Case Study: Optimal Facility Allocation in a Robotic Milking Barn

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Abstract. *A milking robot is a recent technological development; therefore, there are few precedents and little experience to draw upon when designing robotic milking barns. There is wide diversity among farms, so the optimal layout may vary accordingly. We developed a behavior–based simulation model adjustable for any farmer or site. We improved it by using a metamodel, which allows a global optimum to be found. Under the given condition of two specific farms, it resulted in the optimal facility allocation: Farm A, 1 robot, 36 forage lane positions, 60 cubicles (free stall), and 71 cows; Farm B, 2 robots, 3 water troughs, 103 forage lane positions, 105 cubicles, and 132 cows. The optimal layouts calculated in this study are unique for each farm's specific characteristics, but the design methodology developed is universally applicable.*

Keywords. *Robotic milking barn (RMB), Layout design, Free stall, Optimization, Simulation, Regression metamodel.*

The milking robot is the latest important development in dairy farming (the previous development of comparable importance was the milking machine, invented about a century ago). The direct and indirect building costs of a new robotic milking barn (RMB) might exceed the cost of a mid–size factory, and its complexity is considerable. However, while a factory designer can use systems engineering techniques, this option is not yet available for an RMB designer. The design of a barn is still done by traditional methods and rules of thumb.

Milking robots save labor and affect productivity, cow behavior, feeding routine, and management practices, which all need to be taken into consideration when designing an RMB. Researchers have addressed the complexity of designing an efficient RMB in relation to the use of the robot and the cow traffic through the barn (Ketelaar–de–Lauwere, 1999; Ipema, 1998; Stefanowska et al., 1997; Sonck, 1996). In summary, on a milking parlor–oriented farm, the farmer brings the cows to the milking site, while in an RMB, a cow is expected to arrive voluntarily. This voluntary arrival should be supported by the entire system, including barn design, feeding and cow–traffic routines, and management practices. Moreover, the design of a conventional, milking parlor–oriented barn relies on decades of experience, while experience with robotic barns is virtually non–existent. Furthermore, there is a wide diversity among farms. Farmers have their own existing facilities, building structures, ventilation systems, preferred feeding routines, and management practices. Therefore, the optimal RMB layout differs among farmers.

An optimal design balances adequate capacity against over–capacity. The optimal layout for a particular farm is unique to that farm, but the methodology developed in this article is universally applicable and adjustable for any farmer or site. The aim of this study is to find an optimal layout for a robotic milking barn, given the farming conditions described below.

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The Concept

Systems engineering and modeling techniques such as queuing theory, Markov chains, and computer simulation have revolutionized the design of factories, telephone networks, banks, supermarkets, etc. However, these techniques have not yet been used to design complete dairy barns. Under continuous robotic milking and feeding, the milking process is spread over the entire day and night, around the clock. By modeling the use of facilities as a stochastic process, Halachmi et al. (2000a, 2000b) showed a way of using systems theories such as queuing and Markov chains to design robotic milking barns. Likewise, behavior–based simulation (Halachmi, 2000) allows the combined evaluation of equipment, management practices, feeding routine, and layout. Simulation improves communication between designers and barn operators, allows farmers to integrate all relevant factors into their models, and highlights potential design options before a barn is actually built. The main benefit is that the farmer gains assurance that the proposed design will actually work and meet the specified demands before it is built.

The main limitation of simulation lies in its heuristic character: simulation responses are observed only for the selected input combinations, i.e., there is no proof of the optimality of the solution. In an RMB, a great many input parameters can be distinguished. For instance, farm B (described below, two robots) has about 80,000 input combinations. Obviously, we cannot simulate all of them. Therefore, the first step is to select the combination of parameters that is to be simulated in experiments with the behavior–based simulation (BBS). In the simulation literature, this phase is called “design of experiment,” or DOE (Banks, 1998). Regression analysis of the input–output (I/O) data of the simulation gives a metamodel, defined as a model of the underlying simulation experiments, i.e., an approximation of the simulation’s I/O transformation. If this transformation happens to be a first– or second–order polynomial, then Kuhn–Tucker conditions are both necessary and sufficient for a global solution point. The extreme points can be found by ordinary algorithms such as projection methods or the Simplex method (Coleman et al., 1999). The metamodel allows a global optimum to be found and the integrated design methodology to be completed.

Validation and Optimization

We conducted two types of experiments: (1) observation of cow behavior in real (non–simulated) commercial barns, and (2) computer simulation. The real barn offered insight into RMB operation and provided data for validation. The simulation experiments, through variation in the parameters of interests, provided the data needed to enable the metamodel to find the optimal solution.

Real Systems

In order to draw valid conclusions, two typical farms likely to be found in the Netherlands were chosen after consultation with the robot manufacturer (Lely Industries NV, Maasland, The Netherlands).

On both farms, milking frequency was determined by “expected milk quantity” (around 6 L minimum); in practice, this led to four milkings per day (4×) for an above–45 L cow, 3× for an above–20 L cow, and 2× for a below–20 L cow. Cluster detaching was done separately for each quarter and so were the real–time measurements: milk yield, electrical conductivity, and milking time. Milk recording was performed once every six weeks, using at least two samples per cow. In the winter, automatic cleaning of the robot was done every 9 hours, and in the summer every 7 h, with cleaning taking 10 to 15 minutes. The milk flowed to a single milk tanker (6,200 L) and was collected once every two days. The six–week experiment was carried out during July and August 1998. Concentrate food was served in the robot, up to 1 kg per milking. The silage, grass, and the rest of the food components were those commonly used on Dutch farms. The forage was distributed in the morning by a mixing wagon, and any remaining by the evening was pushed toward the cows. The layouts of both milking barns are shown in figure 1.

Farm A, a family farm, is located north of Utrecht. According to the farmer, the robot operated continuously and satisfactorily, and the results presented below were collected at the end of the first year. Around 60 cows were milked by the robot, 24 hours a day. The average milk yield per cow was 9,600 kg, with 4.5% fat, 3.55% protein, somatic cell count of 140,000 cells/mL, and bacteria count of 6,000 to 15,000 cfu/mL. During the previous year, there were only three cases of clinical mastitis. The robot was installed in an existing barn, after reconstruction and refitting. There were about 60 cubicles, enough forage lane positions for almost all the 60 cows, and three water troughs. A one–way gate was located between the forage area and the cubicle area.

Farm B is located north of Amsterdam. An entirely new barn was especially designed for robotic milking, with the aim of installing more than one robot. There were 142 cubicles, enough forage lane positions for about 110 cows, and three water troughs. At the time of the experiment, only a single Lely robot was installed, which milked around 60 cows, as on farm A. According to the farmer, the robot operated adequately, and the results presented below were collected at the end of the second year. The average milk yield was 10,000 L per cow, with 4.35% fat, 3.45% protein, somatic cell count of 190,000 cells/mL, and bacteria count of 14,000 to 20,000 cfu/mL.

Simulation Model

The simulation model was based on empirical data (Halachmi et al., 2000a) and has been described and validated in detail elsewhere (Halachmi, 2000; Halachmi et al., 2001). The main conclusions are summarized below.

The RMB to be optimized had eight input parameters and four response variables, which represent utilization of each facility in the barn. The input parameters were the numbers of cows, cubicles, robots, forage lane positions, and water troughs, together with the type of barn (layout drawing), the cow–traffic routine (which determines transition probabilities between facilities), and the farmer’s preferences for feeding times, maintenance, and treatment routines. The robot’s “service time” varied among farms and was updated in the BBS software. All other variables remained the same as in Halachmi (2000). The simulation output consisted of: (1) facility utilization, measured over 30 days of activity for each facility in the barn, i.e., robot, cubicles, forage lane positions, and water troughs; and (2) queue length, i.e., the number of cows waiting for an unavailable facility. Although the BBS software might be extended to cover more responses, e.g., waiting time (in minutes), in the present study we employed only facility utilization and queue length.

The robotic milking barn, including its facilities, operators, and cows, was modeled with a stochastic, discrete–event simulation. The simulation model was based on a modular approach with the system (barn) being broken down into five modules, whose interactions formed the barn behavior. These modules are the barn facilities: the milking robot, the concentrate feeder, the forage lane, the water troughs, and the cubicles. In a facility (*module*), there are parallel *resources*, which have service times that depend on the cow’s individual attributes. A barn was modeled by using *processorientation*, in which a *process* denotes the sequence of operations or activities through which a cow progresses. For example, in the robot, a process may consist of a cow’s entering the stall, followed by feeding, cluster attachment, milking, cluster detachment, and departure. If a *resource* is empty when a cow arrives, then the cow stays there during its *service time*, measured in minutes; otherwise, the cow is routed to a queue in front of the facility.

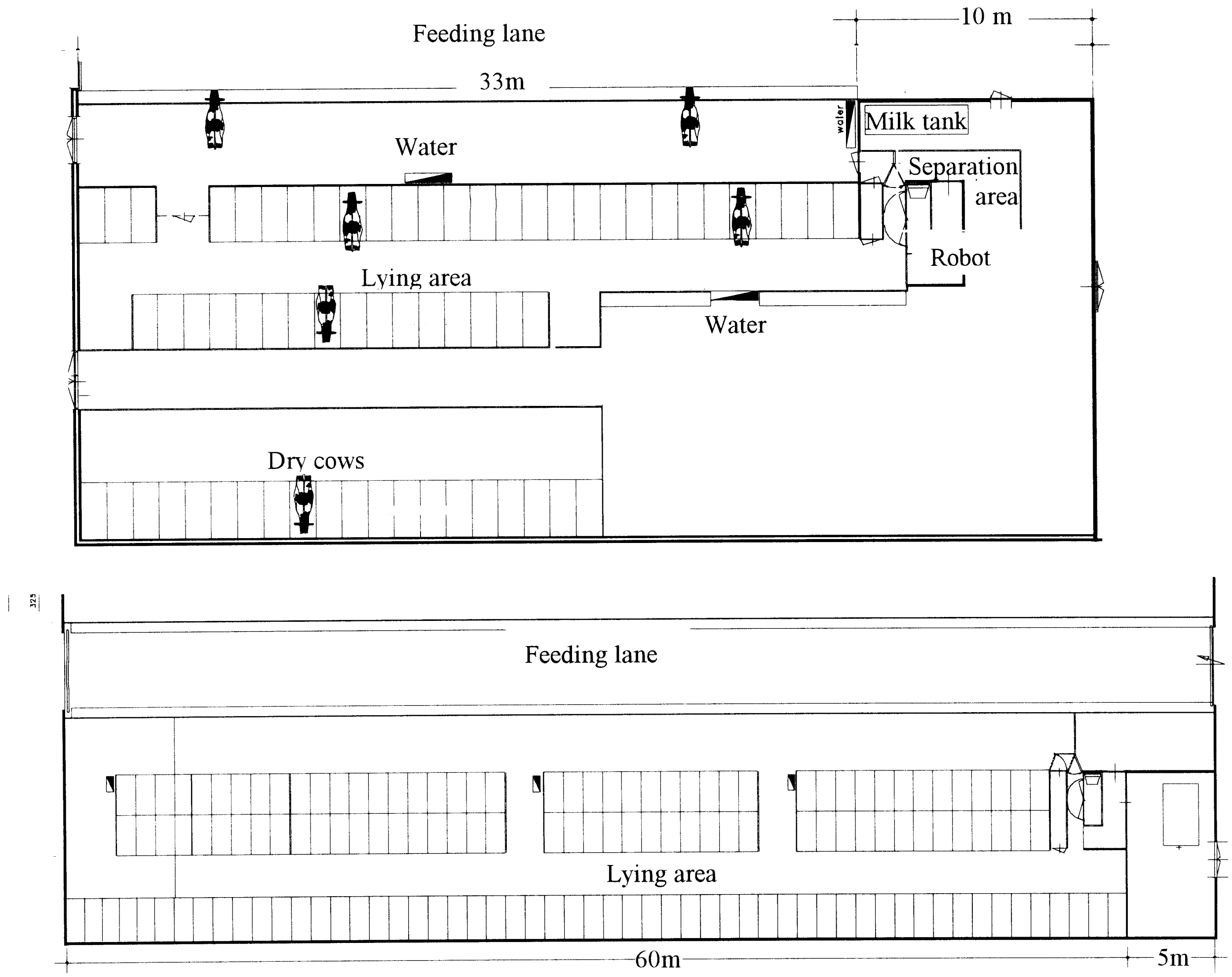

Figure 1. Layouts of the real (non–simulated) barns: farm A (upper drawing) and farm B (lower drawing).

The simulation programming language was Arena (Arena, 1996). We also used CAD software, namely Cadkey (Cadkey, 1995). In order to combine the layout drawing of the barn with the simulation kernel, a DXF file containing the scale drawing of the given barn was loaded into the simulation software. A DXF file can also be created by other CAD software (e.g., Autocad, 1996). The statistics, which keep track of the state of the barn, were automatically transferred to Matlab (Matlab, 1996) for further analysis, multiple regression, and linear programming.

In the animation, vivid colors indicate a cow's state: a green cow is in "working mode," i.e., occupying a facility, eating, being milked, or resting; a blue cow is in a "transit mode," i.e., either walking between facilities or idle. A queuing cow's color is changed to red. The simulation of farm B is presented in figure 2. The layout is shown at the center of the computer screen. During the simulation run, the cows, facilities, tractor, worker, and milk tanker are all shown moving as if in real life, although accelerated in speed. It can be seen that three cows are in front of the robot waiting in a virtual queue, while one cow is being milked in the robot. The clock on the right side of the screen shows the simulated time. Below it, we see the number of cows in the barn (60) and the average milkings per cow per day (MCD). A utilization graph for each facility and queue length are at the bottom of the screen. The digit in the top right corner of each graph is the current value, while the graph shows the historical values during the preceding 540 minutes.

Statistical Validation

The general validity of the BBS model has been discussed and proved elsewhere (Halachmi et al., 2001). However, site–dependent parameters (such as feeding routine and other farmer preferences) vary between farms. Therefore, we re–evaluated the validity of the model for the conditions of farm A and farm B. We compared real–world observations and simulation output data by using the paired–t approach as recommended by Law and Kelton (1991, section 5.6). The following observations are given in table 1: R_i^A was the average utilization of the robot in the real barn A, during day i; R_i^B was the average utilization of the robot in the real barn B, and S_i^A and S_i^B were the output data from the corresponding simulation models. Let W = R – S, and n = 30 days. Then the 95% confidence interval of W can be calculated as (Law and Kelton, 1991):

$$\bar{W} \pm t_{29,0.95} \sqrt{\mathrm{Var}(W)} \qquad (1)$$

If the interval did not contain zero, then the difference between the real barn and the simulation model was statistically significant. Table 1 shows that the simulation model was a valid representation of reality, and therefore it could be used in the metamodel phases.

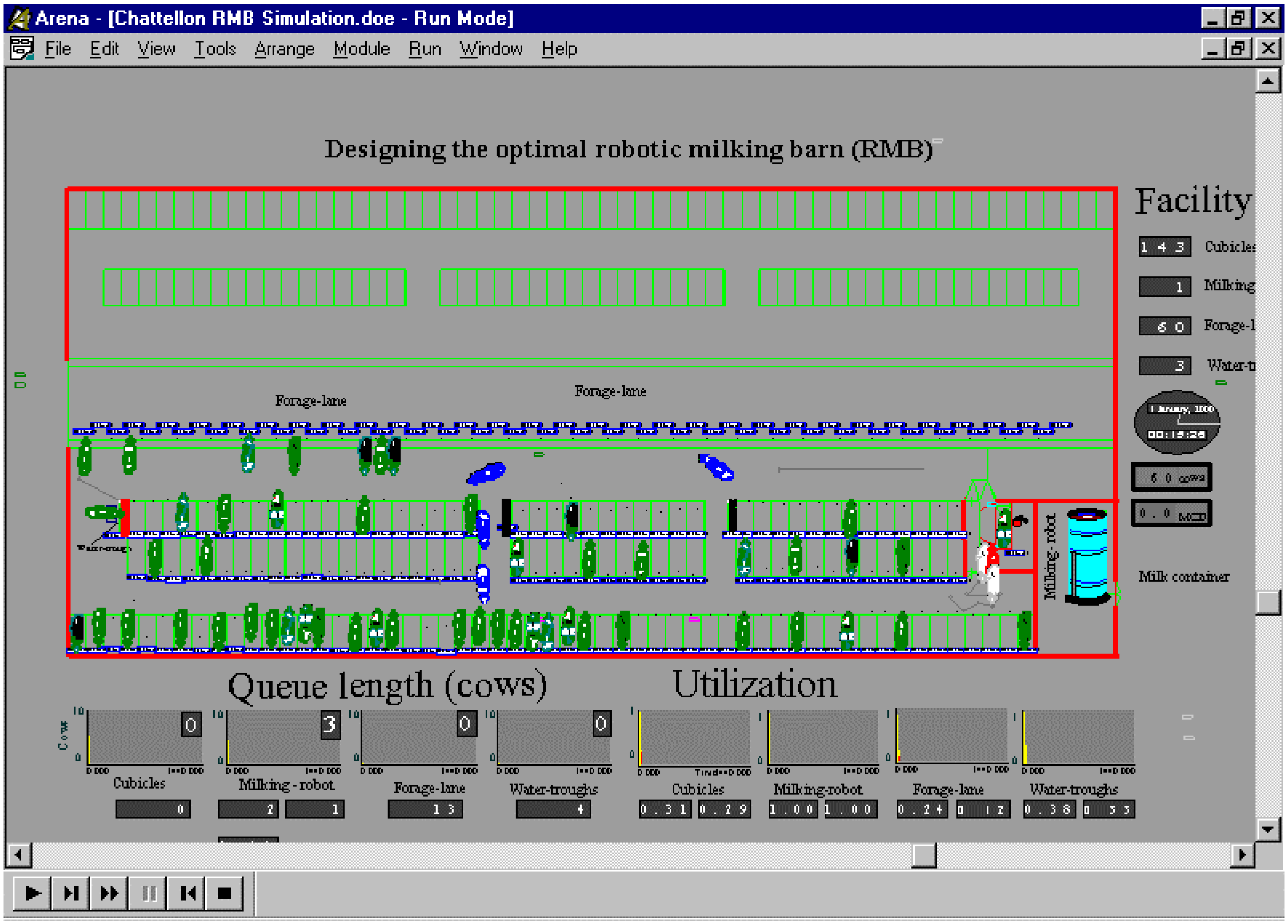

Figure 2. The user interface of the behavior–based simulation (BBS) model of farm B.

Table 1. Model validation: comparing experiments with real and simulated barns.

	Farm A Utilization		Farm B Utilization	
Day	Real (R^A)	Simulation (S^A)	Real (R^B)	Simulation (S^B)
1	0.78	0.77	0.79	0.86
2	0.76	0.75	0.77	0.78
3	0.79	0.69	0.86	0.80
:	:	:	:	:
27	0.80	0.74	0.80	0.84
28	0.80	0.75	0.82	0.78
29	0.80	0.69	0.83	0.85
30	0.83	0.72		
:	:	:		
42	0.82	0.78		
43	0.79	0.77		
44	0.81	0.71		
Mean	0.78	0.73	0.81	0.79
STD	0.027	0.036	0.025	0.039
95% confidence interval (eq. 1)	[–0.03, + 0.14]		[–0.06, +0.10]	

Design of Experiment, Metamodel, and Optimization

Design of experiments (DOE) can be defined as the selection of the combinations of input factor values that will actually be simulated. The goal is to gain insight into the simulation model behavior while observing relatively few factor combinations (Kleijnen and van Groenendaal, 1992). In the first DOE step, the feasible range of each parameter (boundary) was determined through exploration analysis with the BBS software. Changing one factor at a time, we reduced the number of allocated positions in each facility (robot stalls, cubicles, feeding positions, water troughs) until almost 100% facility utilization was reached, and the maximum facility allocation was limited by the number of cows in the herd. An additional simulated point was the middle range of each parameter. After a few such runs, we realized that three water troughs were enough; having fewer would not be practicable, as these are a relatively cheap facility and very important to high milk yield. We recommend that at least three troughs be installed, one in each section of the barn (this follows the recommendations given by Bickert et al., 1997). Therefore, in all our runs, we simulated three water troughs. The number of robots determines the layout, thus a new layout drawing, and thus a new complete set of input factor combinations is needed for each change. Therefore, water troughs and robots were kept constant, namely three water troughs, one robot on farm A, and two robots on farm B. The exploration analysis ended up with rather large boundaries for farm B: the two robots needed between 20 and 120 forage lane positions and cubicles, and between 60 and 120 cows.

After fixing the factor boundaries, we used a full factorial design in the second step. This consisted of all possible combinations of the three factor levels, comprising 27 (3 × 3 × 3) input factor combinations: forage lane positions =

[20,70,120], cubicles = [20,70,120], and number of cows = [60,70,120]. Later, after looking at the simulation results, we added one further run: [150 cows, 120 forage positions, and 120 cubicles]. A simulation run of one combination took only 1.5 minutes on a 200 MHz PC.

At this point, it is convenient to introduce further terminology. In the following list, an uppercase letter denotes a matrix; a lowercase letter indicates a column vector:

y_i = simulation response (namely, facility utilization) of factor combination i (i = 1,…, 28).

$X_{i,j}$ = values of input factor j in combination i. Input factor j (j = 1, 2, 3) represent numbers of cows (j = 1), cubicles (j = 2), and forage lane positions (j = 3).

B = column vector (3 × 1) containing the regression coefficients, namely b_{robot}, b_{cubicles}, and b_{forage}, associated with the robot, cubicles, and forage lanes, respectively.

E = regression fitting error after the least squares fit of y on X.

x^*_i = optimal values of x_i (3 × 1 column vector), namely the number of cows (x_1), the number of cubicles (x_2), and the number of forage lane positions (x_3).

In the third step, we calculated a multiple linear regression, fitting a higher–degree polynomial was not necessary (results below). The output of this step consisted of the regression coefficients: b_{robot}, b_{cubicles}, and b_{forage}.

In the fourth step, we ran the linear programming (LP) model. Its goal was to estimate the optimum values (x^*_i) for the quantitative inputs of the system (x_1, x_2, and x_3). We formulated the design constraints as follows: robot utilization ≤ 0.9, cubicles utilization ≤ 0.95, forage lane utilization ≤ 0.2 (i.e., generally 20% of forage lane positions are occupied), at least 70% of the cows are able to lie down in the cubicles simultaneously, and at least 50% of the cows are able to attend forage simultaneously. Under these constraints, we would like to house the maximum number of cows. This leads to the following LP problem:

$$\begin{aligned} &\min.\ -x_1 \\ &\text{s.t.} \begin{pmatrix} b^t\text{robot} \\ b^t\text{cubicles} \\ b^t\text{forage} \\ 0.7\ \ -1\ \ 0 \\ 0.5\ \ 0\ \ -1 \\ -1\ \ 0\ \ 1 \\ 0\ \ -1\ \ 1 \end{pmatrix} x^* \le \begin{pmatrix} 0.9 \\ 0.95 \\ 0.2 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \\ &x_i^* \ge 0 \end{aligned} \tag{2}$$

For example, the first constrain ($b_{1\ \text{robot}}X_1 + b_{2\ \text{robot}}\ X_2 + b_{3\ \text{robot}}X_3$) means that robot utilization should not equal or exceed 90%. The fourth constrain ($0.7X_1 \le X_2$) means that at least 70% of the cows should be able to lie down in the cubicles simultaneously, and the fifth constrain ($0.5X_1 \le X_3$) means that at least 50% of the cows should be able to attend forage simultaneously. Finally, the number of cows should be bigger than the number of forage positions ($X_3 \le X_1$, the 6th constraint), and there should be more cubicles than forage positions ($X_3 \le X_2$, the 7th constraint). Obviously, for further research, constraints can be chosen differently for each farm under study, after consultation with the farmer and the robot manufacturer.

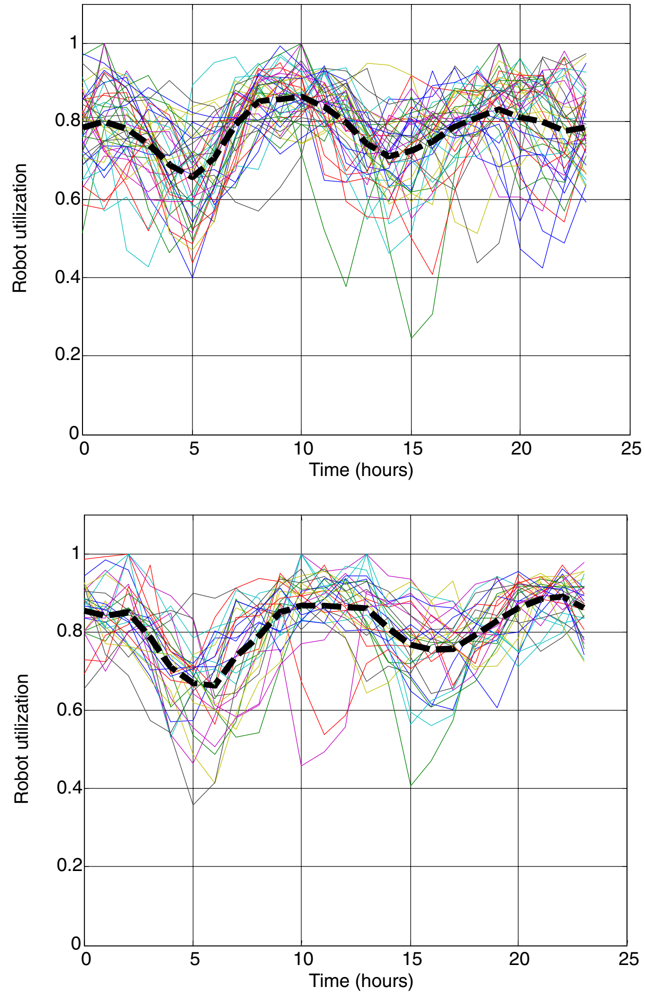

Figure 3. Real (non–simulated) utilization: farm A (upper figure) and farm B (lower figure). Each line represents one day in the experiment; the bold dashed line represents the average for the entire period.

Equation 2 is a convex function, and consequently Kuhn–Tucker conditions are necessary and sufficient for global optimality. Matlab solves this LP problem by a projection method, which is a variation of the well–known Simplex method (Coleman et al., 1999).

Results

We present two types of results: measurements in commercial RMBs, and the optimal solution calculated using metamodel techniques.

The average utilization of the robots in the real barns is shown in figure 3. It can be seen that, in general, practical utilization was around 80% throughout the entire experimental period. This means that the robots' load pressure was rather high, and that the robots' reliability met the demands. Connection failures affected 1.252% of the visits, comprising 1.004% of the robots' time. For a few days, the utilization was lower than 50%, which meant that the robot was not working for a period of half an hour, perhaps because of a technical

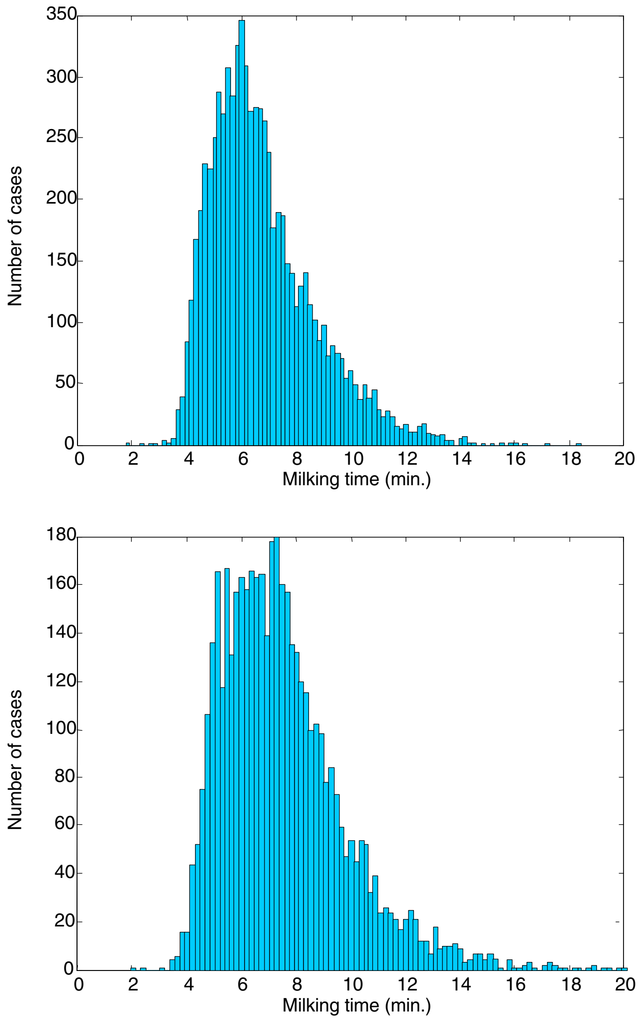

Figure 4. Milking time distribution: farm A (upper figure, mean = 6.76 min; std = 1.92) and farm B (lower figure, mean = 7.52 min; std = 2.29 min).

problem or simply because cows had not arrived. The lower points in the utilization cycles, at around 5:00 a.m. and 3:00 p.m., were the results of the robot cleaning time (cleaning takes about 15 minutes, during which the robot does not operate, so its maximum utilization per hour is only 75%).

Figure 4 presents the real (non–simulated) milking time by the robots (milking duration, minutes per single milking). It can be seen that the milkings on farm B took a little longer, which is related to the higher milk yield in farm B. This result agrees with the findings of Dzidic (1999), who found the correlation among robot milking time, milk yield, and other parameters.

The regression coefficients associated with the utilization of forage lane, cubicles, water troughs, and robots, respectively, that were obtained in the metamodel phase (for two robots) are:

b_{forage} = [0.0027635 –0.0041018 0.0028029]′

$b_{cubicles}$ = [0.0066010 0.0008334 –0.0000343]′

b_{water} = [0.0027133 0.0000967 0.0006888]′

b_{robot} = [0.0062033 0.0000327 0.0003786]′

where R^2 = 0.86, 0.93, 0.95, and 0.99, and the magnitude of error = 0.0796046, 0.0402242, 0.0170108, and 0.0135447 for the forage lanes, cubicles, water troughs, and robots, respectively.

By substituting these regression coefficients and solving the linear programming problem in equation 2, we estimated the optimal solution: x^*_i (farm B, two robots) = 139.683 cows, 69.84 forage lane positions, and 97.7782 cubicles, which we round upward. Obviously, this optimal solution satisfied the constraints:

Robot utilization = $b'_{robot}\ x^*$ = 0.85 ($\leq$0.9, constraint 1)

Cubicle utilization = $b'_{cubicles}\ x^*$ = 0.95 ($\leq$0.95, constraint 2)

Forage lane utilization = $b'_{forage}\ x^*$ = 0.2 ($\leq$0.2, constraint 3).

Compared with the current situation of farm B (fig. 1), the proposed allocation saves 40 forage lane positions and 44 cubicles, without impairing robot utilization. However, additional simulation experiments (fine–tuning of the metamodel's solution) suggested that 105 cubicles would prevent any interference with animal welfare (nearly zero cow queue length to the cubicles).

Given the same constraints, the optimal allocation that was obtained for an RMB containing one robot is:

x^*_i (farm A, one robot)= 65 cows, 60 forage lane positions, and 64 cubicles.

Robot utilization = 0.83 ($\leq$0.9, constraint 1)

Cubicle utilization = 0.95 ($\leq$0.95, constraint 2)

Forage lane utilization = 0.2 ($\leq$0.2, constraint 3).

When we increase the forage constraint from 20% to 90% utilization, we get more cows and less space:

x^*_i = 71 cows, 36 forage lane positions, and 60 cubicles.

subject to:

Robot utilization (constraint 1) = 0.900 ($\leq$0.9)

Cubicle utilization (constraint 2) = 0.950 ($\leq$0.95)

Forage lane utilization (constraint 3)= 0.411 ($\leq$0.9).

Compared with the current situation (see farm A, fig. 1), the proposed allocation offers a reduction of 30 forage positions, about the same number of cubicles, and an additional 10 cows, without impairing robot and cubicle utilization.

Figure 5 shows the trade–off between queue length and robot utilization. It shows the simulation results around the optimal solution. For one robot (left side), it can be seen that if there are more than 65 cows in the barn, then the facility idle time (1 – utilization) is lower than 15%, and the queue is longer than five waiting cows. For 70 cows, the robot idle time is 10%, and the queue length is eight cows. For two robots (right side), if there are about 130 cows in the barn, then the idle time is lower than 15%, and the queue is longer than five cows.

In all the cases, the optimization was terminated successfully.

Discussion

The Link Between Utilization, Cost, and Animal Welfare

As the measure of performance, we chose facility utilization, which can be measured directly in a real farm, and is a standard statistic in our simulation package. Utilization is important both economically and in terms of animal welfare. For example, if a farmer paid 200,000 Dutch Gilder (NLG; $1 U.S. = 2.33 NLG) for a robot capable of 200 milkings per day (at maximum practical utilization of,

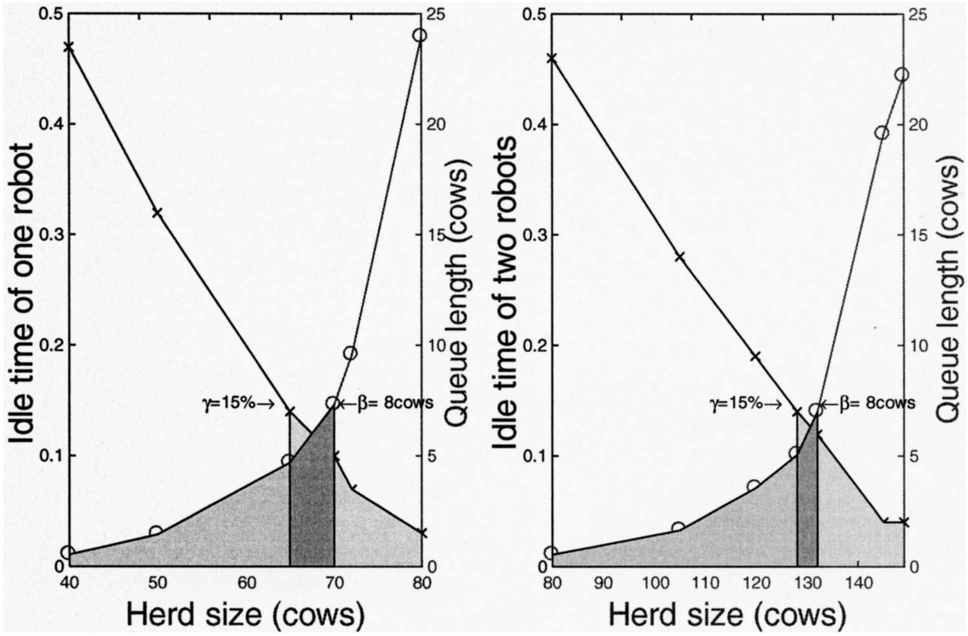

Figure 5. System performance in terms of robot idle time ratio (left–side *y*–axis, lines marked "x") and cow queue length (right–side *y*–axis, lines marked "o") as a function herd size, using a fixed number of facility allocations (left graph: farm B, 1 robot, 60 forage lane positions, 64 cubicles; right graph: farm A, 2 robots, 103 forage positions, 105 cubicles). The constraint levels are: idle time ratio ≤ 15% and queue length ≤ 8 cows.

say, 85%), but that farmer achieved only 118 milkings per day (50% utilization), then there would be a direct loss of 100,000 NLG. In this case, 35% utilization equals 100,000 NLG, i.e., the ratio is about 2,850 NLG per 1% utilization. Utilization can also be interpreted in animal welfare terms such as queue length in front of a facility (how many cows are waiting to lie down, to eat, or to be milked?), and waiting time in the queue can also be easily calculated (Halachmi et al., 2000b). Obviously, if the facility utilization is too high, then a long queue might occur.

Does Our Optimal Solution Hold Elsewhere?

It seems that adjusting only three parameters (milking time, cow traffic, and feeding routines) is sufficient to provide a valid simulation model. However, one should keep in mind that the same basic principles of cow traffic and cubicle housing were maintained in both experiments: the data source (Halachmi et al., 2000a; Halachmi, 2000), the validation sites (Halachmi et al., 2001), and the farm in question. The present article makes no claim to validity for our optimal solution under completely different housing or management principles (for example, an open cowshed such as is used in Israel). Fortunately, the basic principles used in this study are in common use in today's RMBs.

Conclusion

A behavior–based simulation model, together with meta-model and optimization techniques, that formed an integrated design methodology for robotic milking barns was developed. The design focused on optimal facility allocation and its relation with herd size, feeding routine, and management practices. The metamodel allowed a global optimum to be found for a given boundary conditions.

Using the new design methodology and rigid design specifications, formulated in terms of mathematical constraints, suggests that if this design methodology had been developed previously, and if it had been applied prior to installation, then the savings in building costs could have been significant. Farm A could have saved 30 forage positions and added 10 cows, and farm B could have saved eight forage positions and 50 cubicles, while keeping the same level of robot performance and animal welfare.

Operational research into facility usage of two commercial RMBs showed that robot utilization was rather high, and that robot reliability met the practical requirements with very little technical failure and maintenance.

The simulation model is a valid representation of reality (95% confidence level), so it is useful for research as well as for practical design and marketing.

Given the conditions mentioned above, the following optimal facility allocations were determined: farm B (2 robots): 103 forage lane positions, 105 cubicles, and 132 cows; and farm A (1 robot): 36 forage position, 60 cubicles, and 71 cows.

The optimal layout calculated in this study is uniquely appropriate for a specific farmer, but the methodology developed in this article is universally applicable; the parameters can be adjusted to every farmer, site, or milking robot.

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