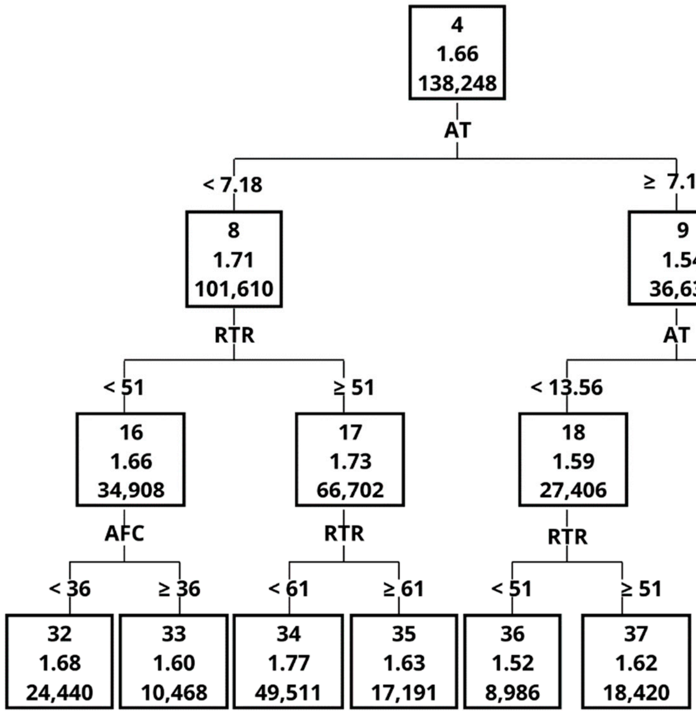

Figure 3. The graphical model of the decision tree—part 2.

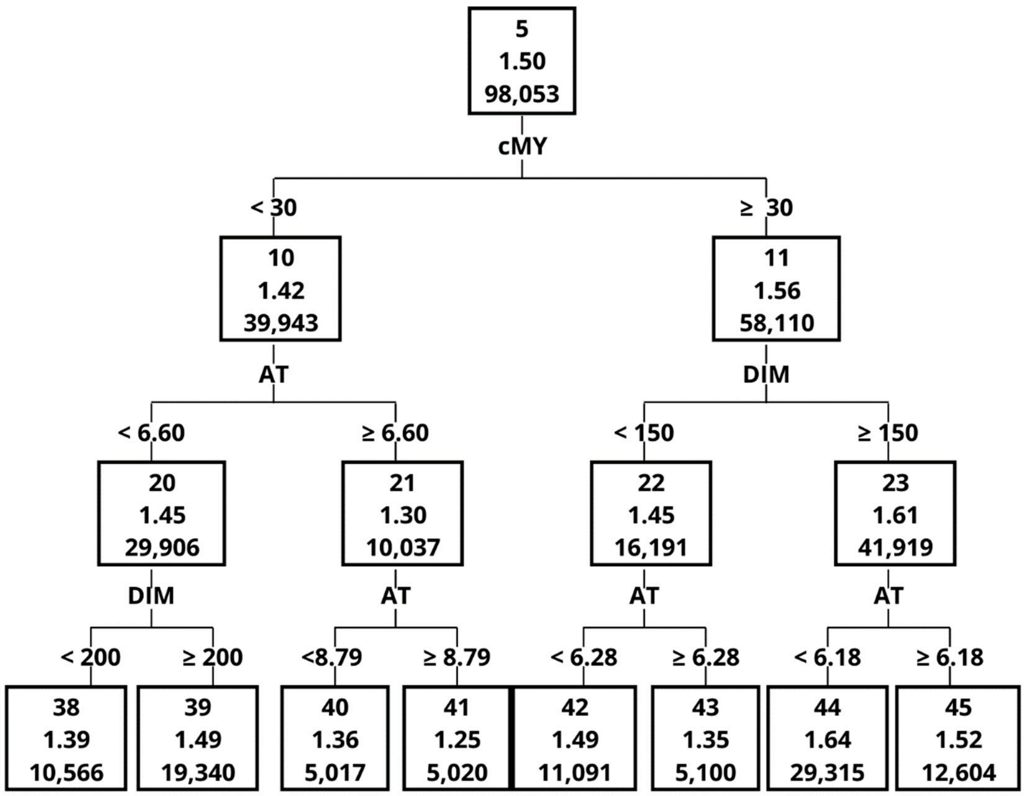

Figure 4. The graphical model of the decision tree—part 3.

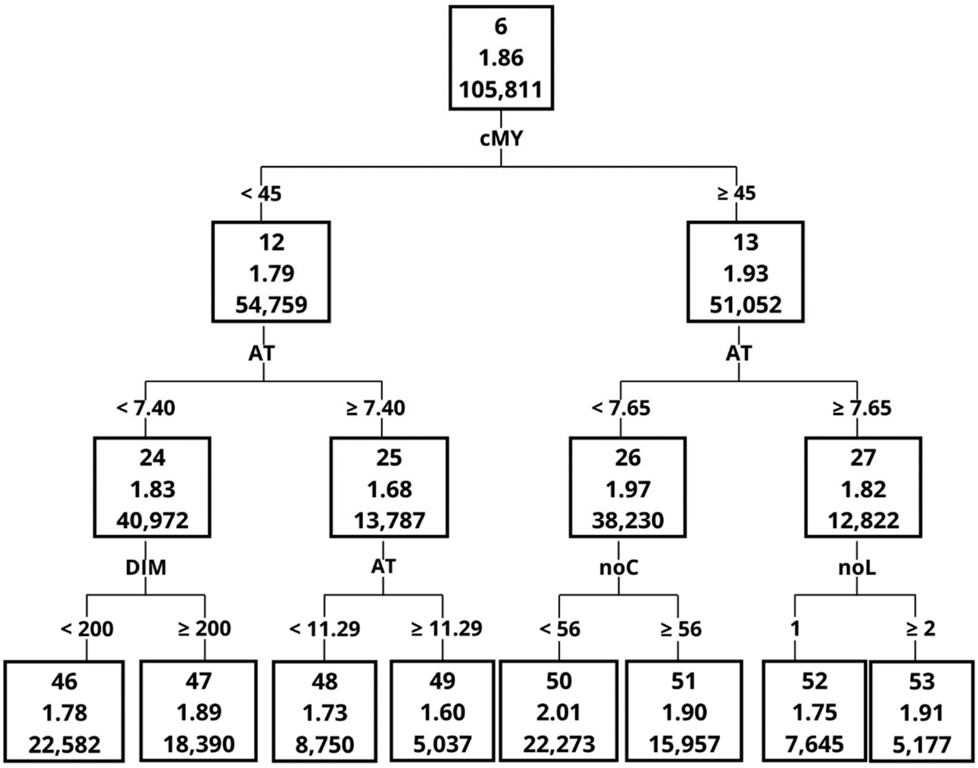

Figure 5. The graphical model of the decision tree—part 4.

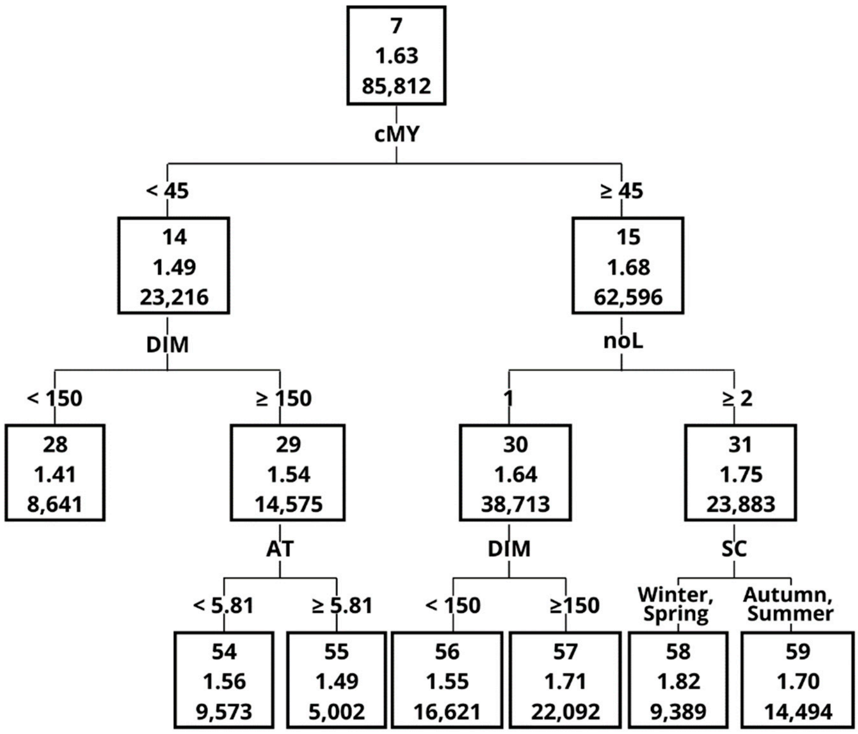

Figure 6. The graphical model of the decision tree—part 5.

The decision tree (Figures 2–6) was 5 levels deep and resulted in the creation of 59 nodes out of which 29 were leaves. The first division in the graphical model of a decision tree was made based on MY, splitting data with MY below 35 kg (Node 2, the average ME at the level of 1.60 kg/min) and above (Node 3, with ME 1.75 kg/min). Node 3 contained data for which ME had a higher value and was further split by MF with 4 times/day as a threshold creating nodes 6 and 7. The leaf with the highest ME was Node 50 with ME of 2.01 kg/min. The leaf was created by splitting the original dataset by the following criteria: MY (≥35 kg/day), MF (<4 times/day), MY (≥45 kg/day), AT (<7.65 s) and number of cows per robot (<56 cows). In contrast, the leaf (Node 41) with the lowest ME (1.25 kg/min) was created by the following splits: MY (<35 kg/day), MF (≥3 times/day), MY (<30 kg/day), AT (≥6.60 s) and AT (≥8.79 s).

4. Discussion

Milking Efficiency and Parameters Affecting It

On average, ME in the present study was 1.67 kg/min. Lower efficiency was described by other authors, including Vosman et al. [21] who reported it to be at a level of 1.61 kg/min for Holstein–Friesian cows. Heringstad and Bugten [13] also reported lower values of ME (the average daily ME was 1.47 kg per min of box time for Norwegian Red cows). Higher ME in our study may have been caused by the fact that cows selected for this study came from herds that are considered to be one of the best in Poland.

The study predicted the creation of a graphical model with the use of decision tree techniques. These methods split datasets in order to indicate what variables affect ME. The algorithm creating the graphical model of a decision tree gave the highest importance in relation to ME to milk yield. Løvendahl et al. [11] concluded that in AMS a cow that gives the most milk in one minute of box time should be called the "AMS milking efficient cow".

The decision tree algorithm indicated MF as second-most important variable (with an Importance of 0.984) that affected the tree creation. Castro et al. [9] reported that in their study on Holstein cows milked in an AMS, the optimal MF was between 2.40 and 2.60 milkings/day. In our study the best Node in the graphical presentation of the tree was created by a split where the threshold for MF was below 4; while the average MF for the whole tested population was 2.83 milkings/day. Some authors consider that a minimum accepted MF of a cow should be determined by a technician on the basis of the age of a cow and the lactation stage [5]. MF is a crucial parameter that affects MY as well as ME [7,11,22]. The automatic milking system allows the animals to independently choose the moment of milking almost all day long and may contribute to the increase of the frequency of milking [5,23]. Løvendahl and Chagunda [24] pointed out that cows (Red Dane and Holsteins) with higher MF gave 20% more milk than cows with lower MF.

The highest number of splits was caused by the variable AT, which suggests, along with the fact that the Importance was also high, that it greatly affects ME. Bach and Busto [25] suggested that attachment failures have a great effect on the overall milk yield. Failure to attach the cups to the target teat negatively affect milk ejection in other, unaffected, quarters. Piwczyński et al. [26] suggested that a short AT may improve the profitability of automatic milking. A rapid attachment of a teatcup to a target teat also reduces the stress on a cow as well as the time a cow stays in the milking robot. This also means that a cow frees up the space in the robot for the next animal increasing the number of cows using one robot, which also affects profitability of the farm.

DIM had an importance of 0.678. The tree showed that cows with DIM lower than 150 days had lower ME. This is in accordance with findings of Heringstad and Bugten [13] who reported that ME tended to be low at the beginning of lactation and increased with time, to start decreasing at the end of lactation when MY also decreased.

While the tree was split based on lactation number only twice, the Importance value was moderate. The study showed that higher ME was recorded in second and third lactations. These results are in accordance with those reported by Vosman et al. [21]. They noted that the difference between the average ME in the 1st and 3rd lactation was 0.25 kg/min. Carlström et al. [27] also reported higher values of milk yield per milking, which contributed to the results showing a higher ME in the 2nd lactation (2.58 kg/min) compared to the 1st lactation (2.36 kg/min), and Spolders et al. [28] confirmed that primiparas had a higher milking performance.

The graphical model indicates that the number of cows using the same robot is also very important and may affect ME. To our knowledge the literature does not provide direct information on the relationship between stocking rate and ME (described as milk yield per day divided by box time) in AMS, but other authors confirm that the occupancy rate affects MY, although not all authors confirmed statistical significance [29,30]. It may be concluded that the optimal stocking level per one AMS is crucial since some authors reported the positive effect of an increase in the number of cows per AMS (average occupancy rate at the level of 55.8 cows per AMS) [29] on MY (kg/cow), while others noted a decrease in MY (kg/cow per day) related to the increase of number of cows/robot [30]. Lee et al. [31] reported that the mean MY per AMS went up with an increase in the number of cows per AMS, however, only until it reached the number of 60 cows per robot; further increase of the stocking level did not improve MY. This suggests that while initial increasing of the number of cows using AMS may reduce the robot free-time, thus contributing to the increase of MY, the number of cows per robot cannot be increased indefinitely, as the maximum robot throughput will eventually be reached. Further increasing the occupancy rate will not improve MY, and on the contrary, may decrease MY due to increasing competition between cows.

RTR was used to split the tree three times. It is well known that different udder quarters have a different time of milking. The difference is especially seen between front and rear quarters [32]. Sitkowska et al. [32] pointed out that in their studies rear quarters took 43 s longer to be milked than front quarters. They also reported the total MY (10.65 kg) as MY per front (4.80 kg) and rear (5.85 kg) quarters. This allowed them to calculate RTR (55.02%) which is higher than that reported in the present study (54.49%). Nevertheless the importance (0.259) of this variable is not very high in tree creation, which suggests that it does not significantly affects ME.

AFC was used only once during the creation of the tree and the importance of that variable was low (0.131) suggesting that it did not affect ME. In Poland in 2020 the average AFC was 812 days [33]. The optimal age of the first calving determines the proper development of the udder and adaptation to automatic milking and may contribute to the reduction of reproductive and health-related disorders. Attempts have been made to indicate the optimal AFC at which a cow reaches its best production potential [34,35]. Nilforooshan and Edriss [36] indicated that for Iranian Holsteins the optimal AFC was 24 months. In our study analysis of variance indicated that the highest ME had cows whose AFC was higher than 36 months.

Also SC had a low Importance in tree creation and did not significantly affect ME; however, analysis of variance indicated that SC had a significant impact on ME (with the highest ME in the spring season and the lowest in summer). Speroni et al. [37] also reported that a hot season had a negative effect on MY in AMS (-4.5 ± 0.6 kg/d).

One of the main goals of a farmer running a dairy farm is a high level of profitability of their herd. Therefore, they are constantly endeavouring to increase the efficiency of milking in AMS. Vosman et al. [21] pointed out that to do so, farmers should breed only those cows that are suitable for AMS (active in the robot, visit it frequently, have high milk yield but at the same time have a relatively low box time). Løvendahl et al. [11] indicated that ME expressed a higher heritability than residual BT, and that it was also highly correlated to other investigated traits, therefore, it may be used in a selection programme aimed at obtaining cows with a high ME in AMS.

5. Conclusions

The decision tree model, in an easily comprehended graph, indicated the best combination of factors and their levels that contributed to the highest ME in herds milked in AMS. The results showed that the highest ME was recorded for cows that produced more than 35 kg per day, were milked in robots that had occupancy lower than 56 cows and were kept in new barns where AMS was installed at least 3 years prior. This research may be beneficial for farmers as it depicts, in a simple way, how different factors may contribute to the increase of the efficiency of their milk production.

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The optimal level of factors for high daily milk yield in automatic milking system☆

Joanna Aerts[a], Beata Sitkowska[b,*], Dariusz Piwczyński[b], Magdalena Kolenda[b], Hasan Önder[c]

[a] Lely Services B.V., Cornelis van der Lelylaan 1, 3147 PB Maassluis, the Netherlands
[b] Department of Animal Biotechnology and Genetics, Faculty of Animal Breeding and Biology, Bydgoszcz University of Science and Technology, Bydgoszcz 85-084, Poland
[c] Department of Animal Science, Ondokuz Mayis University, Samsun, 55139, Turkey

HIGHLIGHTS

- The automatic milking system (AMS) decreases labour time and provides vast amounts of data related to the milking process, cow activity, concentrate feed intake or rumination time.
- The use of the decision tree technique to identify factors and their levels affecting daily milk yield obtained from a milking robot in AMS.
- The graphical model of a tree simplifies the interpretation of the results.

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ABSTRACT

Optimising daily milk yield in automatic milking systems (AMS) became one of the basic issues raised by many farmers. The aim of this study was to determine the best combination of factors and their levels suggested by the decision tree for high daily milk yield per AMS in dairy cattle herds. The study involved 4854 Polish Holstein-Friesian cows milked in 20 barns with Lely AMS. Statistical analysis was performed using two methods: multi-factorial analysis of variance and classification tree technique. Milk yield, number of cows, free robot time, milking speed, and cow treatment time (i.e. cleaning of teats before and after milking) were the significant determinants of total milk yield for all cows per milking robot and were most frequently used to construct the decision tree. The tree shows that the highest total milk yield per robot was observed for the group of cows that produced more than 30 kg of milk per day, with a milking speed of over 2.40 kg/min. and during robot days in which free time did not exceed 10% of the day. In AMS dairy herds, efforts should be made to select animals that transmit high milk yield and high milking speed while shortening free robot time and increasing daily milk yield per robot. Also, attention should be given to the percentage of box time spent on preparing the cow for milking and after milking because prolongation of this variable has a negative effect on daily milk yield per AMS.

1. Introduction

Barns with automatic milking systems (AMS) provide vast amounts of data related to the milking process, cow activity, concentrate feed intake or rumination time, which can be used to improve the herd production level but also the welfare status of animals (de Koning, 2010; Shevchenko and Aliev, 2013; Svennersten-Sjaunja and Pettersson, 2008). As noted by many authors (Jacobs and Siegford, 2012a; Svennersten-Sjaunja and Pettersson, 2008; van der Vorst and de Koning, 2002), AMS performance depends mainly on environmental and feeding

Abbreviations: AMS, Automatic milking system; CMS, Conventional milking system; HS, Height at sacrum (cm); MS, Milking speed (kg/min); cMY, Cow's milk yield per day (kg); NoCow, Number of cows per robot (no/robot/day); DIM, Average milking day (days); pRef, Proportion of refused milkings (%); cTT, Cow treatment time (%); FT, Free robot time (%/robot); PHF, Percentage of Holstein-Friesian inheritance in cow's genome (%).

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* Corresponding author.
E-mail address: beatas@pbs.edu.pl (B. Sitkowska).

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conditions in the barn and also on the commitment of breeders (Hansen et al., 2020; Jacobs and Siegford, 2012b). Dairy farmers often decide to introduce AMS to their barns because they expect to reduce labour input and increase milk yield per cow while increasing milking frequency and improving udder health (Svennersten-Sjaunja and Pettersson, 2008; Wagner-Storch and Palmer, 2003). While optimising farm profitability, daily milk yield per AMS is becoming one of the basic issues raised by an increasing number of farmers who have invested in AMS.

Economically efficient milk production in AMS farms is becoming an important issue widely discussed worldwide (Bach and Cabrera, 2017; Stelwagen et al., 2013; Tse et al., 2017). The question here is whether it is possible to optimise the effect of factors associated with cows' housing, feeding and course of lactation on the milk production level of the herd (John et al., 2016; Sitkowska et al., 2019). The main objective for cattle breeders is to maximise milk production per AMS per day. Milk output per cow and the cow's total time in the robot milking box determine milk production per robot in the herd. Milking frequency, milking duration and speed are the most frequent determinants of high milk yield per cow per day (Sitkowska et al., 2019). Castro et al. (2012) observed that two variables, namely the number of cows and milk flow rate, had the most significant impact on daily milk yield per AMS.

The capacity of an AMS can be expressed in terms of various indicators, one of them being its occupation rate, defined by Castro et al. (2012) as the percentage of hours the AMS is milking per day. According to Lukas et al. (2015), the statistical process control (SPC) method can be used in the barn to evaluate the variation of different parameters, including cows' living conditions in early lactation, to reduce stress stimuli and optimise milk yield. Researchers have tried to determine milk production efficiency using various indices, formulas or advanced statistical tools. For example, Castro et al. (2012) used multiple linear regression to model the relationship between annual milk yield per AMS and the variables: number of cows per AMS, milkings per cow per day, milk flow rate, and refusals per AMS per year.

In automatic milking systems, milk yield per robot is determined mainly by a number of factors. A review of the literature reveals a vast array of non-genetic factors that impact on or contribute to herd production level. For AMS barns, there are numerous science-based recommendations and requirements for animal housing (type of barn, size of lying area and feed table) and feeding conditions (rations, concentrates, additives) (Jacobs and Siegford, 2012a; Piwczyński et al., 2020a; Siewert et al., 2018). Factors often identified as necessary for AMS operations include the number of cows per AMS (Castro et al., 2012; Tse et al., 2017) and the type of cow traffic (free or guided) (Castro et al., 2012; Deming et al., 2013; Tremblay et al., 2016). Factors that have to be considered, for example, those related directly to AMS use, include box time (André et al., 2010; Castro et al., 2012), milking speed (MS) (Gáde et al., 2007; Hogeveen et al., 2001; Lee and Choudhary, 2006), milking frequency (Carlström et al., 2013; Løvendahl and Chagunda, 2011; Madsen et al., 2010; Sitkowska et al., 2018), milk conductivity, and milk temperature. Other factors, such as breed, age at first calving, lactation, birth and calving seasons, and milking season, are also crucial for AMS and CMS farms. It should be remembered that specific groups of traits are connected by numerous, often strong, correlations, which make it hard to determine the optimal solution. Consideration should also be given to Rodenburg (2013), who pointed out that earlier publications based on data from CMS have limited application in AMS herds. The maximum use of AMS potential in herds was addressed by André et al. (2010) and Pezzuolo et al. (2017). André et al. (2010) highlighted the need to monitor the length of the interval between milkings and milking duration, which has a significant effect on daily milk yield per AMS. They concluded that the efficiency of milk yield per robot could be increased by applying individual optimal milking intervals.

The aim of this study was to determine the optimal level of factors for high daily milk yield per AMS in herds of Polish Holstein-Friesian cows.

2. Materials and methods

The study involved 4854 Polish Holstein-Friesian cows used in 20 barns equipped with Lely automatic milking systems (AMS) (Lely Industries N.V., Cornelis van der Lelylaan 1, Maassluis, The Netherlands). The number of lactating cows per herd ranged from 115 to 598. From 2010–2013, these 20 herds changed the milking system from conventional to automatic. In 10 herds, AMS was installed in new buildings, and another 10 herds in modernised facilities. The herds were equipped with one to four Lely Astronaut A4 robotic milking systems. The number of robot days was calculated for each herd (the number of consecutive days for which a robot operated in a herd, e.g. meaning that if one robot has operated in a herd for 400 consecutive days, then the number of robot days is 400, although if 2 robots have operated in the same period of time, then robot days equal 800). The barns had a free-stall system, and animals were fed partial mixed rations (PMR). Stalls were covered with mats in 17 barns and straw bedding in 3 barns; there were concrete walking areas in 6 and slatted walking areas in the remaining barns (Table 1).

The following data (daily indicators) were collected in herds during the first three years of AMS operation as part of the study. Codes were introduced for the 8 factors used in the decision tree:

1. HS - Height at sacrum (cm) – the average height at sacrum for primiparous cows between 15 and 300 days after calving. Measurements are made at a distance from the floor to the dorsal aspect of the caudal sacral joint
2. MS - Milking speed (kg/min) – average milk flow rate of all the milkings occurred throughout the day of robot operation
3. cMY - Cow's milk yield per day (kg) – total milk yield of a cow per day
4. NoCow - Number of cows per robot (no/robot/day) – the average number of cows per milking robot per calendar day
5. DIM - Average milking day (days) – days in milk of all cows milked per AMS per calendar day
6. pRef - Proportion of refused milkings (%) – the percentage of AMS refusals per day defined as the number of all refusals (events in one day when a robot refused to milk a cow that entered the milking box) divided by the number of visits in the robot and multiplied by 100
7. cTT - Cow treatment time (%) – the percentage of box time spent on preparing the cow for milking and after milking
8. FT - Free robot time (%/robot) – the percentage of AMS idle time with no milking

Also included:

1. PHF - Percentage of Holstein-Friesian inheritance in cow's genome (%)
2. Age at first calving (days) – the average age of heifers on the day of first calving
3. Milking frequency (no/day) – the average number of milkings per cow per day by AMS
4. Box time (*sec*/day) – total time spent by a cow per day in the robot milking box
5. Milking time (*sec*/day) – average total milk flow time per cow per day (measured at each milking as the time between the start of milking of the first teat until the end of milking of the last teat)
6. Milk yield per visit (kg) – average milk yield per visit for all cows milked by AMS per day
7. Rumination time (min) – average rumination time of all cows milked per AMS per day. The measurement was made using transponders hung around the cow's neck.
8. Percentage of multiparous cows in a herd (%/robot/day) – i.e. the percentage of multiparous cows milked by AMS per day
9. Number of visits (no/robot) – total number of all cow visits in a robot per day

Table 1
Characteristics of cattle herds with automatic milking systems (AMS) during the three years covered by the studies.

Herd	No. of cows in herd	Mean no. of cows per robot	No. of robot days	Barn	Laying area	Walking area	Dehorning	No. of hoof trimming	Udder singeing
A	115	57.05	629	N	M	G	Yes	1	R
B	130	63.61	916	N	M	G	Yes	2	R
C	215	66.00	1407	N	M	G	Yes	3	R
D	381	54.72	970	N	S	G	Yes	3	R
E	119	56.76	867	M	S	C	Yes	2	R
F	259	55.23	866	M	M	G	No	2	R
G	214	60.94	1093	M	M	C	Yes	3	R
H	197	65.42	1046	M	M	C	Yes	2	R
I	258	62.65	1254	N	M	G	No	2	I
J	186	57.61	929	M	M	C	Yes	2	I
K	139	61.16	939	N	M	G	Yes	2	R
L	116	61.33	918	N	M	G	Yes	1	R
M	598	53.52	788	M	S	C	Yes	3	R
N	330	62.19	2170	N	M	G	No	2	R
O	173	62.28	699	M	M	G	Yes	2	R
P	120	61.64	963	N	M	G	Yes	2	R
R	462	58.17	1624	N	M	G	No	1	R
S	162	56.22	982	M	M	G	Yes	2	R
T	418	66.08	1193	M	M	C	Yes	2	R
U	262	60.48	1133	M	M	G	Yes	2	R

Description: Barn: N – new barn, M – retrofit barn; Lair area: M – mats, S – straw; Walking area: G – grates, C – concrete; Udder singeing: R – regular, I – irregular.

10 Number of milkings (no/robot) – number of successful milkings per AMS
11 Number of refused milkings per robot (no/robot) – total number of events in one day when a robot refused to milk a cow that entered the milking box
12 Number of failed milkings (no/robot) – total number of failed milkings per day, meaning the events in one day when a robot undertakes the attempt to milk a cow yet the attempt is not successful
13 Total milk yield from AMS per day (kg/day/robot).

The collected numerical data were derived from the national milk recording scheme (SYMLEK system) (traits 1, 9, 10) and other traits from the AMS management system (Table 2).

2.1. Statistical analysis

Statistical data analysis was performed concurrently using two methods: multivariate analysis of variance and the classification tree technique. For statistical analysis purposes, the recorded continuous variables were categorised, except height at sacrum (Tables 3-4) and included in this form in the classification models.

To create a ranking of variables based on their importance in splitting the dataset used for tree creation, an "Importance" measure was used (Grochowska et al., 2014), which fluctuates between 0 and 1. A higher value indicates the higher importance of the variable in creating the tree. A detailed description of the methodology, as well as the "Importance" measure, were provided by Grochowska et al. (2014). To identify the sources of variation in total daily milk yields per robot, we used the analysis of variance to construct a linear model only for the effect of the leading 21 factors. Significant differences between categories of factors were determined using the Scheffé test (SAS, 2014).

Table 2
Basic characteristics of the level of selected factors in automatic milking systems (AMS) barns.

Trait	No. robot days	$\bar{x}$	Lower quartile	Median	Upper quartile	Standard deviation	Coefficient of variation (%)
Cows' traits							
Proportion of Holstein-Friesian inheritance in cow (%)	21,386	81.43	72.88	84.53	90.23	12.26	15.06
Age of heifer at first calving (days)	21,386	926.79	835.52	882.77	977.37	146.88	15.85
Height at sacrum (cm)	14,204	143.30	141.20	143.42	145.71	3.11	2.17
Milking frequency (no./day)	21,386	2.72	2.56	2.74	2.91	0.27	9.96
Box time (s/day)	21,386	1124.57	1044.00	1136.00	1217.00	115.37	10.26
Milking time (s/day)	21,386	739.76	660.00	740.00	823.00	109.45	14.80
Milking speed (kg/min.)	21,386	2.49	2.34	2.51	2.66	0.3	12.16
Cow's milk yield per day (kg)	21,386	27.2	24.49	27.06	30.05	4.26	15.68
Milk yield per visit (kg)	21,386	10.07	8.92	10.03	11.01	1.62	16.06
Rumination time (min.)	19,427	442.6	421.61	442.11	462.55	32.51	7.34
Milking robot performance indicators							
Number of cows per robot (no./robot/day)	21,386	60.48	56.00	61.00	65.00	5.74	9.45
Percentage of multiparous cows in herd (%/robot/day)	21,386	51.20	39.29	53.42	64.49	18.42	35.99
Number of visits (no./robot)	21,386	306.41	250.00	294.00	346.00	90.49	29.53
Number of refused milkings (no./robot)	21,386	136.78	84.00	121.00	169.00	83.62	61.13
Number of failed milkings (no./robot)	21,386	5.47	2.00	4.00	7.00	4.64	84.81
Number of milkings (no./robot)	21,386	164.15	153.00	165.00	176.00	17.44	10.62
Proportion of refused milkings (%)	21,386	41.3	33.46	41.43	49.46	12.72	30.80
Cow treatment time (%)	21,386	34.46	31.43	34.08	37.31	4.57	13.25
Free robot time (%/robot)	21,386	17.77	11.39	17.01	23.34	8.01	45.08
Total milk yield from AMS (kg/day)	21,386	1634.56	1435.10	1641.15	1825.20	272.07	16.65

Table 3
Factors and their levels that determine daily milk yield per robot ($p<0.001$).

Factor	Level of factor	N	Mean (kg)	Coefficient of variation (%)
Half-year period after AMS installation	1	3331	1571.39^{E}	17.53
	2	4328	1606.35^{D}	13.97
	3	4353	1633.35^{C}	16.76
	4	4170	1665.49^{B}	16.59
	5	3239	1660.94^{B}	18.07
	6	1965	1697.29^{A}	16.03
Milking speed (kg/min.)	=<22	3050	1363.12^{E}	13.69
	(22 - 24]	3818	1516.96^{D}	14.5
	(24 - 26]	6978	1648.49^{C}	14.95
	(26 - 28]	5089	1794.34^{A}	12.7
	35	2451	1784.12^{B}	13.43
Free robot time (%/robot)	=<10	4072	1857.83^{A}	13.16
	(10 - 15]	4744	1754.62^{B}	12.37
	(15 - 20]	4542	1635.29^{C}	11.9
	(20 - 25]	3880	1532.85^{D}	13.36
	>25	4148	1372.41^{E}	15.4
Number of cows per robot (no./robot/day)	=<55	5127	1497.52^{D}	17.67
	(55 - 60]	5218	1582.18^{C}	14.86
	(60 - 65]	6704	1677.87^{B}	15.14
	>65	4337	1792.62^{A}	13.96
Percentage of multiparous cows in herd (%/robot/day)	=<45	7136	1610.35^{B}	17.72
	(45 - 55]	4320	1614.90^{B}	14.47
	(55 - 65]	4905	1612.56^{B}	16.45
	>65	5025	1707.31^{A}	16.25
Age of heifer at first calving (days)	=<820	3904	1678.14^{A}	15.78
	(820 - 875]	5815	1641.23^{C}	16.24
	(875 - 950]	5179	1668.23^{B}	17.09
	>950	6488	1575.47^{D}	16.52
Milk yield per day (kg)	=<24	4479	1314.76^{D}	12.94
	(24 - 27]	6099	1543.89^{C}	10.77
	(27 - 30]	5388	1737.26^{B}	9.86
	>30	5420	1898.76^{A}	9.69
Average milking day (days)	=<160	6431	1735.26^{A}	15.85
	(160 - 180]	4372	1692.31^{B}	13.49
	(180 - 200]	4439	1611.67^{C}	16.24
	>200	6144	1504.60^{D}	16.5
Milk frequency (no./day)	=<2.50	4213	1560.11^{B}	20.07
	(2.50 - 2.75]	6944	1651.33^{A}	16.24
	(2.75 - 3.00]	7426	1653.65^{A}	15.34
	>3.00	2803	1654.30^{A}	14.63
Cow treatment time (%)	=<30	3141	1750.95^{B}	17.07
	(30 - 34]	7379	1769.93^{A}	13.06
	(34 - 38]	6413	1574.79^{C}	13.49
	>38	4453	1414.21^{D}	15.08
Proportion of refused milkings (%)	=<20	1130	1794.29^{B}	17.77
	(20 - 30]	2584	1801.43^{A}	14.53
	(30 - 40]	5998	1722.42^{C}	13.87
	>40	11,674	1537.02^{D}	15.83
Height at sacrum (cm)	=<141	3260	1572.14	13.71
	(141 - 143]	2902	1685.30	14.53
	(143 - 145]	3293	1638.24	15.36
	>145	4749	1798.52	12.18
Rumination time (min.)	=<420	6500	1550.35^{C}	16.89
	(420 - 440]	4607	1658.31^{B}	16.23
	(440 - 460]	4900	1677.28^{A}	16.03
	>460	5379	1677.05^{A}	15.89
Milking season	Spring and Summer	10,937	1661.98^{A}	15.96
	Autumn and Winter	10,449	1605.85^{B}	17.19
Proportion of Holstein-Friesian inheritance in cow's genome (%)	=<75	5951	1589.38^{B}	14.3
	(75 - 90]	10,028	1574.42^{C}	17.37
	>90	5407	1795.81^{A}	13.89
Number of hoof corrections (n)	1	3171	1623.76^{B}	15.87
	2	13,957	1607.27^{C}	16.71
	3	4258	1732.04^{A}	15.68
Number of robots (n)	1	16,617	1648.83^{A}	16.23
	>1	4769	1584.81^{B}	17.76
Type of barn	New	11,161	1657.13^{A}	15.73
	Old	10,225	1609.92^{B}	17.52
Walking area	Grates	5916	1604.18^{B}	16.54
	Concrete	15,470	1646.18^{A}	16.63

*- Feature not included in the analysis of variance due to the large loss in data.
AA - Means with the same letter do not differ significantly ($p \leq 0.01$).

Table 4
Importance of variables included in the constructed decision tree for total milk yield obtained from a robot per day (kg/robot/day).

Variable	Number of splits caused by the variable	Importance
cMY	4	1.000
NoCow	11	0.468
FT	5	0.439
MS	4	0.258
DIM	2	0.076
cTT	1	0.070
pRef	1	0.036
HS	2	0.035

Abbreviations used in Table 4 and in Figs. 1–6: cMY – total daily milk yield of cow per day (kg/cow); NoCow – Number of cows per robot; FT – Free robot time (%); MS – Milking speed (kg/min.); DIM – Days in milk; cTT – Cow treatment time (%); pRef – Proportion of refused milkings (%) HS – Height at sacrum (cm).

In the next step, the decision tree technique performed a statistical analysis of the total daily milk yield per robot. To this end, the Enterprise Miner 15.1 software included in the SAS package was used (SAS, 2014). Before constructing the decision tree, the initial dataset of 21,386 observations was divided into the training set (60%) and the validation set (40%). The decision tree technique uses the training set to construct and train the model best fitted to the data in the training set. The validation set, sometimes called the test set, is held back from training the model. The previously fitted model is used on this set to predict the results for observations in the validation set. Cows were assigned to the training and validation sets by random sampling methods. CART (Classification and Regression Trees) algorithm was used to generate the tree. This algorithm makes use of the variance reduction division criterion of the dataset. When constructing the analysis model, it was assumed that the minimum size of the final node (leaf of the tree) should not be less than 100 observations, and the depth (number of branches) not be deeper than 5. The leaf size and depth criteria were set to avoid inaccurate overfitting (manipulation) of the tree to the training data, which could reflect random relations within the validation set. Model overfitting causes the creation of a tree that, while well fitted to the available data, is useless when classifying new data.

Each node or leaf in the decision tree contained the following information: node ID (1), mean total daily milk yield per robot (kg) (1631), and the number of observations in a node or leaf (12,832) resulted from the training dataset splitting. (Fig. 1).

3. Results

3.1. General characteristics of the study population

In our study, the average number of cows per herd was approximately 242, and NoCow was 60.48. In the studied population, numbers of primiparous and multiparous cows were at a similar level, the percentage of Holstein-Friesian inheritance in cows averaged 81.43%, and their mean HS was 143 cm (Table 2). The animals had their first calving

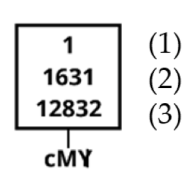

Fig. 1. The description of the root node, including the node ID (1); daily milk yield per automatic milking systems (AMS) (2) and a number of observations in a node or a leaf (3).

at around 927 days (approximately 31 months), and their rumination time averaged 442.6 min. Analysis of milk yield traits showed the following values: milking frequency 2.72 no./day, MS 2.49 kg/min, cMY 27.20 kg, milk yield per visit 10.07 kg, daily milk yield per robot 1634.56 kg (Table 2).

During nearly 3 years, each robot operated on average for 1069 days (Table 1). Our study showed that, on average, cows visited AMS more than 300 times per day (Table 2).

Some of the AMS visits were rejected (refused milkings), and others were unsuccessful (failed milking), giving over 160 successful milkings per day. Basic characteristics of the level of different factors are presented in Table 2. The average box time per cow was around 1124s, including 740 s of milking time. Daily AMS preparation and maintenance time accounted for about 34.50% of the day, and FT per robot per day exceeded 17%.

3.2. Factors affecting daily milk yield per robot – multifactorial analysis of variance

The results of the Multifactorial analysis of variance are presented in Table 3. They showed a highly significant effect of most factors included in the classification model except for the impact of udder singeing on daily milk yield per robot. The results were presented in Table 3. When analysing the effect of the level of studied factors on daily milk yield per robot - it was found that with every 6 months since AMS installation, daily milk yield per robot increased by 8%. In terms of MS, the highest daily milk yield per robot was observed for the milkings in which average MS ranged between 26 and 28 kg/min. (the difference between extreme groups exceeded 30%). We observed a trend for daily milk yield per robot to increase with decreasing free robot time (difference between extreme groups exceeding 35%). With the increasing number of cows per AMS (assuming that they milk faster; thus AMS have less free time), even with lower milk yields per cow, an increase in daily milk yield per robot was observed. The highest daily milk yield per robot was observed for herds with the highest stocking density (> 65 cows), which had almost 20% higher daily milk yield per robot than herds with a stocking density lower by 10 cows. Higher daily milk yield per robot was noted in herds with the highest percentage of multiparous cows, while daily milk yield per robot decreased with the increasing age at first calving and advancing lactation. Our study showed that daily milk yield per robot increased with increasing milking frequency – the difference between extreme groups was over 5.5%. The optimum proportion of refused milkings in daily milk yield per robot was obtained up to 30% of the day, while the poorest yield was obtained where the proportion of refusals exceeded 40%.

Table 3 also gives information about HS. The tallest animals (with height at sacrum exceeding 145 cm) showed the best daily milk yield per robot and the shortest animals the worst. Likewise, cows with the longest rumination time (over 440 min.) had the highest daily milk yield per robot. In addition, daily milk yield per robot was higher by 3.5% on spring and summer days compared to the cool season days. The cows with the highest proportion of Holstein-Friesian inheritance in cow and those from herds with frequent hoof trimming had a high daily milk yield per robot. Daily milk yield per robot was higher in herds with one AMS, in new barns with straw-bedded lying areas and slatted walking areas, where cows were subjected to dehorning and regular udder singeing – the difference ranged from 2.50 to 8.50 percentage points.

3.3. Decision tree

Table 4 presents the Importance values of different variables in the classification tree model. The ranking of variables' importance shows that cMY was the primary factor behind the effect of daily milk yield per robot, followed by NoCow and FT. These variables were also most often used by the CART algorithm to generate the tree and were also involved in the most important (initial) splits of the tree. All the variables listed in Table 4 served as the criteria for dividing the whole dataset into subsets (Figs. 2-6). Our study showed that the differentiating effect of these variables depended closely on the other variables included in the decision tree model. The obtained graphic tree model had 61 leaves and was 5 levels deep. In creating the tree, the largest number of splits was based on the following variables: NoCow (11 splits), FT (5 splits), cMY and MS (4 splits each), DIM and HS (2 splits each). In turn, variables cTT and pRef were used once by the tree forming algorithm, and their importance was low. Due to the complex nature of the tree, only the major splits were described in the study. It should be emphasised that in the nodes constituting the decision tree, the results come only from the training set.

The first division of the training dataset performed based on the average daily milk yield of all cows milked by the AMS in a day produced 2 subsets (Node 2, 3) (Fig. 2). Node 2, with daily milk yield per robot averaging 1442 kg, was established by those robot days on which the average cMY did not exceed 27 kg, while Node 3, with daily milk yield per robot higher by 376 kg, was higher than 27 kg. Variable cMY was involved in the next 3 divisions of the tree. Analysis of the results derived from the splits based on cMY indicates that a higher daily milk yield per robot was always paralleled by higher cMY. The difference between daily milk yield per robot in the subsets identified based on cMY ranged from 144 kg (Node 14, 15) to 232 kg (Nodes 4 and 5).

The number of cows per robot was involved in as many as 11 partitions of the dataset into subsets (Figs. 3-6). In each case, higher daily milk yield per robot was observed when they were accompanied by higher NoCow. The variable FT determined 5 splits of the decision tree (Figs. 2, 3, 4, 5). The lower the percentage, the higher the daily milk yield per robot.

The variable MS was involved four times in the division of the training dataset (Figs. 3 and 5). Higher MS parallelled higher daily milk yield per robot at each division. The difference in daily milk yield per robot between the nodes ranged from 241 kg for Nodes 12 and 13 (Fig. 5), to around 132 kg between Nodes 24 and 25 (Fig. 5) and Nodes 18 and 19 (Fig. 3), to 110 kg for the two end leaves Node 34 and Node 35 (Fig. 3).

Variable DIM was included twice when creating the tree, at Node 21 (Fig. 4) and Node 30 (Fig. 6). Node 42, with daily milk yield per robot averaging 1512 kg, was formed by those robot days on which DIM did not exceed 160 days, while Node 43, with daily milk yield per robot lower by 56 kg, for DIM > 160 days (Fig. 4). A similar trend was observed when Node 30 was divided into Node 58 and Node 59, where DIM was shorter or equal 180 days and longer than 180 days,

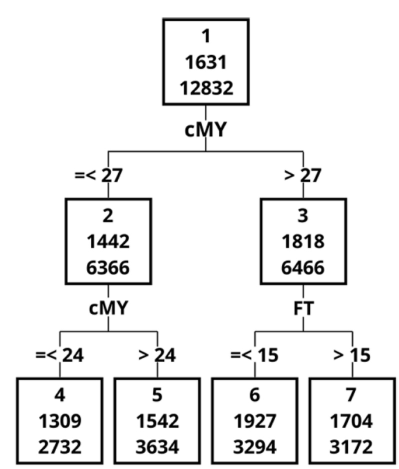

Fig. 2. The graphical model of the decision tree—part 1. Abbreviations used in Figs. 2– 6: cMY - Cow's milk yield per day (kg); NoCow – Number of cows per robot; FT - Free robot time (%); MS - Milking speed (kg/min.); DIM – Average milking day (days); cTT - Cow treatment time (%); pRef - Proportion of refused milkings (%); HS - Height at sacrum (cm).

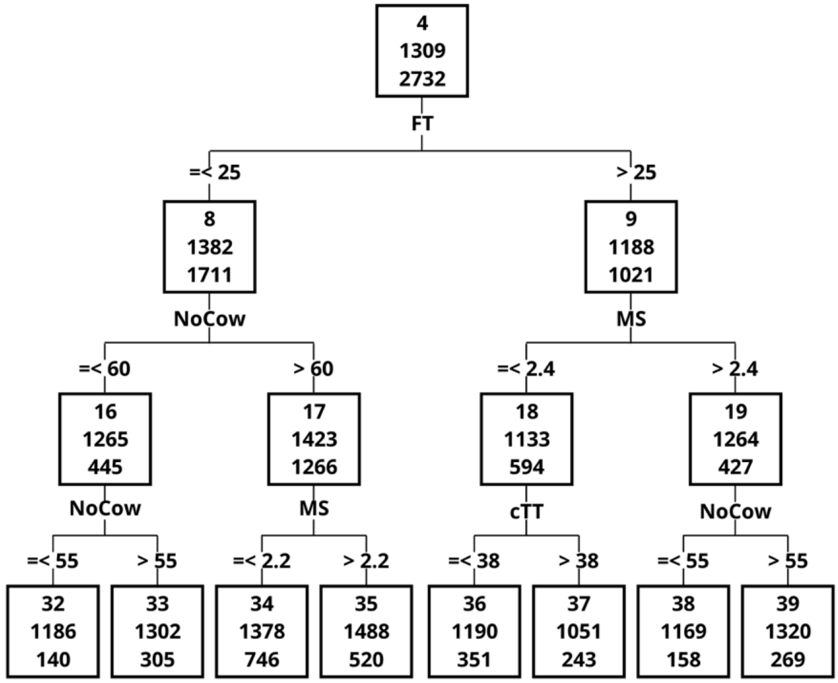

Fig. 3. The graphical model of the decision tree—part 2.

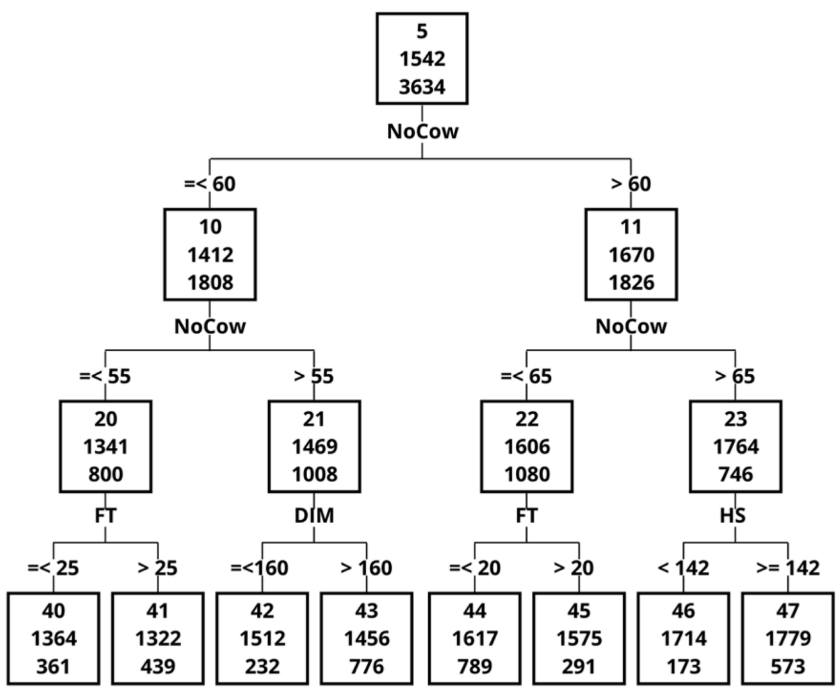

Fig. 4. The graphical model of the decision tree—part 3.

respectively. The difference between these robot days, expressed in daily milk yield per robot, exceeded 109 kg (Fig. 6).

Two variables, cTT and pRef, produced each one division of the decision tree, resulting in Node 36 and Node 37 for cTT (Fig. 3) and Node 48 and Node 49 for pRef (Fig. 5). The differences in daily milk yield per robot between the nodes on these robot days were 139 kg for cTT and 84 kg for pRef. Both the shorter daily AMS preparation time and the lower percentage of milking refusals resulted in robot days for which a higher daily milk yield per robot was observed.

One variable that was omitted from the analysis of variance of cows' milk yields, but proved important when constructing the decision tree, was HS. In the division of the training dataset, it occurred twice and resulted in four end leaves Node 46, Node 47 (Fig. 4), Node 54 and Node 55 (Fig. 6). For both divisions of the tree, cows with greater height at the sacrum had daily milk yield per robot of 65 and 33 kg, respectively.

Based on the generated tree diagram, it is concluded that the lowest daily milk yield per robot (Node 37, 1051 kg) (Fig. 3) was to be expected from cows yielding less or equal to 24 kg of milk per day on average, having milking speed lower or equal 2.40 kg/min. For these cows, preparation for milking, post-milking procedures, and concentrate

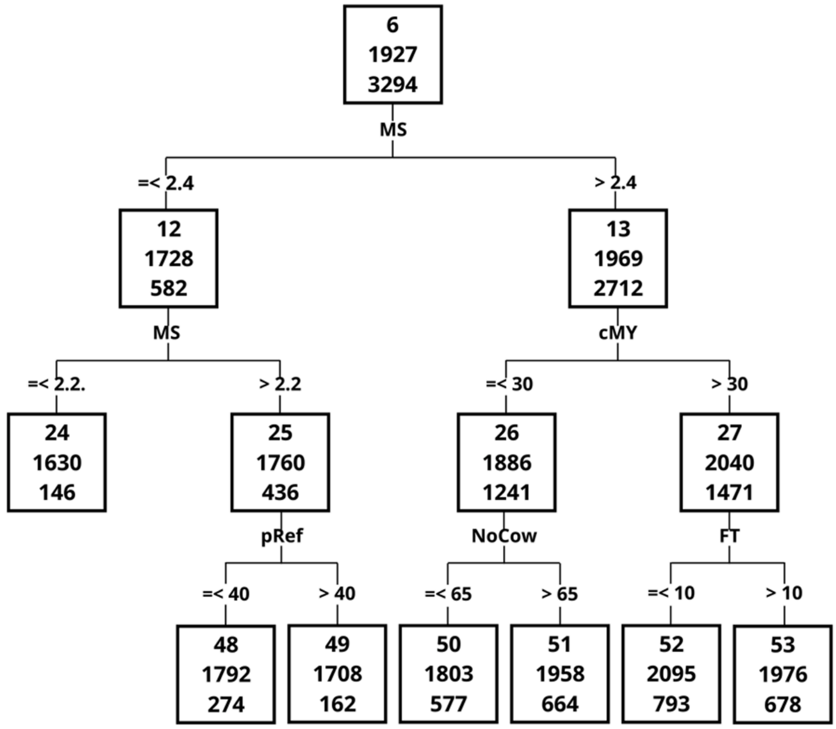

Fig. 5. The graphical model of the decision tree—part 4.

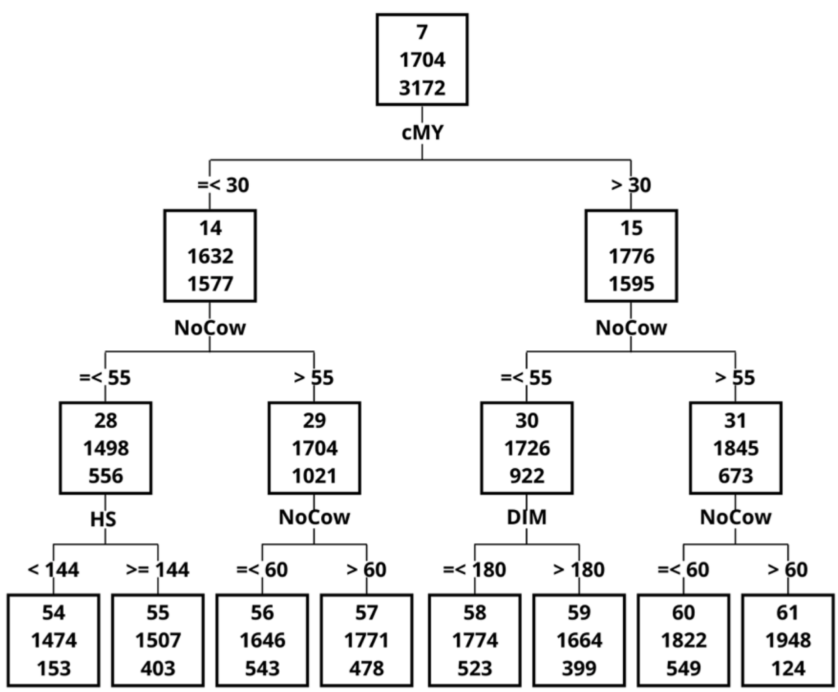

Fig. 6. The graphical model of the decision tree—part 5.

intake took $\geq$ 38% of the box time, and which occupy barns in which free robot time is higher than 25% of the time available for milking (with allowance made for robot cleaning time). In turn, the highest daily milk yield per robot (Node 52, 2095 kg) (Fig. 5) is expected from cows producing more than 30 kg milk per day on average, with milking speed over 2.40 kg/min. and during robot days, free time was equal to 10% or less of the day.

4. Discussion

4.1. General characteristics of the study population

In AMS barns, daily milk yield per robot can be considered a critical factor in production profitability (Salfer et al., 2017). Piwczyński et al. (2020b) showed that daily milk yield per robot might vary widely from 1199 to 1898 kg depending on the variables such as country and year of robot use. In the study by Siewert et al. (2018), milk yield per AMS ranged from 1726 to 2078 kg, depending on the variables. In the study by Castro et al. (2012), daily milk yield per robot was approximately 1950 kg, with an average NoCow of 52.90 animals per robot. In the study by Tremblay et al. (2016), daily milk yield per robot was 1626.80 kg with NoCow of 50.53 cows per robot, the milking frequency was 2.91 per day, and box time was 6.84 min. In our study, the daily milk yield per robot was 1634.56 kg with a markedly higher NoCow of 60.48 on average. In the study by Pezzuolo et al. (2017), daily milk yield per robot was on a higher level and reached 1947 kg with NoCow of 60.8. According to Piwczyński et al. (2020b), the average NoCow for the compared countries was 55.18, as opposed to over 60 in our study. According to Rodenburg (2017), the maximum occupancy rate should not exceed 60 cows per milking robot. According to Castro et al. (2012), who studied AMS herds in Galicia, AMS milk yield could be increased by increasing the number of cows per AMS (up to 68 cows per robot), thus increasing the annual milk yield per robot (185,460 ± 137,460 kg). This would make it possible to recoup the cost of the system earlier. These results indicate that it is possible to increase the number of cows per robot, but the optimal NoCow should be considered to reduce the housing and feeding costs for a greater number of animals.

Piwczyński et al. (2020b) reported that daily milk yield per robot for the analysed countries averaged 1504 kg with a milking frequency of 2.70. Castro et al. (2012) considered 2.40 – 2.60 milkings the optimal milking frequency. Our study population was at the average production level. It has been found that many factors influence daily milk yield per robot.

4.2. Factors affecting daily milk yield per robot – multifactorial analysis of variance

The analysis of variance demonstrated that the additional eleven variables omitted from the training tree did affect daily milk yield per robot. They included: the period after AMS installation, the proportion of multiparous cows in the herd, proportion of Holstein-Friesian inheritance in cow's genome, age at first calving, milking frequency, milking season, rumination time, hoof trimming, and factors related to barn equipment: type of barn, walking area, and the number of robots per barn. Most of them have been extensively discussed in the literature, and their relationship with cMY and daily milk yield per robot in AMS was often reported (Castro et al., 2012; Siewert et al., 2018; Piwczyński et al., 2020c); therefore, they were not investigated further in the study.

Many examples are available in the literature showing that the post-AMS installation period affects the milk production level of the herd and increases milk production with AMS operation time (Brzozowski et al., 2020; Siewert et al., 2018; Sitkowska et al., 2015). The predominance of multiparous cows was noted in the group of cows with higher milk yield (Bogucki et al., 2017) and the high percentage of Holstein-Friesian genotype. Many studies showed also that the optimal age at first calving is 24 months (Ettema and Santos, 2004; Nilforooshan and Edriss, 2004; Sitkowska et al., 2019, 2018). In our study average age at first, calving was higher - more than 30 months. The highest daily milk yield per robot had cows calving the first time before 27 months.

Numerous studies concerning the effect of AMS on herd yield revealed that optimal milking frequency should be in the 2.30–2.79 range (Drach et al., 2017). It has also been repeatedly observed that cows had better milk yield in the spring and summer seasons. Longer rumination time is conducive to higher milk yield, as confirmed by Johnston & DeVries (2018). Soriani et al. (2013) showed that elevated temperature associated with the year's warm seasons negatively impacts rumination time and milk yield. Our study showed a positive effect of frequent hoof trimming on daily milk yield per robot, which may indicate better herd health and more frequent visits of the cows to the AMS.

The barn type was proved important amongst the factors related to the building in which the cows were housed, as confirmed earlier by Piwczyński et al. (2020c). High daily milk yield per robot was also favoured by the installation of a milking robot in the barn and the presence of a slatted walking area.

4.3. Decision tree

Due to the importance of variables included in the finally constructed decision tree, the discussion is confined to eight most important variables contributing to the highest and the lowest milk yield per robot (cMY; NoCow; FT; MS; DIM; cTT; pRef; HS) with decisive effects on daily milk yield per robot. The decision tree helps to identify the factors and their levels that contribute to the highest and the lowest values of daily milk yield per robot – creating the best (Node 52) and worst (Node 37) nodes. The path that leads from the parent node to the Node 52 shows the group of cows with the highest daily milk yield per robot (2095 kg/robot/day), which was created by the splits based on FT (≤10%/robot), cMY (>30 kg), MS (>2.40 kg/min.). On the other hand, Node 37 contain cows that were characterised by CTT >38%, MS ≤2.40 kg/min., FT>25%/robot, cMY ≤24 kg. The two statistical methods used in parallel in the study, i.e., analysis of variance and decision tree technique, conclusively showed that daily milk yield per robot increased with increasing daily milk yield of the cows. This is consistent with the findings of Piwczyński et al. (2020c) and Castro et al. (2012). In the studies conducted by a large group of authors (Bach et al., 2009; Drach et al., 2017; Siewert et al., 2018; Sitkowska et al., 2018; Tse et al., 2018), cMY in AMS in herds ranged from 28 to over 40 kg per day. In our study, we observed the highest daily milk yield per robot in the cows whose cMY exceeded 30 kg per milking. The average cMY in the study herds was 27.20 kg, similar to the value of 27.92 kg reported by Piwczyński et al. (2020b), where the analyses were performed for selected EU countries and the USA, and cMY exceeding 30 kg was found in the USA and Italy.

The tree shows that FT influences the daily milk yield per robot (FT≤10% to higher and FT>25% to lower yield). Tse et al. (2018) reported an FT of 23%, while Castro et al. (2012) almost 28%. Our analysis showed that lower daily milk yield per robot was accompanied by longer FT periods. The influence of FT and its length should be further analysed.

MS contributed to creating the decision tree, which indicated that MS>2.40 kg/min. (as in Node 52) may increase daily milk yield per robot. Piwczyński et al. (2020b) reported that MS varied between 2.10 kg/min. (in Lithuania) and 2.79 kg/min. (in Italy). High MS (2.74 kg/min.) was also noted by Siewert et al. (2018). In our study, MS averaged 2.50 kg/min., similar to the studies of Lee and Choudhary (2006) and Sitkowska et al. (2018). The results show that a high MS is preferable regarding milk yield, making it reasonable to select animals that are characterised with a higher MS for breeding. However, it also should be noted MS that is too high may cause some damage to the teats and may cause mastitis (Lee and Choudhary, 2006; Sitkowska et al., 2017).

The tree also shows that a high cTT (>38%) has a negative impact on the daily milk yield per robot (as shown by Node 37). That means that the time a cow spends in a robot not used for milking is not productive and causes an economic loss. To our knowledge, no article provides information on the impact of cTT on daily milk yield per robot.

5. Conclusions

It is concluded from the present study that FT (≤10%/robot), cMY (>30 kg/cow/day), and MS (>2.40 kg/min) contributed to the highest daily milk yield per robot (as in Node 52). The group with the lowest daily milk yield per robot consisted of robot days that had low cMY and MS, as well as long FT and cTT. By dividing the dataset and creating homogenous groups, the decision tree technique shows factors and their levels that may contribute to the highest and lowest values of the investigated trait. Following the path of divisions from leaves to parent node, one can point factors and explore them further to confirm or reject this association.

According to the tree created in this study, in AMS dairy herds, efforts should be made to select animals that transmit high milk yield and high milking speed while shortening free robot time, increasing daily milk yield per robot. At the same time, attention should be given to the robot preparation time because prolongation of this variable has a negative effect on daily milk yield per AMS.

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Data availability statement

Data is contained within the article or supplementary material

Ethics statement

No ethical statement was required in these studies.

Software and data repository resources

None of the data was deposited in an official repository.

CRediT authorship contribution statement

Joanna Aerts: Conceptualization, Methodology, Validation, Investigation, Writing – original draft, Writing – review & editing. **Beata Sitkowska:** Conceptualization, Methodology, Validation, Investigation, Writing – original draft, Writing – review & editing. **Dariusz Piwczyński:** Conceptualization, Methodology, Validation, Investigation, Writing – original draft, Writing – review & editing. **Magdalena Kolenda:** Investigation, Writing – original draft. **Hasan Önder:** Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare no conflict of interest.

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Article

Genetic Parameters Estimation of Milking Traits in Polish Holstein-Friesians Based on Automatic Milking System Data

Joanna Aerts [1], Dariusz Piwczyński [2,*], Heydar Ghiasi [3], Beata Sitkowska [2], Magdalena Kolenda [2] and Hasan Önder [4]

1 Lely Services B.V., Cornelis van der Lelylaan 1, 3147 PB Maassluis, The Netherlands; JAerts@lely.com
2 Department of Animal Biotechnology and Genetics, Faculty of Animal Breeding and Biology, UTP University of Science and Technology, 85-084 Bydgoszcz, Poland; beatas@utp.edu.pl (B.S.); kolenda@utp.edu.pl (M.K.)
3 Department of Animal Science, Faculty of Agricultural Science, Payame Noor University, Tehran P.O. Box 19395-3697, Iran; ghiasei@gmail.com
4 Department of Animal Science, Ondokuz Mayis University, Samsun 55139, Turkey; honder@omu.edu.tr
* Correspondence: darekp@utp.edu.pl; Tel.: +48-52-3749807

Simple Summary: The automatic milking system provides a large amount of information characterizing the course of each cow milking, which is not available in the conventional system. From a breeding point of view, it is interesting to establish the genetic variability of these traits, as well as to establish the relationship between them. The aim of our study was to estimate heritability and genetic correlations for milk yield (MY), milking frequency (MF), and speed (MS) for 1713 Polish Holstein-Friesian primiparous cows milked in barns with an automatic milking system. Our study conclusively indicated that it is possible to carry out effective selection for milking speed, which provides an opportunity to increase the number of cows per milking robot, and thus increase the profitability of production in the herd. We proved that selection for milk yield and daily milking frequency is also feasible. Our research showed a high, positive genetic correlation between milking frequency and milk yield, which allows us to conclude that preferring breeding cows with a natural tendency to frequent visits to the milking robot should indirectly improve the genetic basis of milking.

Abstract: The automatic milking system (AMS) provides a large amount of information characterizing the course of each milking cow, which is not available in the conventional system. The aim of our study was to estimate heritability and genetic correlations for milk yield (MY), milking frequency (MF), and speed (MS) for 1713 Polish Holstein-Friesian primiparous cows milked in barns with an AMS. Daily heritability indicators estimated using second-order Legendre polynomials and Random Regression Models showed high variation during lactation, ranging 0.131–0.345 for MY, 0.153–0.322 for MF, and 0.336–0.493 for MS. The rates of genetic correlation between traits ranged: 0.561–0.929 for MY-MF, (−0.255)−0.090 for MF-MS, (−0.174)−0.020 for MY-MS. It is possible to carry out effective selection for milking speed, which provides an opportunity to increase the number of cows per milking robot, and thus increase the profitability of production in the herd. The results proved that selection for milk yield and daily milking frequency is also feasible. The research showed a high, positive genetic correlation between milking frequency and milk yield, which allows us to conclude that preferring breeding cows with a natural tendency to frequent visits to the milking robot should indirectly improve the genetic basis of milking.

Keywords: milk; Holstein-Friesian; milking robots; heritability; correlations

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1. Introduction

Genetic parameters can be estimated from varying amounts of information concerning milk yield traits of evaluated animals and their relatives—in the simplest case, based on lactation milk yield or milk yield standardized to 305 lactation days [1–3]. The current standard for estimating the genetic parameters in most countries is to use test-day (TD) yields recorded regularly as part of cow milk recording schemes [4–8]. Test-day models (TDM) allow for modeling daily milk yield based on changing environmental conditions on different days and stages of lactation [9]. An important issue related to the estimation of the genetic parameters, which has been the subject of research since the 1960s, is the choice of a function describing the shape of the lactation curve. Many different proposals for lactation curve modeling have been presented, including the functions, among other of Ali and Schaffer [10], Wilmink [11], and, since 1994, Legendre orthogonal polynomials [12], which produce varied results in terms of lactation curve modeling quality [13]. Functions of the lactation curve can be included in the calculations as fixed regression models or random regression models (RRM) [6,8,9,14,15]. The first model assumes that the effects of animal and fixed environmental factors are identical on each day of lactation, while the latter assumes they are different [16]. RRM enables genetic parameters to be estimated for the whole lactation and successive days of lactation, and furthermore the lactation curve can be individually modeled for every animal. An important aspect of the models for estimating genetic parameters is that they account for the heterogeneity of variance of milk yield on successive days of lactation [17]. This solution increases the accuracy of estimating genetic parameters and breeding values by reducing residual variances. According to Jamrozik et al. [18], the model can be simplified if residual variances is assumed to be fixed-width intervals.

In the overwhelming majority of countries with advanced dairy breeding systems, RRM associated with Legendre orthogonal polynomials is currently used in the official assessment of the genetic value of populations to model the lactation curve [5,6,19–21]. One of the problems of using Legendre orthogonal polynomials also implies higher parametrical complexity which may imply determinant coefficient inflation, which is not corrected by the inclusion of logarithmic or exponential terms in the function. However, intensive research continues to address the degree of polynomials used for lactation curve modeling as well as the way observations are grouped according to the heterogeneity of variance [22,23].

Strabel et al. [23] demonstrated that the order of polynomial influences the values of estimated genetic parameters, and that it is appropriate to use fifth-order polynomials to estimate genetic variation in Polish Holstein-Friesian (PHF) cattle. The optimum order of Legendre polynomial was investigated by Khanzadeh et al. [24]. These authors estimated genetic parameters as well as the breeding value for the fat and protein (%) content of milk by modeling the lactation curve using third- to sixth-order Legendre polynomials. They found from their study that the best fit for the additive genetic (AG) and permanent environmental (PE) effects of fat and protein percentages were obtained using the polynomials: 5-AG, 5-PE (fat) and 5-AG, 6-PE (protein). Biassus et al. [6] estimated h^2 for milk yield (MY), milk protein and fat percentage in Holstein cows using RRM and Legendre polynomials of orders 3 to 6, assuming fixed residual variances during successive days of lactation. It should be highlighted that in this study, genetic variations for milk yield and protein and fat contents, as well as the heritability indicators of these traits followed a similar trend regardless of the order of the polynomial, and the possible differences concerned the beginning and the end of lactation. Similar findings were presented by Costa et al. [15], i.e., variation in AG, PE, h^2 of milk yield depending on Legendre polynomial as well as the need to use polynomial of 5th order. Moreover, the same authors [15] evaluated the quality of the models and showed the best fit for a model assuming heterogeneity of variance in different lactation periods. Higher order polynomials for modeling the effect of AG and PE than in previous studies were proposed by Bignardi et al. [25] namely seventh- and twelfth-order polynomials, respectively. Contrary results were reported by Naderi at al. [19] for Holstein-Friesian cattle in Iran—out of the different order Legendre polynomials (3rd to 6th), the best fit of the model for the AG and PE effect was obtained for third-order polynomial.

Automation of the milking process, which has been ongoing for around 30 years, as shown by many studies [26,27], may contribute effectively to improving milk yield and quality. At the same time, the automation of milking allows for recording many parameters of the milking process, which are not commonly or directly measured in the conventional system. The extra information includes the interval from the previous milking, number of milkings and cluster attachment time, milking duration, milking speed, milking box time, milk efficiency (milk yield per minute in the milking box), electrical milk conductivity [21,28–35]. It should be highlighted that there are relatively few studies addressing the estimation of genetic parameters for AMS recorded traits [20,32,36].

This study aimed to estimate heritability and genetic correlations for daily milk yield, daily milking frequency and daily milking speed recorded by an automatic milking system throughout the lactation for Polish Holstein-Friesian primiparous.

2. Materials and Methods

2.1. Data

Data with daily (24-h) records of 1713 primiparous Polish Holstein-Friesian cows from 21 farms with automatic milking systems (AMS) were collected. Herds were equipped with Lely AMS (Astronaut A4).

Cows were housed in free-stall barns and fed a Partial Mixed Ratio (PMR) feed. The cows received a varied dose of the concentrate, either in the milking robot or the feeding station, depending on the level of their milk yield. Primiparous cows calved from 2011 to 2015 at the age of 18–45 months.

The following data from AMS were chosen for analysis:

- Milk yield (MY) (kg)—daily milk yield of cow summed during 1 day in milk,
- Milk frequency (MF) (no.)—number of milking per cow per day,
- Milking speed (MS) (kg/min)—average milk flow rate during milking (Table 1).

Table 1. Descriptive statistics of primiparous cows-milked in automated milking systems traits.

Trait	Number of 24-h Records	$\bar{x}$	Standard Deviation	Coefficient of Variation (%)
Milk yield (kg)	538,688	28.591	8.823	30.859
Milking frequency (no.)	538,688	2.915	0.886	30.420
Milking speed (kg/min)	538,688	2.526	0.908	35.931

Data on milk performance of primiparous cows milked in AMS was derived from the T4C management and data registration system by Lely East.

Data with outside $\mu \pm 3\sigma$ were deleted from the data file. The pedigree file (cows with records and their ancestors) contained 4231 animals in total. Cows were daughters of 702 sires and 1562 dams. Only cows with complete pedigree data were included in the estimation of genetic parameters. Finally, 491,632 records were used for the estimation of (co)variance components.

Two traits RRM were used to estimate the genetic parameters for studied traits. For analysing traits with RRM, Legendre polynomials for the regression on the number of milking day (from test day 5 to test day 305) were used. Two RRM models with first (linear) and second (quadratic) order of fit were used. The residual variance for these two models were homogenous and heterogeneous. The logarithm of the likelihood (logL), Bayesian information criterion (BIC) and Akaike's Information Criterion (AIC) were used to select the suitable models. The use of RRM in the estimation of genetic parameters makes it possible to determine the heritabilities for individual days of lactation, as well as the genetic correlation coefficients between the daily MF, MY and MS recorded on the same as well on different days of lactation. The obtained results are presented in Figures 1–5. The Wombat package [37] was used to estimate parameters. The models with the lowest value of AIC and BIC were the best models.

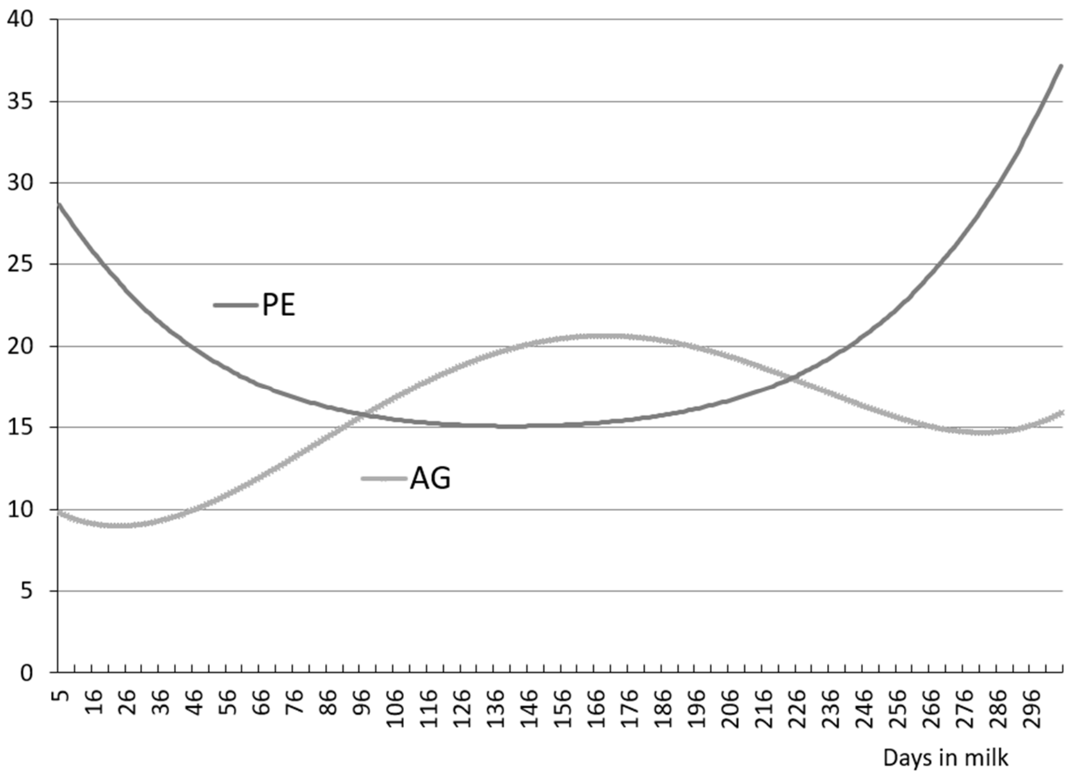

Figure 1. Genetic (AG), permanent environmental (PE) variances for milk yield of primiparous cows.

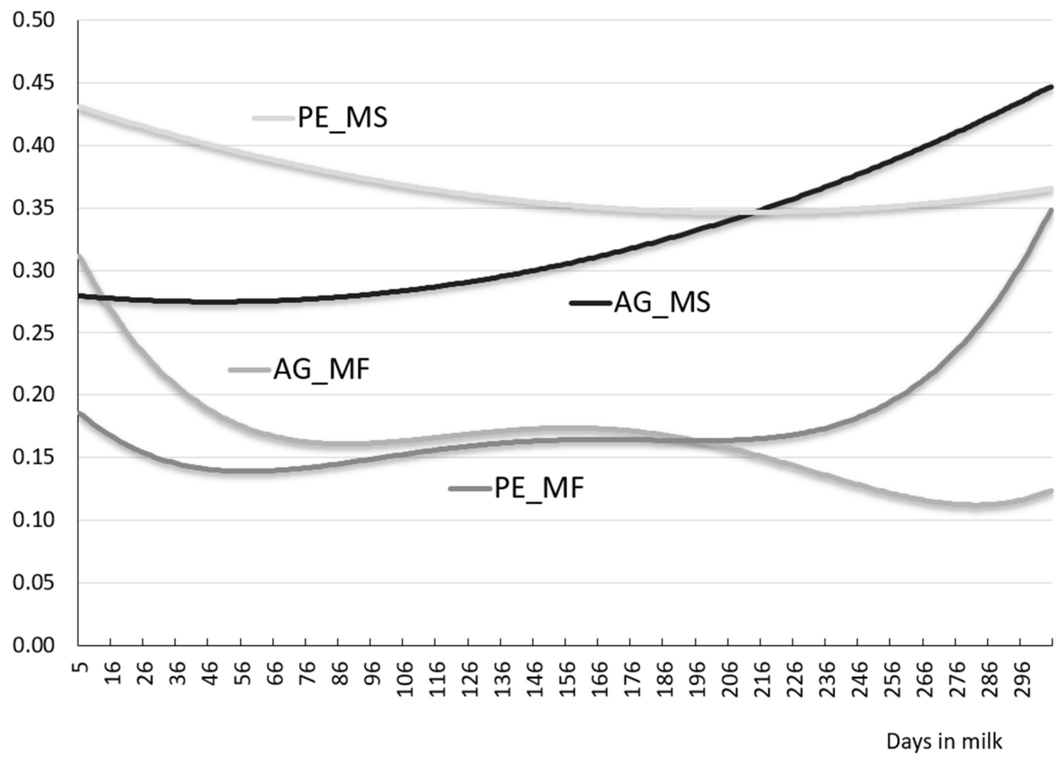

Figure 2. Genetic (AG), permanent environmental (PE) variances for milking frequency (MF) and milking speed (MS) of primiparous cows.

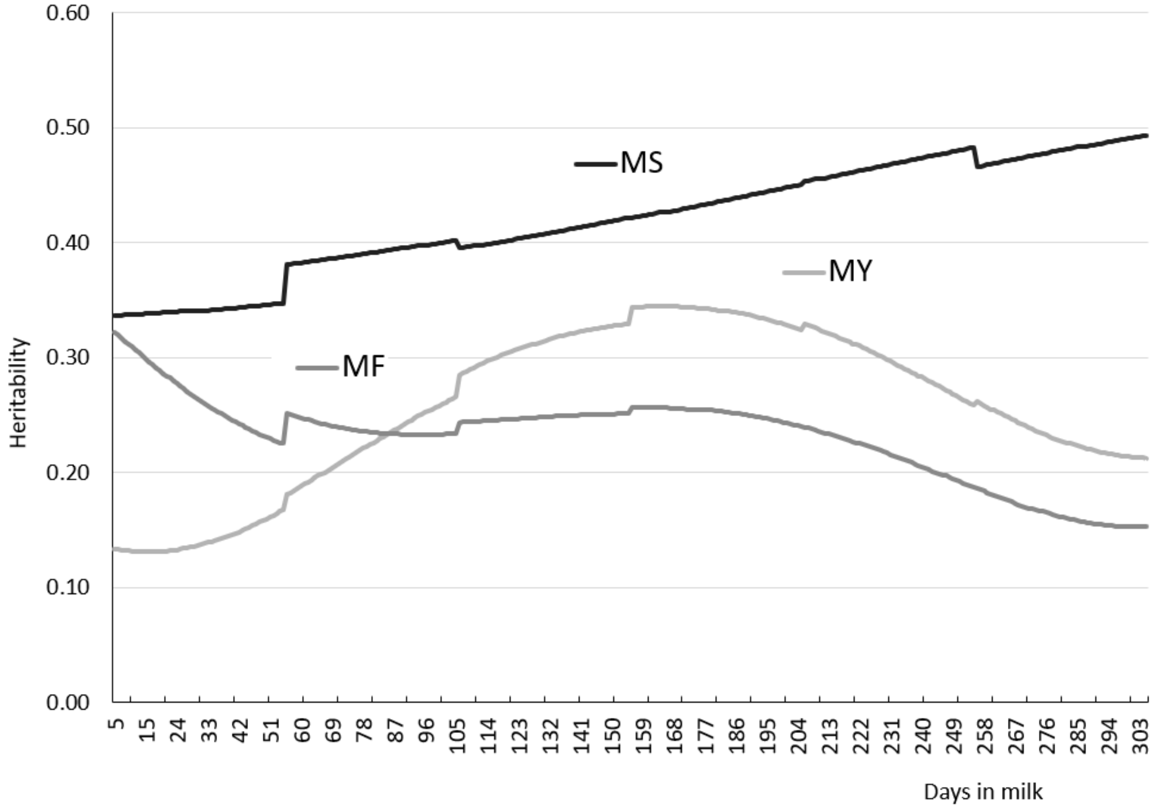

Figure 3. Heritabilities of milk yield (MY), milking frequency (MF) and speed (MS) in subsequent days in milk.

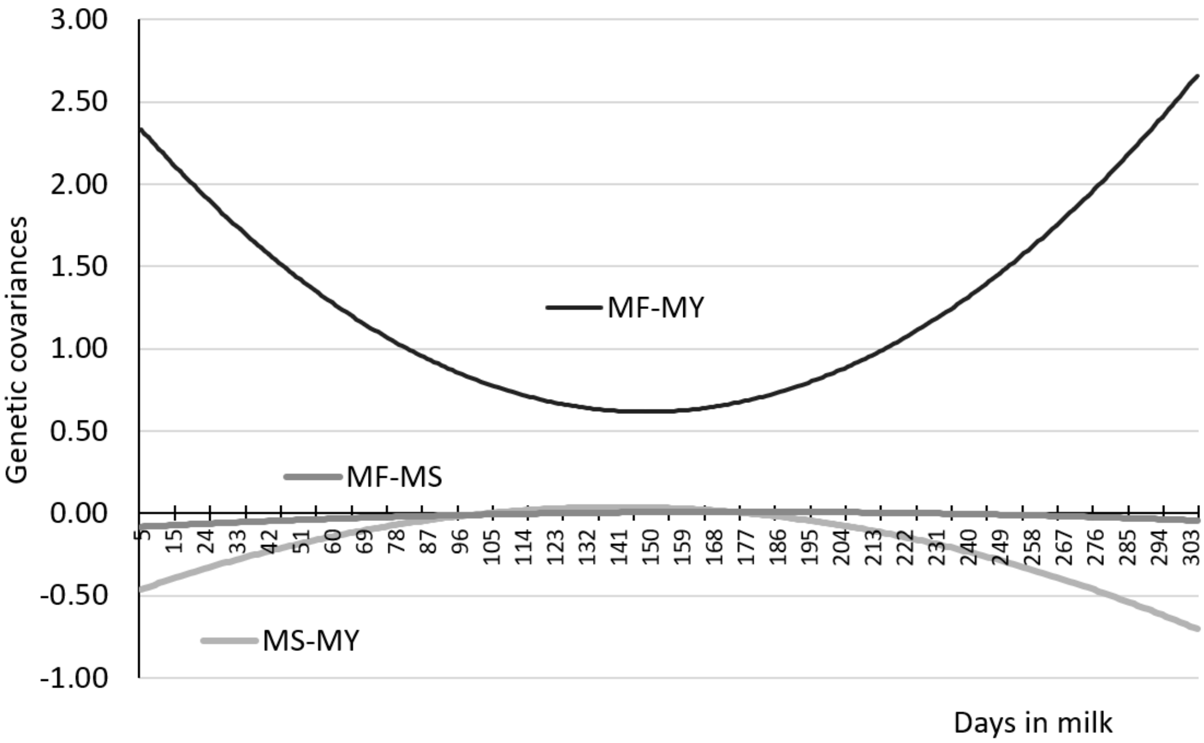

Figure 4. Genetic covariances for controlled pairs of traits primiparous cows, where MS-MY—milking speed and milk yield covariance, MF-MY—milking frequency and milk yield covariance, MF-MS—milking frequency and milking speed covariance.

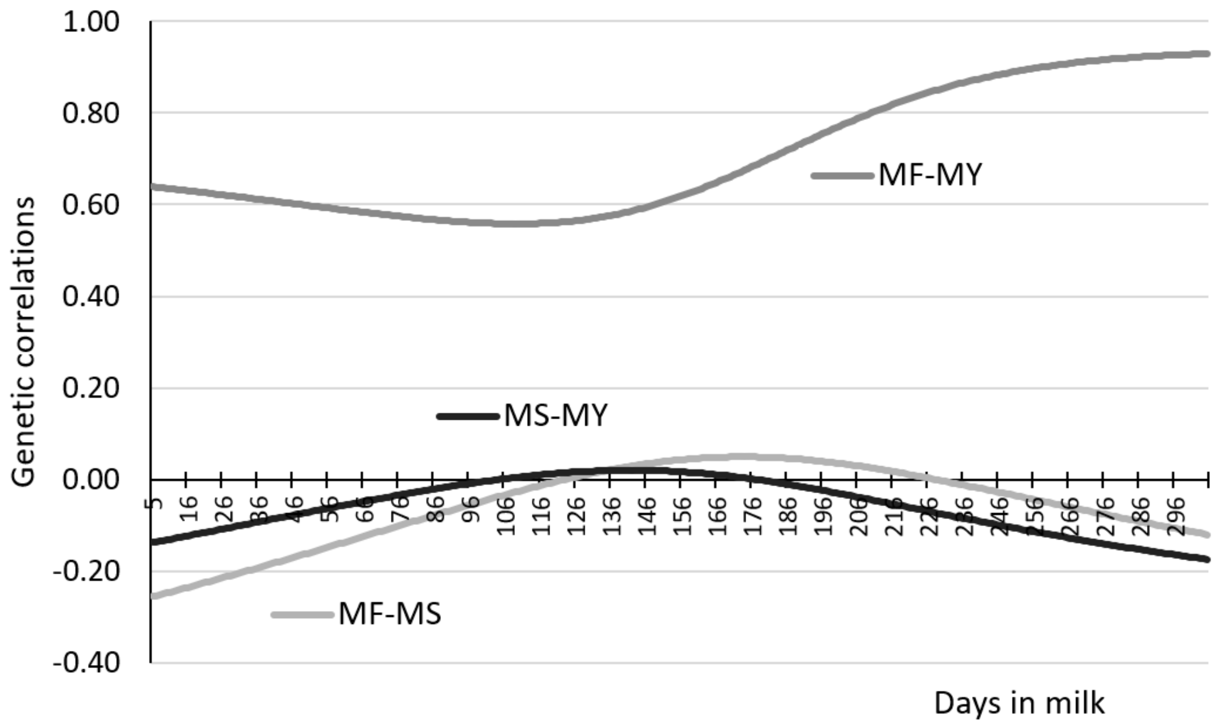

Figure 5. Genetic correlations (rG) for controlled pairs of traits primiparous cows, where MS-MY—milking speed and milk yield covariance, MF-MY—milking frequency and milk yield covariance, MF-MS—milking frequency and milking speed covariance.

2.2. Statistical Model

In the study we considered using fourth- and fifth-order polynomials, but because convergence could not be reached, we made the estimations with second-order polynomials.

The following model Equation (1) is assumed to be the same for MY, MF and MS:

$$y_{ilm} = Herd_i + \sum_{k=1}^{n} b_{mk}\, z_{lmk} + \sum_{k=1}^{n} a_{lk}\, z_{lmk} + \sum_{k=1}^{n} pe_{lk}\, z_{lmk} + e_{ilm} \quad (1)$$

where y_{ilm} = milking day record m of cow l obtained in herd i, $Herd_i$ = fixed effect of herd i, b_{mk} = fixed regression coefficient specific to days in milk m, a_{lk} random regression coefficients for additive genetic effect, pe_{lk} random regression coefficient for permanent environmental, z_{lmk} are Legendre polynomials on DIM, n represent the order of fit and e_{ilm} is residual effect for each observation and z_{lmk} covariables of Legendre polynomials for the standardized value of the milking day records.

The model assumptions were expressed by Equation (2):

$$E\begin{bmatrix} \mathbf{b} \\ \mathbf{a} \\ \mathbf{pe} \\ \mathbf{e} \end{bmatrix} = \begin{bmatrix} \mathbf{b} \\ 0 \\ 0 \\ 0 \end{bmatrix},\ v\ (a) = \mathbf{K}_a \otimes \mathbf{A},\ v\ (pe) = \mathbf{K}_{pe} \otimes \mathbf{I}_{nr}\ \text{and} v\ (e)\ =\ R \quad (2)$$

with $\mathbf{K}_a$ and $\mathbf{K}_{pe}$ = matrices of (co)variance between random regression coefficients for additive genetic and permanent environmental effects, respectively; $\mathbf{A}$ = additive relationship matrix; $\mathbf{I}_{nr}$ = identity matrix; nr = number of animals with records; ⊗ = Kronecker product, and, $\mathbf{R}$ = diagonal matrix with a homogeneous residual variance on the diagonal for homogeneous. To fit heterogeneous residual variances model residual covariances differed across 6 stages in each lactation days in milk (DIM): 6 to 50 DIM, 51 to 100 DIM, 101 to 150 DIM, 151 to 200 DIM, 201 to 250 DIM, and 251 to 305 DIM. The number of DIM varied from 64 to 300.

3. Results

Random regression models with the order of fit higher than 2 for single-trait analysis and for two trait random regression analysis with the order of fit higher than 1 were not converged due to convergence problems. For MY and MF random regression model with order 2 with heterogeneous residual variance and for MS random regression with order 1 with heterogeneous residual variance was the best model (Table 2). Therefore, the result for MY and MF were reported based on order 2 and for MS based on order 1 was reported (Table 3).

Table 2. Number of parameters (P), log-likelihood value (Log L), Akaike's information criterion (AIC) and Bayesian information criterion (BIC) for different models in single trait random regression analysis.

Model	Order of fit	Log L	AIC	BIC	*p*
Milk yield (kg)	1	−1,081,429.608	2,162,883.216	2,163,016.482	12
Milk yield (kg)	2	−1,062,894.572	2,125,825.144	2,126,025.042	18
Milking frequency (no.)	1	−25,033.237	50,090.474	50,223.738	12
Milking frequency (no.)	2	−10,201.294	20,438.588	20,638.484	18
Milking speed (kg/min)	1	382,535.783	765,047.566	764,914.300	12
Milking speed (kg/min)	2	415,176.076	830,316.152	830,116.254	18

Table 3. Estimates of additive genetic variance (diagonal), covariance (lower diagonal) and correlations (upper diagonal) between random regression coefficient and percentage of variance associated with each eigenvector (EV%).

Trait	Regression Coefficients	Intercept	Linear	Quadratic	EV%
Milk yield (kg)	Intercept	24.13	0.19	−0.73	81.66
	Linear	2.14	4.84	−0.04	14.72
	Quadratic	−5.97	−0.17	2.74	3.63
Milking frequency (no.)	Intercept	0.20	−0.12	−0.53	67.35
	Linear	−0.016	0.086	−0.31	27.73
	Quadratic	−0.043	−0.016	0.032	4.92
Milking speed (kg/min)	Intercept	0.61	0.3144		94.66
	Linear	0.048	0.038		5.34

For two traits RRM, based on the model's quality measures (LogL, AIC, BIC), one can conclude that for MY-MF and MY-MS random regression with order 2 with heterogeneous residual variance and for MF-MS random regression model with order 2 with homogenous residual variance was the best model (Table 4). The result of estimates of additive genetic covariance between random regressions coefficients with the best models were presented in Table 5.

Figures 1 and 2 present changes in genetic variance (AG) and permanent environment (PE) for MY, MF and MS over 305 days of lactation. The curve showing a change of genetic variance MY (AG_MY) is similar to an inverted parabola with higher values in mid-lactation. In turn, the curve showing variance changes for permanent environmental effects MY (PE_MY) has the opposite shape, resembling a parabola with higher values in early and late lactation, and lower values in mid-lactation.

Our study demonstrated that the curves showing changes of genetic variance and permanent environment effects MF were similar in shape to the initial downward trend up to around 50–60 days of lactation, followed by a mildly upward trend. The essential difference between the shape of the two curves was that there was an upward trend for

PE variance further into lactation (>230 days) and a downward trend for AG. A markedly different shape concerning to those described earlier for MY and MF, was represented by the curves showing changes of genetic variance and permanent environment effects for milking speed. There was an upward trend over 305-day lactation for AG and a downward trend for PE.

Table 4. Log-likelihood value (Log L), Akaike's information criterion (AIC) and Bayesian information criterion (BIC), number of parameters (P), for different models in two-trait trait random regression analysis.

Model [1]	Order of Fit [2]	Log L	AIC	BIC	*p*
MY-MF	1	−1,036,614.637	2,073,247.274	2,073,353.46	9
MY-MF	2 HOM	−923,334.831	1,846,715.662	1,846,987.03	23
MY-MF	2 HET	−907,256.912	1,814,589.824	1,815,038.17	38
MY-MS	1	−909,037.893	1,818,093.786	1,818,199.972	9
MY-MS	2 HOM	−728,555.075	1,457,156.15	1,457,427.518	23
MY-MS	2 HET	−711,685.300	1,423,446.6	1,423,894.946	38
MF-MS	1	−671,185.362	1,342,388.724	1,342,494.91	9
MF-MS	2 HOM	337,838.394	675,630.788	675,359.422	23
MF-MS	2 HET	348,202.475	696,328.95	695,880.604	38

[1] MY—Milk yield (kg); MF—Milking frequency (no.); MS—Milking speed (kg/min); [2] HOM: homogeneous residual variance; HET: heterogeneous residual variance.

Table 5. Estimates of additive genetic covariance between random regression coefficients in two-trait random regression analysis.

		Milking Speed (kg/min)		Milk Yield (kg)	
		Intercept	Linear	Intercept	Linear
Milking frequency (no.)	intercept	0.015	0.055	1.240	0.210
	linear	−0.033	−0.047	−0.020	1.250
Milk yield (kg)	intercept	0.063	−0.610		
	linear	0.470	−0.410		

Daily heritability indicators of the recorded traits showed high variation during lactation, ranging from 0.131 to 0.345 for MY, from 0.153 to 0.322 for MF, and from 0.336 to 0.493 for MS (Figure 3). It must be stressed that the irregular progression in Figure 3 results from the fact that the model accounted for different residual variances in the 305-day lactation periods.

When analysing the shape of the curve showing the values of heritability indicators MY, we observed a moderate downward trend from 5 (0.133) to 21 days of lactation (0.131), and an upward trend to day 160, when heritability reached the maximum value of 0.345. The heritability indicator (0.345) retained its maximum value until 169 days of lactation, after which heritability decreased steadily until the end of lactation (0.212).

We found that MF heritability was highest (0.322) during the early stage of lactation. It decreased to 0.225 over the next 50 days of lactation (until day 55) and increased to 0.227 on day 156 of lactation. The curve showed a downward trend from day 166 to the end of lactation. Regarding daily MS heritability, there was a consistently upward trend (from 0.336 to 0.493) throughout the lactation period (Figure 3).

The trends shown by the curves (Figure 3) are quantitatively confirmed by averaged daily heritabilities of the recorded traits for the whole lactation, as presented in Table 6. Our study revealed the highest averaged heritability for MS (0.420), followed by MY (0.257) and MF (0.230).

Figure 4 depicts additive genetic (AG) covariances for the pairs of traits MF-MY, MF-MS and MS-MY, which were measured on the same days of lactation. The constructed MS-MY curve resembles an inverted parabola with higher values in mid-lactation. In turn, the curve showing genetic covariance of MF-MY traits has the shape of a parabola with higher values in early and late lactation, and lower values in mid-lactation. Our study showed that genetic covariance for MF-MS was essentially similar throughout the 305-day lactation, with slightly lower values observed in the early and late lactation compared to the mid-lactation. Tables 7–9 present genetic correlations calculated from (co)variance components, between daily MF, MY, and MS at different stages of lactation, while Figure 5 those for the same days of lactation.

Table 6. Mean daily heritabilities (h^2) through the whole 305-d lactation.

Trait	AG	SE	PE	SE	R	SE	P	SE	h^2	SE
MY	15.853	3.091	19.681	2.752	26.789	0.135	62.323	1.311	0.257	0.047
MF	0.164	0.030	0.175	0.027	0.369	0.002	0.709	0.013	0.230	0.041
MS	0.325	0.061	0.367	0.054	0.078	0.000	0.770	0.025	0.420	0.074

Where: MY—Milk yield (kg); MF—Milking frequency (no.); MS—Milking speed (kg/min); AG—additive genetic variances; PE—permanent environmental variances, R—residual variances, P—phenotypic variances, SE—standard error of AG, PE, R, P variances and $h^{2.}$

The genetic correlations estimated between daily MF and MY recorded on different days of lactation ranged from (−0.461) to 0.929. Most of the genetic correlations assumed positive values (Table 7). The strongest genetic relationships between MF and MY (from 0.561 to 0.929) were noted when the results of both traits came from the same days of lactation (Figure 5)—0.705 on average (mean from daily genetic correlations). At the same time, it was observed that the curve showing genetic correlations between MF and MY measured on the same days of lactation tended to assume clearly higher values in the final stage of lactation (Figure 5). It was also observed that the magnitude of these correlations decreased with increasing distance between the days on which MF and MY were recorded (Table 7). In an extreme case, where MF and MY correlated on the extreme days of lactation, the estimated genetic correlations assumed negative values.

The genetic correlations between MF and MS, recorded on different days of lactation, ranged from −0.272 to 0.362. Thus, these estimates are indicative of a weak to moderate correlation between these traits, which in most cases was negative (Table 8). Positive, moderate (>0.3) genetic relationships were observed between MS on around 100 days and MS during the last 60 days of lactation (Table 8).

The curve for the daily correlations between MF and MS, measured on the same days of lactation, showed an upward trend from the beginning to around 180 days of lactation, followed by a downward trend (Figure 5). The estimated correlations ranged from −0.255 to 0.090 (−0.054 on average). Positive relationships between MF and MS were observed in mid-lactation, i.e., from days 123 to 228.

The genetic correlations between MS and MY measured on different days of lactation varied between −0.213 and 0.355, being mostly indicative of a negative relationship (Table 9). The strongest, positive correlations were observed between MS measured beyond 100 days of lactation and MY recorded during the first 100 days of lactation. At the same time, it was noticed that these relationships declined with increasing distance between MS and MY measurement days, after which they gradually changed their sign (direction) from positive to negative (Table 9). Analysis of the daily genetic correlations between MS and MY on the same days of lactation showed that they ranged narrowly from −0.174 to 0.020, averaging −0.057 (Table 9, Figure 5). The curve for the correlation values up to 142 days of lactation showed a mild upward trend and then a downward trend (Figure 5). Positive values of the correlation coefficients between MS and MY were recorded from 104 to 172 days of lactation.

Table 7. Genetic correlations between milking frequency and milk yield in different days of lactation.

		Milk Yield (kg) on Different Days of Lactation										
	Days	**5**	**30**	**60**	**90**	**120**	**150**	**180**	**210**	**240**	**270**	**305**
Milking frequency on different days of lactation	5	0.638	0.632	0.613	0.573	0.495	0.364	0.188	0.010	−0.134	−0.237	−0.318
	30	0.619	0.617	0.606	0.577	0.513	0.398	0.236	0.068	−0.071	−0.173	−0.255
	60	0.582	0.587	0.589	0.577	0.536	0.448	0.312	0.161	0.031	−0.068	−0.150
	90	0.519	0.534	0.553	0.564	0.556	0.506	0.407	0.283	0.167	0.074	−0.005
	120	0.416	0.444	0.484	0.526	0.561	0.564	0.518	0.433	0.341	0.260	0.186
	150	0.262	0.304	0.368	0.447	0.532	0.603	0.626	0.597	0.539	0.478	0.416
	180	0.067	0.121	0.208	0.321	0.458	0.597	0.696	0.731	0.717	0.683	0.639
	210	−0.124	−0.062	0.039	0.175	0.349	0.543	0.707	0.800	0.829	0.823	0.801
	240	−0.275	−0.211	−0.104	0.044	0.239	0.467	0.674	0.810	0.873	0.891	0.888
	270	−0.381	−0.317	−0.209	−0.058	0.146	0.391	0.624	0.788	0.875	0.911	0.922
	305	−0.461	−0.399	−0.294	−0.144	0.063	0.317	0.567	0.751	0.855	0.906	0.929

Table 8. Genetic correlations between milking frequency and milk speed in different days of lactation.

		Milk Speed (kg/min) on Different Days of Lactation										
	Days	**5**	**30**	**60**	**90**	**120**	**150**	**180**	**210**	**240**	**270**	**305**
Milking frequency on different days of lactation	5	−0.255	−0.199	−0.126	−0.050	0.025	0.096	0.162	0.221	0.273	0.318	0.362
	30	−0.261	−0.205	−0.131	−0.054	0.021	0.093	0.160	0.219	0.272	0.317	0.362
	60	−0.268	−0.212	−0.138	−0.061	0.015	0.088	0.154	0.214	0.267	0.313	0.359
	90	−0.272	−0.217	−0.144	−0.068	0.006	0.078	0.144	0.203	0.255	0.301	0.346
	120	−0.267	−0.215	−0.147	−0.076	−0.005	0.062	0.124	0.181	0.230	0.273	0.317
	150	−0.244	−0.200	−0.141	−0.080	−0.020	0.038	0.092	0.141	0.184	0.222	0.260
	180	−0.198	−0.166	−0.124	−0.079	−0.034	0.009	0.049	0.085	0.118	0.147	0.175
	210	−0.139	−0.121	−0.097	−0.072	−0.046	−0.020	0.004	0.025	0.045	0.063	0.080
	240	−0.081	−0.076	−0.069	−0.061	−0.052	−0.043	−0.034	−0.026	−0.018	−0.011	−0.003
	270	−0.034	−0.039	−0.045	−0.051	−0.055	−0.059	−0.062	−0.064	−0.066	−0.066	−0.067
	305	0.006	−0.007	−0.024	−0.041	−0.057	−0.071	−0.084	−0.095	−0.104	−0.112	−0.120

Table 9. Genetic correlations between milk speed and milk yield in different days of lactation.

		Milk Yield (kg) on Different Days of Lactation										
	Days	**5**	**30**	**60**	**90**	**120**	**150**	**180**	**210**	**240**	**270**	**305**
Milking speed on different days of lactation (kg/min)	5	−0.137	−0.149	−0.166	−0.186	−0.204	−0.213	−0.204	−0.178	−0.148	−0.120	−0.094
	30	−0.090	−0.101	−0.119	−0.140	−0.161	−0.177	−0.179	−0.166	−0.146	−0.126	−0.107
	60	−0.028	−0.039	−0.056	−0.078	−0.104	−0.129	−0.145	−0.148	−0.142	−0.133	−0.122
	90	0.034	0.024	0.007	−0.015	−0.045	−0.079	−0.109	−0.128	−0.136	−0.137	−0.135
	120	0.095	0.085	0.069	0.046	0.013	−0.029	−0.072	−0.107	−0.128	−0.140	−0.147
	150	0.151	0.143	0.128	0.105	0.069	0.019	−0.037	−0.085	−0.119	−0.141	−0.156
	180	0.203	0.196	0.182	0.158	0.120	0.064	−0.003	−0.064	−0.110	−0.140	−0.163
	210	0.248	0.242	0.229	0.206	0.166	0.105	0.029	−0.044	−0.100	−0.138	−0.168
	240	0.288	0.283	0.271	0.248	0.207	0.141	0.057	−0.026	−0.090	−0.136	−0.171
	270	0.322	0.317	0.306	0.284	0.242	0.173	0.082	−0.009	−0.081	−0.133	−0.173
	305	0.355	0.351	0.341	0.319	0.277	0.204	0.107	0.009	−0.071	−0.128	−0.174

4. Discussion

In terms of MY, the study group of Polish Holstein-Friesian cows represented a typical level for the milk recorded cows of this breed [4]. The average levels of MF, MS, and MY in our study fell within the ranges reported by Piwczyński et al. [38] for a population of automatically milked cows in selected European countries and in the USA, namely: MF: 2.50–2.81 milkings/24 h, MY: 22.22–34.07 kg/min, MS: 2.05–2.83 kg/min.

According to Costa et al. [15], it is appropriate to use estimation models with fewer parameters. This derives from the fact that the use of TD results multiplies (ten-fold on average) the amount of data needed to estimate the genetic parameters and breeding value compared to the lactation yield models. This is paralleled by a rapid increase in the number of equations in the system of mixed-model equations necessary for estimating the genetic parameters and breeding value [39]. This is even more justified when estimating the genetic parameters of milk yield traits based on AMS data, which provides information on each milking.

Finally, our study compared the use of first- and second-order polynomials to model variation of MY, MF, and MS. Based on the obtained AIC and BIC values, the best fit was found for the models using second-order polynomials, for both the additive genetic and permanent environmental effects, which additionally accounted for different residual variances at different stages of lactation.

The curve showing the daily heritabilities of milk yield during lactation has the shape of an inverted parabola, which coincides with the results of other authors [8,15,32]. However, many studies reported that the parameters of milk yield were higher in the initial and final stages of lactation than in mid-lactation [9,20,24]. Jamrozik et al. [40] and Strabel et al. [23] consider that this trend is especially evident when assuming the fixed effect of PE for each day of lactation, and, unlike in our study, they assumed a random effect of PE. This course of action is supported by the results of Cobuci et al. [15], who compared the curves of daily h^2 obtained using two RRM models differing in the mode of PE treatment (fixed or random effect). The model accounting for PE as a fixed effect during the entire lactation period resulted in high h^2 values in early lactation unlike the model with random PE. Literature on the subject provides several studies which present a completely different shape of the curve for h^2 values of milk yield per lactation. Kheirabadi [7] and Cobuci et al. [41] presented a curve that showed an upward trend throughout the lactation for h^2 of milk yield. Yet another trend for h^2 of MY during successive days of lactation was shown by Bignardi et al. [25] and Nixon et al. [20]. The curves from these studies, showing the values of these heritability values, at first showed a downward trend, followed twice by an upward and a downward trend until the end of lactation. A very similar shape of the curve for daily MY heritabilities, compared to Bignardi et al. [25] and Nixon et al. [20] was obtained by Naderi [19]. The only difference was that there was no downward trend in the initial shape of the curve. Our daily MY heritabilities ranged from 0.131 to 0.345. A similar range of fluctuations for daily heritabilities during lactation to ours, estimated based on TD, was obtained by Biassus et al. [6] (0.14–0.31) and Cobuci et al. [41] (0.15–0.31), and different ranges by Strabel and Misztal [23] (0.14–0.19), Costa et al. [41] (0.27–0.42), Jamrozik and Schaffer [9] (0.40–0.59), Naderi [19] (0.45–0.60) and Moretti et al. [42] (0.14–0.53). In the study by Nixon et al. [20] using 24-h AMS data, the range of daily h^2 was narrower (0.14 to 0.20) than in our study. In the context of these results, it is necessary to highlight the results obtained by Piwczyński, Sitkowska and Ptak [32] in AMS herds for MY heritability estimated only from the test-day data. The MY heritabilities in this study ranged from 0.162 to 0.338, which is in strict compliance with the range presented here. The averaged MY heritability, calculated from 300 daily indicators (0.257), falls within the ranges reported by other authors (0.12–0.34): Gray et al. [43], Nixon et al. [20], Kirsanova et al. [44], Sasaki et al. [8] and Kheirabadi [7].

Interesting results of studies on genetic variation of AMS recorded traits were reported by Santos et al. [30] based on AMS data from German HF herds. The authors observed that heritabilities differed markedly depending on udder quarter: from 0.05 (left front) to 0.19 (right front). The average MY heritability was 0.10.

Brzozowski et al. [27] and Piwczyński, Brzozowski and Sitkowska [45] demonstrated that changing the milking system from conventional to AMS has a positive effect on increasing the milk yield. According to de Koning, Slaghuis and van der Vorst [46] and Österman et al. [47], this results from increased milking frequency per day. It is therefore important to determine the genetic background of this trait, especially since there are relatively few studies in this area [20,30,32,48]. Carlström et al. [49] estimated that MF heritabilities for Swedish Holstein-Friesian and Swedish Red cows for the first lactation and the second and third lactations together, ranged from 0.02 to 0.07. In turn, König et al. [48] estimated MF heritability for three consecutive 100-day lactation periods to be low: 0.16, 0.19, and 0.22, respectively. In our study, the average heritability calculated from daily values was 0.230, which means that cows can be effectively selected for increased milking frequency. In turn, low heritability (0.05–0.08) of MF was reported by Santos et al. [30].

Nixon et al. [20] estimated daily MF heritabilities based on 24-h AMS data. The constructed curve showed an initial downward trend, followed by an upward trend, a downward trend after mid-lactation, and an upward trend in the last month of lactation. To a certain extent, the shape of the curve coincides with our curve. The difference concerns the much lower range of 24-h heritabilities estimated by Nixon et al. [20] than in our study, which was in the range of 0.02–0.08 vs. 0.153–0.322. A broader range of daily MF heritabilities than in our study was reported by Piwczyński, Sitkowska and Ptak [32] (0.156–0.444). Our study revealed a relatively high MF heritability during the early stage of lactation, which had a direct impact on the range of variation of this indicator during lactation. Strabel and Misztal [50] suggest that the relatively high heritability is due to the small number of test-day milkings that are used to estimate the (co)variance components in these periods and to the fact that the then performed test-day milkings provide the least information. Pool and Meuwissen [51] suggested that the use of milkings only from completed lactations reduces differences between mid-lactation and early and late lactation. Jamrozik and Schaeffer [9] justify the high heritabilities for milk yield and composition (fat, protein) in the early lactation by the importance of this period for calf survival. The authors argue that there is a strict relationship between the quantity and quality of milk, including colostrum that contains antibodies that protect against disease in the first days after calving, and calf survival.

From the viewpoint of production profitability in AMS barns, milk output from the AMS per unit of time is a key factor [52]. For this reason, fast-milking cows are particularly desirable in robotic barns. Research to date has shown relatively high differences in the coefficient of MS heritability (0.14–0.55), which may stem from the way a trait is treated (threshold vs. continuous) and the recording frequency per lactation (recorded for every milking, daily average, or resulting from TD milkings) or in successive lactations.

Research to determine the genetic background (heritability) of milking speed in Canadian Holstein cattle expressed on a 5-point scale was conducted by Sewale, Miglior and Kistermaker [53], who obtained low values depending on the applied model (single, bivariate): 0.14 and 0.1429.

In turn, Berry at al. [28] estimated that h^2 of average milk flow (kg/min) for Irish Holstein herds using test-day records was 0.21. Gäde et al. [35], Gäde et al. [54], Wethal and Heringstad [31], Carlström at al. [49] and Santos et al. [30] made the estimations in German, Norwegian and Swedish barns with automatic milking. Heritability estimates were based on single milking or 24-h milk yields and ranged from 0.25 to 0.55.

In the studies performed by the authors, the coefficients of heritability were obtained using random regression models (RRM). This modeling method was employed by Amin [14] for estimating the heritability of milk flow in Hungarian Holstein-Friesian cows based on test-day records. The values estimated during lactation ranged from 0.02 to 0.50 (0.20 on average). The curve for heritability changes showed a downward trend in the early lactation (up to 14–16 weeks), followed by an upward trend until the end of lactation. In the study by Piwczyński et al. [32], who also used RRM, daily heritability of MS ranged from 0.252 to 0.665, while the posterior means of heritabilities for 305-d lactation were 0.431. It should be underlined that the curve for changing daily heritabilities in this study assumed relatively high values in the first and last months of lactation. During the remaining period, the curve tended to increase up to 170–180 days of lactation, after which it decreased until 250 days.

In our study, the results pointed to moderate heritability of MS (0.336–0.493), which provides a basis for efficient selection of this trait, and thus for making the farm production more profitable—resulting, inter alia, from the possibility of increasing the number of cows per milking robot. Our findings fall in the upper range of estimates presented by the authors cited above for MS heritability. Of course, profitability of milk production is also affected by other factors, which can be further investigated in subsequent studies.

In the studies performed by the authors, RRM was used to estimate genetic correlations. This allowed for determining the coefficients of genetic correlations between the traits recorded on different days of lactation, as illustrated on surface charts proposed for this type of analysis by Kheirabadi [7]. At the same time, linear graphs were used to illustrate daily coefficients of genetic correlations between correlated traits from the same day of lactation.

As reported by Tse et al. [55], higher yields of the cows milked in AMS barns compared to conventionally milked cows are due to the fact they have free access to the milking robot. In our study, we found generally positive, moderate or even high genetic relationships between MF and MY measured on different days of lactation. This holds in particular for daily coefficients of correlation (0.561–0.929) between MY and MF recorded on the same days of lactation. Santos et al. [30] stressed that high-yielding cows visit AMS more often per day (genetic correlation = 0.49).

Our results are supported by König et al. [48], who estimated the coefficients of genetic correlation between MY and MF for successive 100-day periods of lactation to be 0.47–0.57, 0.46–0.48, and 0.49–0.53, respectively. Differences in the coefficients of genetic correlation in that study depended on the statistical model used. Also consistent with ours are the values of daily coefficients of genetic correlation, reported by Nixon et al. [20] to range from 0.27 to 0.80. It should be underlined that the above authors observed the strongest genetic relationships between MF and MY in the final stage of lactation, which is strictly consistent with our findings Alongside estimating the parameters based on single milking, Nixon et al. [20] determined genetic correlations between MF and MY from TD results. The average coefficient of genetic correlation was 0.14.

In the study by Nixon et al. [20], genetic correlations between daily (24-h) MY and daily (24-h) MF were highest at the end of lactation (0.80) and lowest in mid-lactation (0.27), which concurs with our findings. In the studies conducted by the authors, negative coefficients of genetic correlations were also observed between MF and MY, but this concerned measurements of the correlated traits from opposite periods of lactation. König et al. [48] observed that MF heritability is 0.18, which they considered sufficient for selecting cows against infrequent milkings per day.

Wethal and Heringstad [31] analyzed the relationship between MF and MS based on daily yields recorded by AMS. Their coefficient of genetic correlation (0.14), as in our study (−0.054), shows a weak relationship between these traits. However, in our study, the coefficients generally assumed negative values, which suggests that selection for increased daily milking frequency may contribute to a slight genetic deterioration in milking speed, especially up to 60 days of lactation ($rG < (-0.138)$). According to the authors, the difference between our estimates and those of Wethal and Heringstad (2019) may result from the applied statistical model. In our study, we used RRM associated with Legendre polynomials, while the authors cited above included the effect of test day and the effect of herd-test day (HTD) as fixed effects.

We concluded from our study that the selection of cows for increased MY in the initial stage of lactation has a positive effect on improving the genetic value of primiparous cows in terms of MS beyond 100 days of lactation. However, the relevant literature revealed no studies exploring the relationship between MY and MS on different days of lactation. Our estimates for the genetic correlations between MY and MS measured on the same days of lactation show weak, mostly negative relationships between these traits. In turn, the average coefficient of genetic correlation (−0.057), based on daily estimates from the whole lactation, indicates there is no relationship between MY and MS.

Our results for the genetic correlations between MY and MS are contradictory to those reported by other authors. Santos et al. [56] estimated genetic correlations using sire models between MY and MS to range widely between 0.36 and 0.73. Such a large variation in the estimates results from the application of different statistical models: recursive linear, linear, linear with regression. In the next study, Santos et al. [30], based on the data collected over 30 days, estimated the coefficient of correlation between MY and MS to be 0.40. Berry et al. [28] estimated the coefficient of genetic correlations between MY and average milk flow (AMF) based on TD results to be 0.69. Gäde et al. [35] estimated the coefficients of genetic correlation between MY and AMF, recorded based on single milking and daily yields in AMS barns, to be 0.51 in both cases. An even stronger relationship between MY and MS was reported by Amin [14]—the coefficients of genetic correlation during lactation ranged from 0.83 to 0.93, while the coefficient for the whole lactation was 0.94. In turn, the curve for daily coefficients of genetic correlations from the beginning to the 8th week of lactation showed a downward trend, followed by an upward trend up to the 28th week, after which it reached a plateau above 0.94.

5. Conclusions

The estimated heritabilities for daily milking speed were moderate, while and for daily milking frequency and milk yield were low, which makes it possible to carry out an effective selection, in particular for the first trait. It is known that heritability decreases with increasing breeding pressure. The fact that the genetic variance of milking speed is higher than the milk yield may also provide an advantage in terms of the sustainability of breeding. Considering the high, positive genetic correlation between daily milking frequency and milk yield, it is concluded that giving preference to breeding cows with a natural propensity for making frequent visits to the milking robot, should indirectly improve the genetic base of milk yield.

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6.2. OŚWIADCZENIE AUTORA ROZPRAWY DOKTORSKIEJ

Z.16.2021.2022

Załącznik nr 3 do
Instrukcji drukowania, gromadzenia, rejestrowania i udostępniania rozpraw doktorskich przez rady naukowe dyscyplin (dyscyplin artystycznych) prowadzących postępowanie w sprawie nadania stopnia naukowego doktora

Oświadczenie Autora rozprawy doktorskiej

Mgr inż. Joanna Aerts
(tytuł zawodowy, imiona i nazwisko autora rozprawy doktorskiej)

Lely Services B.V., Cornelis van der Lelylaan 1, 3147 PB Maassluis, The Netherlands
....
(miejsce pracy/afiliacja)

OŚWIADCZENIE

Oświadczam, iż mój wkład autorski w niżej wymienionych artykułach naukowych stanowiących cykl publikacji rozprawy doktorskiej był następujący*:

1. Aerts J., Piwczyński D., Ghiasi H., Sitkowska B., Kolenda., Önder H., 2021. Genetic parameters estimation of milking traits in Polish Holstein-Friesians based on automatic milking system data. Animals 11(7), 1943; 1-16, https://doi.org/10.3390/ani11071943. MEiN = 100; IF = 2,752.
   Wykonane zadania przez Doktoranta w ramach artykułu:
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   co stanowi 60% indywidualnego wkładu w przygotowanie ww. publikacji.

1. Aerts J, Kolenda M, Piwczyński D, Sitkowska B, Önder H., 2022. Forecasting Milking Efficiency of Dairy Cows Milked in an Automatic Milking System Using the Decision Tree Technique. Animals 2022, 12, 1040, 1-13. https://doi.org/10.3390/ani12081040; MEiN = 100; IF = 3,231.
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   co stanowi 57% indywidualnego wkładu w przygotowanie ww. publikacji.

3. Aerts J., Sitkowska B., Piwczyński D., Kolenda M., Önder H., 2022. The optimal level of factors for high daily milk yield in automatic milking system. Livestock Science 264(2022), 105035, 1-10. https://doi.org/10.1016/j.livsci.2022.105035; MEiN = 140; IF = 1,929.
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Podpis promotora

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Z.16.2021.2022

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Co-author's Declaration

Dr.Heydar Ghiasi

Department of Animal Science, Faculty of Agricultural Science, Payame Noor University, Tehran, Iran

DECLARATION

I declare that my author's contribution to the journal articlementioned below was as follows*:

1. Aerts J., Piwczyński D., Ghiasi H., Sitkowska B., Kolenda., Önder H., 2021. Genetic parameters estimation of milking traits in Polish Holstein-Friesians based on automatic milking system data. Animals 11(7), 1943; 1-16, https://doi.org/10.3390/ani11071943. MNiSW = 100; IF = 2,752.
   Tasks completed as part of the article:
   a) methodology
   b) writing – original draft preparation, review and editing

which represents 10% of the individual contribution to the preparation of the above-mentioned publication.

At the same time, I hereby agree to the submission of the above-mentioned paper(s) by M.Sc. Joanna Aerts as part of the doctoral dissertation based on a collection of published and thematically related scientific papers.

22 october 2022
Place, date

Heydar Ghiasi
Co-author'signature

* *In the case of two- or multi-author papers, declarations of a candidate for the doctoral degree and co-authors are required, indicating their substantive contribution to the creation of each paper (e.g. the creator of the research hypothesis, the originator of the research, performance of specific research – e.g. carrying out particular experiments, developing and collecting questionnaires, etc., analysis of the results, preparation of the article manuscript and others). Identification of the contribution of a given author, including a candidate for the doctoral degree, should be precise enough to allow for an accurate assessment of his/her participation and role in the creation of each paper.*

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Co-author's Declaration

Prof. Dr. Hasan ÖNDER
(Professional title, name(s) and surname of the Co-author)

Ondokuz Mayıs University, Agricultural Faculty, Dep. Animal Science, 55139, Samsun, Türkiye
(Workplace/affiliation)

DECLARATION

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   Tasks completed as part of the article:
   a) writing – review and editing

which represents 5% of the individual contribution to the preparation of the above-mentioned publication.

2. Aerts J, Kolenda M, Piwczyński D, Sitkowska B, Önder H., 2022. Forecasting Milking Efficiency of Dairy Cows Milked in an Automatic Milking System Using the Decision Tree Technique. Animals 2022, 12, 1040, 1-13. https://doi.org/10.3390/ani12081040; MEiN = 100; IF = 3,231.

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   Tasks completed as part of the article:
   a) writing – original draft, review and editing

which represents 7% of the individual contribution to the preparation of the above-mentioned publication.

At the same time, I hereby agree to the submission of the above-mentioned paper(s) by M.Sc. Joanna Aerts as part of the doctoral dissertation based on a collection of published and thematically related scientific papers.

Samsun, 21.10.2022
Place, date

H Önder
....
Co-author'signature

* *In the case of two- or multi-author papers, declarations of a candidate for the doctoral degree and co-authors are required, indicating their substantive contribution to the creation of each paper (e.g. the creator of the research hypothesis, the originator of the research, performance of specific research – e.g. carrying out particular experiments, developing and collecting questionnaires, etc., analysis of the results, preparation of the article manuscript and others). Identification of the contribution of a given author, including a candidate for the doctoral degree, should be precise enough to allow for an accurate assessment of his/her participation and role in the creation of each paper.*

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Oświadczenie Współautora

Dr inż. Magdalena Kolenda
(tytuł zawodowy, imiona i nazwisko współautora)

Katedra Biotechnologii i Genetyki Zwierząt,
Wydział hodowli i Biologii Zwierząt,
Politechnika Bydgoska im. J.J. Śniadeckich
....
(miejsce pracy/afiliacja)

OŚWIADCZENIE

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Jednocześnie wyrażam zgodę na przedłożenie wyżej wymienionych prac przez mgr inż. Joanne Aerts jako część rozprawy doktorskiej opartej na zbiorze opublikowanych i powiązanych tematycznie artykułów naukowych.

Bydgoszcz 11.01.23
miejscowość, data

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Oświadczenie Współautora

Prof. dr hab. Dariusz Piwczyński
(tytuł zawodowy, imiona i nazwisko współautora)

Katedra Biotechnologii i Genetyki Zwierząt,
Wydział hodowli i Biologii Zwierząt,
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   b) opieka naukowa
   c) przygotowanie oryginalnego tekstu, recenzje i poprawki edytorskie
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3. Aerts J., Sitkowska B., Piwczyński D., Kolenda M., Önder H., 2022. The optimal level of factors for high daily milk yield in automatic milking system. Livestock Science 264(2022), 105035, 1-10. https://doi.org/10.1016/j.livsci.2022.105035; MEiN = 140; IF = 1,929.
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Bydgoszcz 20.01.2023
miejscowość, data

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---

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Oświadczenie Współautora

Dr hab. Beata Sitkowska, prof. PBŚ
(tytuł zawodowy, imiona i nazwisko współautora)

Katedra Biotechnologii i Genetyki Zwierząt,
Wydział hodowli i Biologii Zwierząt,
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....
(miejsce pracy/afiliacja)

OŚWIADCZENIE

Oświadczam, iż mój wkład autorski w niżej wymienionych artykułach naukowych był następujący*:

1. Aerts J., Piwczyński D., Ghiasi H., Sitkowska B., Kolenda., Önder H., 2021. Genetic parameters estimation of milking traits in Polish Holstein-Friesians based on automatic milking system data. Animals 11(7), 1943; 1-16, https://doi.org/10.3390/ani11071943. MNiSW = 100; IF = 2,752.
   Wykonane zadania w ramach artykułu:
   a) koncepcja
   c) przygotowanie oryginalnego tekstu, recenzje i poprawki edytorskie
   co stanowi 5% indywidualnego wkładu w przygotowanie ww. publikacji
2. Aerts J, Kolenda M, Piwczyński D, Sitkowska B, Önder H., 2022. Forecasting Milking Efficiency of Dairy Cows Milked in an Automatic Milking System Using the Decision Tree Technique. Animals 2022, 12, 1040, 1-13. https://doi.org/10.3390/ani12081040; MEiN = 100; IF = 3,231.
   Wykonane zadania w ramach artykułu:
   a) koncepcja
   c) przygotowanie oryginalnego tekstu, recenzje i poprawki edytorskie
   co stanowi 10% indywidualnego wkładu w przygotowanie ww. publikacji
3. Aerts J., Sitkowska B., Piwczyński D., Kolenda M., Önder H., 2022. The optimal level of factors for high daily milk yield in automatic milking system. Livestock Science 264(2022), 105035, 1-10. https://doi.org/10.1016/j.livsci.2022.105035; MEiN = 140; IF = 1,929.
   Wykonane zadania w ramach artykułu:
   a) koncepcja i metodologia
   c) przygotowanie oryginalnego tekstu, recenzje i poprawki edytorskie
   co stanowi 20% indywidualnego wkładu w przygotowanie ww. publikacji

Jednocześnie wyrażam zgodę na przedłożenie wyżej wymienionych prac przez mgr inż. Joanne Aerts jako część rozprawy doktorskiej opartej na zbiorze opublikowanych i powiązanych tematycznie artykułów naukowych.

Bydgoszcz, 24.10.2022
miejscowość, data

B. Sitkowska
podpis Współautora

* W przypadku prac dwu- lub wieloautorskich wymagane są oświadczenia kandydata do stopnia doktora oraz współautorów, wskazujące na ich merytoryczny wkład w powstanie każdej pracy (np. twórca hipotezy badawczej, pomysłodawca badań, wykonanie specyficznych badań – np. przeprowadzenie konkretnych doświadczeń, opracowanie i zebranie ankiet itp., wykonanie analizy wyników, przygotowanie manuskryptu artykułu i inne). Określenie wkładu danego autora, w tym kandydata do stopnia doktora, powinno być na tyle precyzyjne, aby umożliwić dokładną ocenę jego udziału i roli w powstaniu każdej pracy.