Proceedings of the 2022 Winter Simulation Conference
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A SIMULATION MODEL FOR COOPERATIVE ROBOTICS IN DAIRY FARMS

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ABSTRACT

Clean floors in dairy farms are of vital importance to mitigate risks regarding cow welfare and to avoid ammonia emissions. In modern dairy farms it is common to deploy manure cleaning robots to automate the cleaning task. In the current state-of-the art, robots operate in relative solitude with no coordination or cooperation within the fleet. This paper employs discrete-event simulation to test the effectiveness of different strategies for cooperative, team-based cleaning in dairy farms. Special attention is paid to the impact of various team compositions and robot characteristics on team routing. The results look promising: the minimum cleanliness can be increased by deploying teams while simultaneously reducing the number of cow-robot interactions.

1 INTRODUCTION

The dairy farm industry faces many challenges regarding responsible food production. To feed a growing population in a sustainable way, the industry is challenged to reduce environmental impact, decrease resource usage, increase animal welfare, while simultaneously intensifying productivity and improving human safety and quality of life. Animal welfare also has an influence on productivity and thus provides an economic rationale. For example, foot disorders caused by unhygienic environments (due to manure and urine eliminations of cows), cause economic losses due to less milk yield (Ettema et al. 2010). As such, cleaning the barn floor is of vital importance to mitigate risks regarding cow welfare. Moreover, clean floors reduce ammonia emissions (Galama et al. 2020), a strong contributor to fine particulate matter pollution and associated premature human mortality (Giannakis et al. 2019).

To facilitate clean barn floors, manure cleaning robots are often deployed as a cost-effective measure to reduce foot disorders compared to non-robotic solutions (Sagkob et al. 2011). Besides economic rationale, the investment in robotic systems is also motivated by increasing farm sizes, lack of skilled workers, technical progress and striving for a better quality of life (Bijl et al 2007; Mathijs, 2004). There are two types of manure cleaning robots: (i) pushers (that remove manure through a slatted floor), and (ii) collectors (that collect elimination and dump it at specific locations). In this paper, we focus on the latter type of robot. Although being commonly used in practice, these robots are often 'pre-programmed' and follow a static schedule and pre-determined routes. Particularly in larger barns, where multiple cleaning robots are deployed, robots are assigned to (non-overlapping) areas, without cooperation or coordination between the robots to (jointly) achieve their goal: a clean barn floor. Given the highly unpredictable nature of the environment they work in, it is a challenge to create robots that are able to interact with such an environment in real time. Efficient mechanisms for task allocation, ability to perform operations in parallel, and information exchange between robots, allow the design of flexible, robust and effective robotic systems

(Krieger et al. 2000). Ultimately, a group of cleaning robots may even become self-organizing, similarly to workers in an ant colony, and show efficient and robust behavior in unpredictable environments through cooperation. Opposed to the current state-of-the-art, such self-organizing systems are expected to have numerous benefits, including the ability to cope with dynamic environments, reduction of decision-making complexity, less computational efforts, increased adaptivity, ease of implementation, and minimal data requirements (Bartholdi et al. 2010). As a first step towards self-organizing robotic systems, we focus on cooperative cleaning. We transition from solo-based cleaning to team-based cleaning, where multiple robots clean the barn as a team; similarly to how snowplows jointly clean all lanes of a highway as a team in a single pass. Such an approach is also discussed in Hess et al. (2009), and applied for snow shoveling on airports, with a specific focus on trajectory planning of the robots. Several other topics regarding cooperative cleaning have been studied in literature, although not applied to dairy farms. Interesting examples, which also deploy simulation, include cooperative control of unmanned vehicles to clean oil spills in oceans (Bella et al. 2021; Bhattacharya et al. 2011), multi-robot systems for the area coverage problem (Hofmeister and Kronfeld 2001), cleaning of general regions by a swarm of robots (Altshhuler 2018), a bio-inspired approach for area partitioning of cooperating cleaning robots (Chatty et al. 2014), deadlock avoidance of cooperating cleaning robots (Luo and Yan 2002) and cooperative cleaning of residential buildings with multiple rooms (Costa et al. 2016).

In this paper we study the effect of teamwork on robot productivity, barn cleanliness and, as a result, on cow welfare. We present a flexible and reusable simulation model to test the effectiveness of different strategies for cooperative cleaning robots in dairy farms. Although (discrete-event) simulation is widely used in other sectors, including manufacturing and logistics, the use of (discrete-event) simulation in agriculture, and particularly in dairy farm robotics, seems to be limited. Some noteworthy exceptions include Pavkin et al. (2021) who focus on feed pusher robots, and Hyde and Engel (2002) who deploy Monte Carlo Simulation to study the break-even point of robotic milking systems. However, simulation of cleaning robots (and more generally the analysis of these systems) is underexposed in the current literature stream. To the best of our knowledge, this is the first paper to address the simulation of cooperative cleaning robots in dairy farms.

The remainder of this paper is composed as follows. Section 2 provides a cooperative cleaning approach for manure collecting robots. In Section 3, we present our conceptual model. The corresponding simulation model is described in Section 4. The results are discussed in Section 5. The paper closes with conclusions and directions for further research in Section 6.

2 COOPERATIVE ROBOTICS

We focus on team-based cleaning of dairy farms using manure collecting robots to increase barn cleanliness and increase animal welfare. This is a first step towards cooperative dairy farm robotics, and ultimately a self-organizing robotic system. For example, cooperativity between cleaning robots and feed-pushing robots may establish additional insights into whether or not (many) cows are present at the feeding area. Based on this information, cleaning robots may decide to skip this area temporarily when it is too crowded. Moreover, establishing interaction between the robotic fleet and the cows themselves (e.g., through location sensors), may enrich the decision-making process for cleaning robots to clean efficiently in both time and space. In this paper, however, we focus solely on the interaction between cleaning robots and omit cooperativity with other (robotic) systems.

To establish cooperative behavior for manure collecting robots, we distinguish between three steps: team composition (strategic), team routing (tactical), and team maneuvering (operational). Each of these steps are discussed in separate sections below.

2.1 Team Composition

On a strategic level, the composition of the team(s) needs to be determined. For example, the size of the barn determines the number of cleaning robots required and therefore also the possibilities to form teams. Moreover, different sections of the barn may have different widths, as exemplified in Figure 1. The team composition determines the maximum area a team can cover in a single pass (i.e., their collective width). For example, let W_R denote the width of a single robot, and let N denote the number of robots per team, then a team of N robots can cover a maximum width of $W_R N$. Moreover, let W_i denote the width of a rectangular area i of the barn that has to be cleaned. Then, if $W_i > W_R N$, the team needs to cross it at least $\lceil W_i / W_R N \rceil$ times to clean the entire section. The team composition thus also influences the routing of the team, which is further discussed in Section 2.2. On the other hand, if a section is smaller than the maximum width of a team (i.e., $W_R N$), the cleaning robots can also change their lateral distance, creating some overlap in the paths of the robots. If we let W_T denote the (chosen) width of a team of robots, then W_T can be arbitrarily chosen, as long as it satisfies $W_R \leq W_T \leq W_R N$. Lastly, if the size of the barn allows multiple teams, also a decision needs to be made whether to deploy one large team or multiple smaller teams. As we will see in Section 5, simulation can aid in this decision-making process to quantify the impact of different team configurations on important Key Performance Indicators (KPIs).

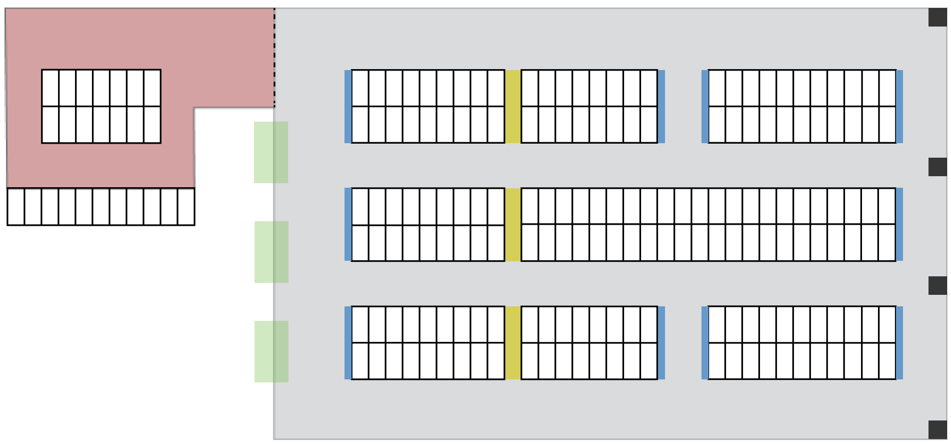


Figure 1: Illustration of a top-down view of a dairy farm. The grey area needs to be cleaned. The other areas are further discussed in Section 3.1.

2.2 Team Routing

On the tactical level, the routing of the robot team(s) needs to be determined. The goal is to minimize the length of the route while covering the entire surface of the floor. The team composition(s) are an important input to determine effective routes. For example, when a certain section i of the barn is $W_i = 2W_T$ wide, the team can clean this section by simply going back and forth. On the other hand, if a section i is slightly wider (e.g., $W_i = 2.1W_T$), the team of robots needs to traverse this section three times to clean it entirely. Hence, there is a clear interplay between the team composition and the ability to create effective routes. In our view, a useful starting point would be to determine the widest section of the barn (i.e., max W_i) and making sure that the team can clean this section in a single pass to avoid traversing it multiple times. In narrower sections of the barn, the robots in the team can adjust their relative position to match the width of these sections, as discussed in Section 2.1. However, depending on the layout of the barn and the positions of the manure dumping spots, traversing the widest section in a single pass is not a prerequisite for an effective routing strategy. For example, suppose the widest section needs to be traversed multiple times in order for the robots to return to their starting points, regardless of the team composition, then this section may not be a bottleneck in determining effective routing strategies. As we focus on tactical decision-making, we do not elaborate on calculating effective routing strategies (i.e., solving an arc routing problem).

In our approach, the cleaning cycles are determined on the tactical level. It is common practice to deploy a periodic cleaning strategy in which robots start their routes at fixed intervals. These intervals need to be chosen such that the robots (i) have sufficient time to clean the entire barn (i.e., based on the routes determined), (ii) have sufficient time to dump the collected manure at the idling areas, and (iii) have sufficient time to recharge their batteries. Furthermore, the departure point of the team needs to be determined. In practice it is common that each robot has its own idling area. These idling areas are located at areas where robots can dump their collected manure, as well as recharge their batteries. In our approach, we select one of the idling areas of the barn as the departure point of the team. Opposed to solo-based cleaning, the formation of the team requires some maneuvering at the idling area to properly align the robots. This is further discussed in Section 2.3.

Lastly, the following distance between each robot (i.e., the longitudinal distance) needs to be determined. When the team of robots drive very close behind each other, cows may have trouble in stepping away when the team approaches. On the other hand, large gaps between the robots may invoke waiting times (as will be discussed in Section 2.3), causing communication problems between the robots or a possible break-up of the team (e.g., when an obstacle comes between the robots).

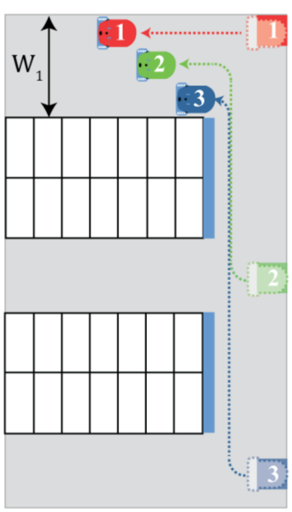
2.3 Team Maneuvering

On the operational level, the team-based cleaning needs to be controlled. We distinguish between four steps: (i) robots move from their idling areas to the pre-determined departure point, (ii) the team is established, (iii) cleaning as a team, and (iv) return to individual idling areas.

First, each robot needs to move from its idling area to the departure point. As stated in Section 2.2, we chose to select one of the idling areas as the departure point. For simplicity, we assume that each robot has a dedicated idling area and thus each robot starts and ends at the same idling area. To avoid congestions, we chose to move each robot one-by-one to the departure point.

Second, the team needs to be positioned correctly (similarly to a team of snowplows). This depends on three factors: (i) the team composition, (ii) the following distance, and (iii) the width of the first section to be cleaned at the departure point. As discussed in Section 2.1, the width of the team and the following distance can take multiple values. Figure 2a shows the positioning of a team of three robots with short following distances, able to clean the first section in a single pass (i.e., $W_1 \leq 3W_R$). Note that Figure 2a is equal to the top-right corner of Figure 1.

Third, the cleaning process starts as the team travels through the first straight part of their collective route. Whenever a team encounters a corner, some more complex maneuvering is required depending on the specifics of the corner and the section after the corner. As an example, let us denote the section *before* the corner by index 1, and the section *after* the corner by index 2. Regarding the widths of these sections,



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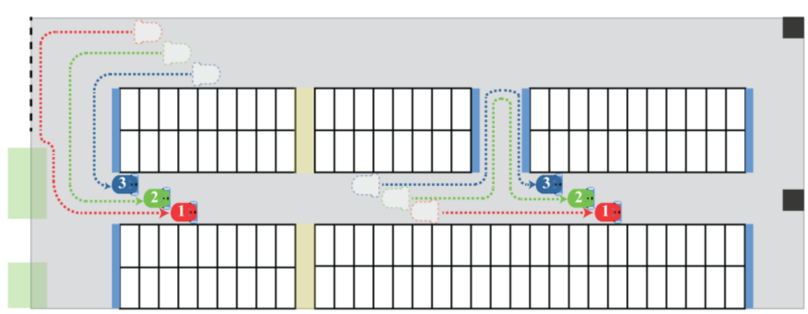

b

Figure 2: (a) Illustration of moving to a departure point for three configurations, (b) Illustration of a team cleaning two types of corners. Note that a robot is only allowed through a corner when its predecessor has reached the position where the team will be reinstated.

there are obviously three options: (i) $W_1 = W_2$, (ii) $W_1 > W_2$, or (iii) $W_1 < W_2$. In our approach, the routing is taken care of on the tactical level, so the route of each robot is known beforehand. However, on the operational level we require some fine-tuning regarding the timing of each robot going through a corner to avoid collisions. It makes sense for the robots to go through the corner in the order of the position in the team (i.e., the robot driving in front goes first, the last robot goes last). Similarly to positioning the team at the departure point, the positioning of the team should be reinstated after the corner. As a typical barn has many corners and edges, this may require complex maneuvering. In our approach however, we take care of these idiosyncrasies by fixing the routes on the tactical level, and thus only stop-and-go decisions need to be made on the operational level. This is illustrated in Figure 2b for a team of three robots going through two different types of corners.

Lastly, at the end of each cleaning cycle, the team breaks up and each robot moves to its dedicated idling area. In our approach, we make sure that the route ends at the departure point (i.e., one of the idling areas), and that the last part of the route contains all other idling areas. This way, the robots can easily leave the team when they reach their respective idling area to dump the collected manure and charge their battery. The four-step process is repeated upon the next cleaning cycle.

3 CONCEPTUAL MODEL

Before presenting the implemented simulation model, an abstraction is made using a conceptual model. Given our aim to develop a reusable and highly configurable simulation model (e.g., to quickly analyze different team compositions and barn layouts), we require some abstraction. The following elements are described: the inputs (Section 3.1), outputs (Section 3.2), experimental factors (Section 3.3), and model assumptions (Section 3.4).

3.1 Inputs

Regarding the inputs, we distinguish between (i) the barn layout, (ii) cow behavior, (iii) the cattle composition, and (iv) the robotic system.

1. **Barn layout.** For our purposes, it suffices to focus on the part of the dairy farm where the cows are located, and thus where the cleaning robots are deployed. Although many barns share similar components, each barn has its own dimensions, corners and edges. To facilitate flexible modeling, we propose a so-called *tile-based* approach where we define rectangles of a certain size and assign a specific *function area* to each tile. To exemplify, recall the layout of the barn presented in Figure 1, which we use as a case study from practice in this study. We chose to model the layout of the barn as a collection of tiles using the following logic. First, we measure the dimensions of all areas in the barn and find the greatest common denominator in both length and width. We fix this as the size of our tiles. To model the barn, we define a collection of tiles and each tile is assigned an x- and y-position. Moreover, each tile is assigned a function area. We distinguish between seven function areas, each of them color-coded in Figure 1: the barn floor (grey), cubicles, where cows rest (white), dumping areas (black), milking areas (green), drinking areas (blue), separation areas (red), and concentrate feeding areas (yellow). The separation area is used for non-lactating cows, and is not accessible for other cows. Each tile is thus assigned to one of these function areas and a collection of tiles allows us to model the barn in a flexible manner. Lastly, we note that the floor of a barn can differ between farms. This has to do with a so-called *drainage fabric* and determines the permeability of urine and manure. As this is important for our research, we add three additional properties to the tiles with the function area *Floor*: (i) permeability of urine, (ii) permeability of manure, and (iii) the current level of manure and urine.
2. **Cow behavior.** Since the location of manure and urine elimination is the result of cow movements and (duration of) activities, we pay specific attention to cow behavior. Realistically modelling cow behavior is of vital importance to gain proper insight into how the various ways of cleaning impact

the cleanliness of the barn. Moreover, the position and movements of cows impact the number of interactions between cows and robots. To model cow behavior, we deploy a transition matrix and model the duration per activity using a probability density function. The transition matrix shows the probability a cow goes from one activity to another. Similarly to Halachmi (1999), we distinguish between five activities: laying in a cubicle, milking, feeding, concentrate feeding, and drinking. The transition matrix in combination with the duration per activity results in the total daily time spent per activity.

3. **Cattle composition.** The cattle composition consists of three elements: (i) the number of cows, (ii) the fraction of lactating and non-lactating cows, and (iii) the parity of each cow. As discussed above, the non-lactating cows are accommodated in the separation area, and the lactating cows in the remainder of the barn. The parity denotes the number of times a cow has calved. The manure and urine elimination depends on the type of forage and the milk production. Furthermore, milk production depends on the parity and the day of the lactation cycle. These elements combined determine the total urine and manure elimination per cow. In combination with the elements on cow behavior discussed above, a spatiotemporal pattern of manure and urine is established. To realistically model elimination, data has to be gathered on all these elements. The data used in this research is further discussed in Section 5.1.
4. **Robotic systems.** Modern dairy farms contain multiple robotic systems. In this research, we focus on manure collecting robots and milking robots. As milking is an important cow-related activity and directly relates to manure and urine elimination, we explicitly model the milking robots. Regarding the manure collecting robots, their task is to suck up cow manure and urine from the barn floor. These robots are characterized by their dimensions, speed, collection capacity, battery capacity, and battery consumption. Additionally, in our cooperative approach, the team composition and following distance are also properties of the robotic fleet. As discussed above, each robot has a dedicated dumping area. In our setting, cows are free to move to a milking robot when they deem necessary, typically two to three times per day. Our case study features three milking robots. The milking robots are characterized by their location, (average) duration of the milking process, the size of the waiting area, the cleaning cycle and the success-ratio. The latter denotes the percentage of cows that are actually milked when a milking robot is visited. Lastly, the milking robots need to be periodically cleaned, resulting in down-time. This is a parameter that can be tweaked based on (manufacturer-dependent) technical specifications.

3.2 Outputs

The simulation model has the following outputs: (i) the activity-distribution of the manure collecting robots, (ii) the activity-distribution of the cows, (iii) the duration of a cleaning cycle, (iv) the amount of manure collected per robot, (v) the number of robot-cow interactions, and (vi) the barn cleanliness. The activity-distribution of the cows is used to verify whether the transition-matrix and the probability density function, as discussed in Section 3.1, result in realistic cow behavior. Regarding the number of robot-cow interactions, we distinguish between soft interactions (i.e., a robot closely passes by a cow) and hard interactions (i.e., a robot touches a cow). For the barn cleanliness, we periodically measure the manure levels on all relevant tiles. With this approach, we are able to accurately measure the cleanliness throughout the barn using multiple KPIs: (i) the average amount of manure during the day, (ii) the amount of manure at the beginning of a cleaning cycle, (iii) the amount of manure at the end of a cleaning cycle, (iv) the course of the amount of manure during cleaning, and (v) the distribution of the manure in the barn, represented by a *manure heatmap*. The latter also serves for verification purposes, to verify whether the distribution of the manure over the barn floor resembles reality.

3.3 Experimental Factors

Given our interest in how cooperative manure collecting robots can improve barn cleanliness and cow welfare, we define several experimental factors. We design different team configurations with different robot widths, and number of robots per team. We experiment with the width of each robot as we have seen that the maximum width of a team of robots influences the routing and cooperative cleaning possibilities. Therefore, we are interested in the impact of (hypothetical) smaller and wider robots, compared to the width of robots currently used in practice. Moreover, we experiment with the team composition. More specifically, we experiment with the number of robots per team (3 and 4) and the number of teams deployed (1 and 2). This is determined by the barn under consideration that requires at least three manure collecting robots. Our base scenario contains three robots, that operate solo. We experiment with three robot widths (small, regular and large) and various team compositions, as discussed in Section 5.1.

3.4 Model Assumptions and Limitations

To reduce complexity of the simulation model, several assumptions are introduced. First, the separation area containing non-lactating cows is not included in the analysis as the manure elimination is drastically lower than in the rest of the barn. Second, cow behavior does not change during the day, nor when interacting with a cleaning robot (e.g., the cows do not step away). Third, cows do not defecate when they are in a cubicle, concentrate box or milking robot. Moreover, the cleaning robots are assumed to never fail, have a fixed (short) following distance, have adequate capacity to collect the manure of a single cleaning cycle and are able to fully charge their battery during idling. Lastly, we assume that a robot perfectly cleans the floor when driving over it and a team always stays together, even when encountering a cow. In practice, cows are familiarized with robots and typically the cows move around the robots after a period of getting acquainted. However, it does happen that a cow does not move away and the robot has to make an evasive maneuver. We currently omit these kind of maneuvers from the simulation model.

4 SIMULATION MODEL

Based on the case study and conceptual model described, a discrete-event simulation model is proposed, implemented in Tecnomatix Plant Simulation. This discrete-event simulation is also capable of modeling agents, as in virtually all agent-based simulation models state changes occur at a countable number of points in time (Law 2015). An impression of the simulation model is shown in Figure 3, and a video can be found in Andringa and Gerrits (2022). Below, the following three main components of the model are discussed: (i) barn layout, (ii) cow behavior, and (iii) manure collecting robots. The components are discussed based on the case study and this software, but the modeling approaches are also applicable for other case studies and other discrete-event simulation tools. From Figure 3 we observe a team of three robots on the top of the barn. The cubicles are the light-blue areas and the concentrate areas are yellow. The feeding areas are located on the top and bottom, as can be seen from the orientation of (some of the) cows who are feeding. The blue areas at the end of every cubicle area are the drinking areas. On the left-hand side of the barn, the three milking robots (with the red roofs) are located. Lastly, the amount of manure and urine on the floor is visualized as a scale between white and dark red, with the latter being the most dirty.

4.1 Barn Layout

We translate the barn layout from our case study to a 3D simulation environment. The simulation is built in such a way that it is highly configurable and different layouts can be created. Several input parameters are included to model the physical layout of the barn and its components, including: the length and width of the barn, dimensions and locations of the tiles (as discussed in Section 3.1), and as a result: the dimensions and positions of the cubicles, concentrate boxes, milking areas, feeding areas, drinking areas and the separation area. By tweaking these parameters, various layouts can be generated at the initialization of the simulation. The tiles are modelled as *Markers* and visualized as squares and can therefore also be used for the routing of both cows and robots. The tiles are also used to measure the cleanliness of the barn. To illustrate, when a cow is located on a specific tile and defecates, the produced urine and/or manure is registered in the *AmountOfUrine* and *AmountOfManure* properties of the tile. We assume that 20% of the urine (due to drainage fabric), and 100% of the manure remains on the floor.

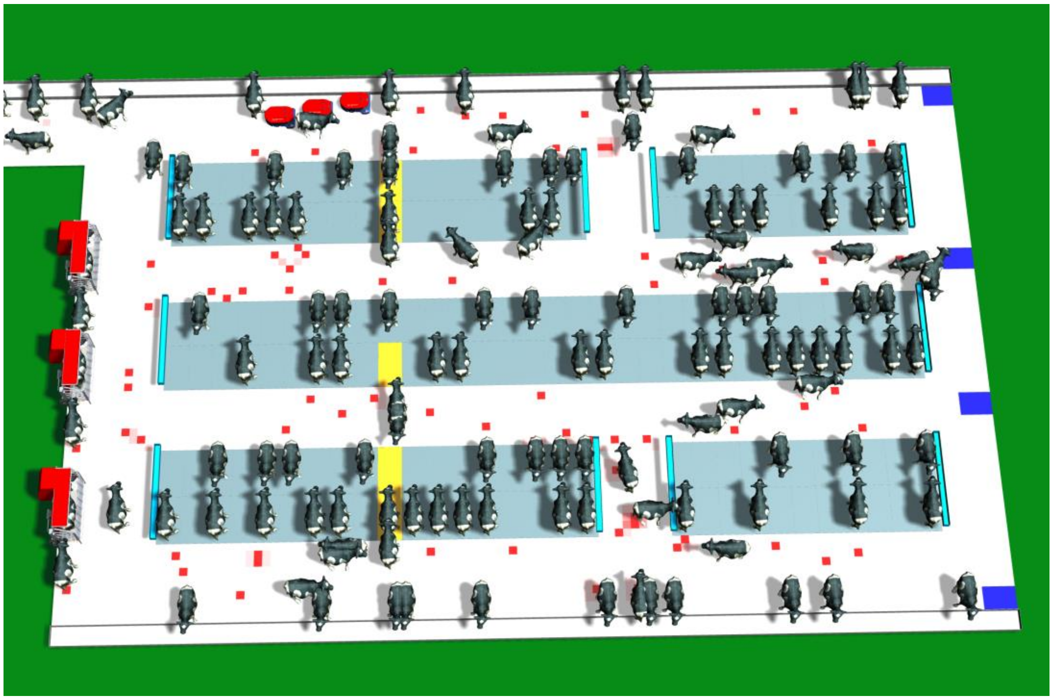

Figure 3: Visualization of the simulation model. For a video, see Andringa and Gerrits (2022).

4.2 Cow Behavior

At the initialization of the simulation model, all cows, which are modelled as *Transporter* objects, are located in a cubicle. Via an exponential distribution with an activity-specific mean, the duration of each activity is determined. When an activity is finished, the next activity is determined using a transition matrix. The location of this activity is chosen randomly from all tiles that have the corresponding *function area*. The route from the cow's current position to its destination is defined as a collection of connecting tiles (i.e., *Marker* objects) and is determined as follows. First, a cow can orient itself in one of the four wind directions. We calculate the Manhattan distance to the destination, for each of these four wind directions. We take into account that cows cannot move through the cubicles and thus have to move around them. Second, we select the direction that results in the shortest route. As there are still many route options for a given direction (with equal Manhattan distances), we select the route that has the largest straight path. This promotes cows walking into a straight line. To introduce some variations to the walking behavior, a cow has a probability to move slightly to the right or left on each *Floor* tile. Lastly, on each *Floor* tile, the speed of the cow is slightly altered to more realistically model the walking behavior. The route thus consists of a set of connecting *Floor* tiles.

At the initialization of the simulation model, the parity of each cow is assigned according to the distribution shown in Table 1, and the day of the lactation cycle is chosen randomly. These two parameters combined determine the milk production per cow and, in combination with the type of forage, the (daily) urine and manure production. The average number of eliminations per day is based on the work of Aland et al. (2002). Consequently, the number of urine and manure eliminations per day is simply calculated by dividing the daily urine and manure production by the average number of eliminations per day. There are thus two types of eliminations: (i) defecations (manure production), and (ii) urinations (urine production). The time between each elimination is assumed to be Poisson-distributed with an elimination-type dependent mean λ. Moreover, eliminations do not take place when a cow is in a cubicle, a concentrate box, or at a milking robot. If an elimination is scheduled during such an activity, the elimination takes place immediately after the activity is finished (i.e., when walking on the floor).

4.3 Manure Collecting Robots

The manure collecting robots are also modelled as *Transporters*. They make use of the network of *Markers* (i.e., the *Tiles* discussed above) to move around the barn. The width of the manure collecting robots is an experimental factor (small, regular, and large), where the regular size is based on the width of robots commonly used in practice. During cleaning, the robot sucks up all urine and manure on the tiles it crosses and stores it in its manure reservoir. This reservoir is emptied at the end of each cleaning cycle at a dedicated dumping spot. The dumping spots are modelled as *AGVPools*. The cleaning routes are pre-determined and depend on the number of cleaning robots deployed and the width of each robot. The route of each robots consists of a set of connecting *Markers*. Each robot is positioned diagonally behind the preceding robots and the exact position depends on the width of the section to clean. To exemplify, when a team can clean a section i exactly in a single pass, they are evenly distributed across the width of the section (i.e., $W_T = W_R N = W_i$). When a team of robots is not wide enough to clean a section in a single pass, we use the following logic. Recall that if $W_i > W_R N$, the team needs to cross section i at least $\lceil W_i / W_R N \rceil$ times to clean it entirely. The width of the team W_T at section i is then set at $W_i / \lceil W_i / W_R N \rceil$. For example, when a section needs to be traversed twice, the team is positioned such that it cleans half of the section in a single pass. To maintain the desired formation, the robots communicate with each other whenever they reach a *Marker*, and wait for the conformation that the others robots in the team have also reached the *Markers* associated with the formation. For straight segments this is rather straightforward, but corners require some additional consideration, as discussed in Section 2.3.

5 RESULTS

This section presents the simulation results of the case study under consideration. First, the experimental design is discussed in Section 5.1. Next, we present the results of varying the team composition (Section 5.2) and of varying the robot width (Section 5.3).

5.1 Experimental Design

To evaluate the impact of cooperative cleaning, we focus on different team compositions and robots widths. Specifically, we experiment with team size (3 or 4 robots), and the number of teams (1 or 2). As discussed in Section 2.3, we also experiment with three different robot widths, as this influences the span of the team and thus influences the routing of the team. Moreover, we define a base experiment with three robots (regular width), in which there is no cooperation between the robots, representing the current way of working. As the type of simulation is non-terminating with steady state parameters, we use a warmup period of 12 hours to reach the steady state, and a run length of 60 hours (24 cleaning cycles). Twenty replications are used for each experiment, resulting in a relative error of at most γ = 0.01 using a significance level α = 0.05. The specific values for the inputs, as described in Section 4, are obtained from a robot manufacturer and a dairy farm research institute. For an overview of the input parameters and their values, see Table 1.

We experiment with six scenarios: Scenario 0 (base scenario with three robots operating solo, regular size), Scenario 1 (one team of three robots, regular size), Scenario 2 (one team of four robots, regular size), Scenario 3 (two teams of two robots, regular size), Scenario 4 (one team of four robots, small size), and Scenario 5 (one team of three robots, large size). We omitted the scenario with one team of three smaller robots, as this configuration violated the assumption that the duration of the route is less than the cleaning cycle. Moreover, we omitted the configuration with 4 larger robots as this resulted in the same routing as Scenario 5. The cleanliness is measured as the fraction between the amount of elimination collected and the amount of elimination produced. Table 2 gives an overview of the results, which are further discussed in Sections 5.2 and 5.3.

Table 1: Input parameters and their values. [1] Barn width excludes the separation area. [2] Percentage of summer feeding.

Input	**Value**	**Input**	**Value**
Barn layout and routing-related		**Cleaning robot related**	
Barn width (meters) [1]	500	Base scenario	3 robots
Routing protocol (robots)	Manually	Number of robots	3 or 4
Routing protocol (cows)	See Section 4.2	Number of teams	1 (1x3, 1x4) or 2 (2x2)
Number of cubicles	200	Robot width	small, regular, large
Number of milking robots	3	Speed	0.15 m/s
Number drinking areas	10	Length cleaning cycle	2 hours
Number of concentrate boxes	5		
Cow-related		**Activity-related (time-spent)**	
Number of cows	200	Cubicle	54%
Non-lactating cows (%)	12.5	Walking	23%
Lactating cows (%)	87.5	Feeding	20%
Type of forage [2]	50%	Drinking	2%
Speed (m/s)	1	Milking	1%
Parity 1 (percentage of cattle)	30%		
Parity 2 (percentage of cattle)	25%		
Parity 3 (percentage of cattle)	45%		

5.2 Varying the Cleaning Team Configuration

From Section 2.2, we saw that the team composition influences the routing of the robots. We clearly see this effect in Table 2. In Scenario 1-5, the cleaning time per cycle increases compared to Scenario 0. In Scenario 0, each of the three robots has to clean roughly 1/3rd of the barn, whereas in team-based cleaning, the team has to clean the barn in its entirety, resulting in different routes and longer cycle times. When two teams are deployed (Scenario 3), we see that the cycle time decreases and approaches Scenario 0. Longer cycle times also result in robots being less idle every cleaning period and thus cleaning the barn more effectively. We see this effect in Table 2 regarding the barn cleanliness. In Scenario 0, robots are driving only 28% of the periodic cycle. The barn is thus quickly cleaned which results in a high maximum cleanliness (88%). However, the barn is not cleaned during the remainder of the cycle (72% idling), and as manure elimination continues, the minimum cleanliness is rather low (52%). This is improved when deploying teams, mainly because teams are more active during a cycle. Although team-based cleaning invokes waiting time (getting together and maneuvering through corners), the minimum cleanliness is improved in for example Scenario 1 (63%) and Scenario 4 (68%). Deploying an additional robot (i.e., Scenario 2 compared to Scenario 1) does not result in a higher minimum cleanliness. This has to do with the effectiveness of the routing, established on the tactical level. Moreover, when dividing a team of four robots (Scenario 2) into two teams of two robots (Scenario 3), the minimum cleanliness decreases, as the idling time goes up (from 51% to 70%), due to shorter routes. On the other hand, as cleaning takes longer, the maximum cleanliness decreases, particularly in Scenario 4 (75%), having the longest route. Given our periodic cycling strategy, we do not expect that the average cleanliness changes when deploying teams. We expect that the average cleanliness can be improved when deploying trigger-based cleaning, as discussed in Section 2.2. Moreover, we see that team-based cleaning reduces the number of robot-cow interactions, even though idling time is lower. With team-based cleaning where the team can clean an aisle in a single pass, and where a single robot needs to traverse the aisle multiple times in order to clean it, the probability of an encounter between the team and the robot decreases.

Table 2: Simulation results. For the results regarding cleanliness and interactions: bold-faced values indicate a significant difference when using a t-test with $\alpha = 0.05$. Scenarios 1-3 are compared to Scenario 0, Scenario 4 compared to Scenario 2, and Scenario 5 compared to Scenario 1.

Scenario	**0**	**1**	**2**	**3**	**4**	**5**
Team configuration (robot width)	**base (regular)**	**1x3 (regular)**	**1x4 (regular)**	**2x2 (regular)**	**1x4 (small)**	**1x3 (large)**
Robot related						
Cleaning time per cycle (min)	33	70	59	36	92	49
Driving (%)	28	38	25	25	39	25
Waiting (%)	0	20	24	5	37	16
Idling (%)	72	42	51	70	24	59
Cleanliness related						
Max. cleanliness	88%	**82%**	**84%**	89%	**75%**	**87%**
Avg. cleanliness	68%	69%	68%	67%	68%	69%
Min. cleanliness	52%	**63%**	**59%**	52%	**68%**	**57%**
Interactions (per cow per day)						
Hard interactions	7.8	**4.7**	**4.9**	**4.4**	4.7	4.7
Soft interactions	2.2	**1.1**	**1.7**	**1.3**	1.6	1.1

5.3 Varying the Robot Width

In Scenario 4, we deploy four small robots and compare this with Scenario 2 (four regular robots). In Scenario 5 we deploy three large robots and compare this with Scenario 1 (three regular robots). From Table 2 we see that the team of small robots requires 22 minutes more to clean the barn. This also results in a higher minimum cleanliness (9pp increase), but a lower maximum cleanliness (9pp decrease). In Scenario 5, we see that the team of large robots more quickly cleans the barn (21 minutes shorter cycle). This has mainly to do with the routing, i.e., a team of three large robots can clean a section in a single pass, whereas a team of three regular robots cannot. Similarly to the other experiments, this results in a lower minimum cleanliness (6pp) and a higher maximum cleanliness (5pp).

6 CONCLUSIONS AND FURTHER RESEARCH

This paper proposes a cooperative robotics concept for dairy farms in which manure collecting robots cooperate to clean the barn floor as a team. We present an approach to transition from solo-based cleaning to team-based cleaning and distinguish between decisions on strategic, tactical and operational levels. Moreover, we present a flexible simulation model to study cooperative robotics for dairy farms in a simulation environment. Results from our simulation experiments suggest that cooperative manure collecting robots are able to increase the minimum cleanliness of the barn whilst simultaneously decreasing the number of robot-cow interactions. The latter is directly related to increasing cow welfare. We identify the following topics for further research: (i) introducing capacity restrictions and charging strategies, (ii) developing (dynamic/trigger-based) cleaning strategies to optimize barn cleanliness and cow welfare, and (iii) expanding the cooperative fleet (e.g., including milking- and feeding robots).

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