Ant Colony Optimisation for Community Pharmacy Dispensing Process Based on In-field Observations

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The community pharmacy dispensing process is an integral part of delivering effective primary care to patients around the world. However, dispensing error rates and related patient safety issues are always a concern in the sector, where studies have found dispensing error rates to be between 0.014% and 3.3% of items. In an attempt to identify the optimum performance within community pharmacies, a simulation model of small-medium sized UK pharmacies was built using a Colored Petri Net (CPN) method (Naybour et al., 2019). The model mimics how staff complete prescriptions and how errors occur during the dispensing process. Decisions by pharmacy managers need to be made about the number of staff to employ and their work pattern, as well as the prescription checking strategy, so that the pharmacy performance can be optimized without reducing process safety.

This paper focusses on the optimization aspect of pharmacy processes. An Ant Colony Optimization (ACO) algorithm is proposed and the results of the CPN simulations are integrated within this optimization framework. A multi-objective optimization is developed using a three-parameter utility function, including the number of prescriptions completed, the number of errors, and the average waiting time for customers. These parameters are outputs of the CPN simulations. The optimization routine can find a number of viable solutions for a range of cost and process reliability values.

In addition, this paper uses in-field data collected by the authors from observations of two pharmacies in the UK. A large number of times to complete each stage of the dispensing process have been collected and analyzed. The estimates of the distribution parameters were used in the CPN simulation and the ACO framework.

Keywords: Min Max Ant System, Ant Colony Optimisation, Coloured Petri Net, Community Pharmacy, Patient Safety, Dispensing Efficiency

1. Introduction

1.1 *Background*

The delivery of high quality healthcare services has become reliant on minimising patient safety risk and pitfalls of practice, while also providing an efficient service. Community pharmacy is no exception. Although error rates are generally thought to be low (Chua et al., 2003 & Knudsen et al., 2007), the relationship between customer satisfaction and waiting times requires that pharmacies can delivery patient prescriptions within a reasonable time (Afolabi & Erhun, 2003). However, many companies also have an incentive to reduce their staff costs.

This paper addresses the problem of how to select an optimal number and skill mix of staff, considering the conflicting requirements of delivering best performance in terms of safety and efficiency.

1.2 Literature Review

Previous work has been carried out in modelling and evaluating community pharmacies. The work has frequently focussed on evaluating the dispensing process in terms of one of the two measures of performance: safety or efficiency of the service. Projects working on improving the safety of dispensing have included an FMEA method (Stojkovic et al., 2017) and a socio-technical probabilistic risk assessment (ST-PRA) (similar to a fault tree analysis) (Cohen et al., 2012). These papers have identified risks in the pharmacy dispensing process and proposed ways of reducing the exposure to risk. Patient waiting times have been evaluated using a discrete event simulation model (Tan et al., 2009), and a multiple server model based on queuing theory (Bahadori et al., 2014). Further modelling has been done to optimise inventory levels (Vila-Parrish et al., 2012) and resource allocation (Augusto &Xie, 2014). The authors' previous work has involved developing a simulation model of community pharmacies, based on Coloured

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Petri Net (CPN) method, and the process analysis in terms of reliability and efficiency (Naybour et al., 2018, 2019). This paper focusses an evaluating the dispensing process in terms of safety and efficiency in a single model. It uses the CPN model within a proposed Ant Colony Optimisation framework, in order to evaluate different pharmacy set-ups and their working patterns, and to identify optimal solutions.

1.3 Optimisation

Ant colony optimisation is one of a number of Heuristics Derived from Nature (HDN) that can be used to analyse combinatorial optimisation problems. This paper uses an extension of the original technique, known as Min-Max Ant System, to optimise the CPN model. Further details with an introduction to the alternative ant colony algorithms can be seen in (Dorigo & Stutzle, 2004).

In this paper, section 2 introduces the ACO methodology, and section 3 shows how it has been applied to the CPN model. Section 4 explains the data collection method and data collected during in-field observations. Section 5 presents the results of the optimisation, and section 6 concludes the paper.

2. Ant colony Optimisation

2.1 *Introduction*

Ant colony optimisation (ACO) uses agents to mimic the behaviour seen in biological ant colonies while finding the minimum path between their nest and food sources (Deneubourg et al., 1990). ACO uses agents that walk over a graph representing the solution space, and leave a trail of pheromone marking their journey which will influence the way other agents move over the solution space. Each member of the colony of agents can influence future searches in this way, and over time the probabilistic reinforcement of good paths, coupled with a memory of previous paths taken, enables the algorithm to come up with suitable solutions.

2.2 *Solution Construction*

Ants move on a graph of nodes to construct solutions to combinatorial problems. There are two key features of the ants' behaviour to consider in ACO algorithms: solution construction and pheromone update. Solutions are constructed probabilistically using the repeated application of a decision policy, used for finding a node the ant should move to next. The policy depends on the concentration of pheromone on edges connecting two nodes, and the heuristic value associated with each edge.

Assuming that the concentration of pheromones on arcs from node *i* to *j* is denoted by τ_{ij}, and the heuristic value indicating a prior quality of node *j* is denoted by ν_{ij}, this policy can be generalised by Eq. (1):

$$p_{ij}(\mathrm{t}) = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha}[\,\nu_{ij}]^{\beta}}{\sum_{l\in N_i}[\tau_{il}]^{\alpha}[\,\nu_{il}]^{\beta}} & \text{if } j \in N_i \\ 0 & \text{if } j \notin N_i \end{cases} \quad (1)$$

where $p_{ij}(\mathrm{t})$ is the probability that an ant on node *i* chooses to move to node *j* next. N_i is the set of nodes neighbouring node *i*, i.e. nodes that can be reached from node *i* by travelling along 1 arc, except the node previously visited. The two values α and β weight the preference given to heuristic or pheromone information respectively, during the construction of solutions.

2.3 *Pheromone update*

Once each ant has finished building a solution to the combinatorial problem, the pheromone trails on all paths are updated. This is done by evaporating some pheromone from all paths using Eq. (2):

$$\tau_{ij} \leftarrow \tau_{ij}(1-\rho) \quad (2)$$

where ρ is the constant rate of evaporation. Then additional pheromone is placed onto the arcs used by each ant, using Eq. (3):

$$\tau_{ij} \leftarrow \tau_{ij} + \Delta\tau_{ij}^{k} \quad (3)$$

where $\Delta\tau_{ij}^{k}$ is the additional pheromone deposited on the edge (i, j) by the *k*th ant. The amount of pheromone deposited is proportional to the solution quality, and is given using Eq. (4):

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{1}{O^{k}} & \text{if } (i,j) \in P_k \\ 0 & \text{if } (i,j) \notin P_k \end{cases} \quad (4)$$

where O^{k} is the objective value returned by the *k*th ant, and P_k is the set of edges belonging to the *k*th path of the ant. The additional pheromone placed onto the path increases the chance that other ants will use the path again in the future. Furthermore, ants finding better solutions will deposit more pheromone.

2.2 *Max-Min Ant System*

Max-Min Ant System (MMAS) is a variant of the ACO algorithm which was designed to improve performance by limiting the tendency for premature convergence to poor solutions (Stutzle & Hoos, 2000). The main improvement

in the MMAS is the use of a flexible bound on the value of pheromone on all paths, so that every path's pheromone trail is within some factor of the highest concentration path. The bound used is given in Eq. (5):

$$\tau_{\min}(t) \leq \tau_{ij}(t) \leq \tau_{max}(t) \quad \forall\, i,j \qquad (5)$$

The upper bound is set using Eq. (6):

$$\tau_{max}(t) = \frac{1}{1-\rho}\frac{1}{O^{best}(t)} \qquad (6)$$

where O^{best} is the best solution found up to time *t*. The lower bound is set using Eq. 7:

$$\tau_{min}(t) = \frac{\tau_{max}(t)(1-\sqrt[n]{p_{best}})}{(avg-1)\sqrt[n]{p_{best}}} \qquad (7)$$

where *avg* is the average number of choices ants have at each decision point, and p_{best} is the probability of an ant choosing to use a path when it is marked with the highest allowed concentration of pheromone. Thus p_{best} defines how exploratory the ants are when convergence has been reached.

3. Application of the Ant Colony Optimisation method

3.1 Scope of the application

The process of dispensing can be described by the following six stages, shown in Figure 1.

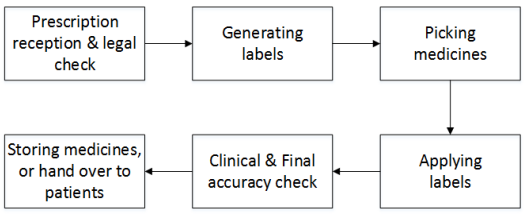

Fig. 1. The main stages of dispensing.

In addition to the provisions of medicine prescriptions, advanced services are also carried out by UK community pharmacies, such as the morning after pill or malaria vaccinations. The previous work of the authors (Naybour et al., 2018, 2019) have focussed on detailed modelling of these processes in a community pharmacy, using the CPN method, and their analysis in terms of process reliability and efficiency.

Note that the process is divided into primary and secondary tasks, where primary tasks can be completed by either dispensers or pharmacists, but the secondary tasks – by pharmacists only. Primary tasks consist of receiving prescriptions, generating labels, picking medicines and applying labels, whereas secondary tasks include final accuracy checking, handing prescriptions over to patients (along with patient counselling) and storing medicines for delivery, and completing advanced pharmacy services.

The optimisation problem for a pharmacy process can be defined as a framework to search for best pharmacy set-ups in terms of numbers and skill mix of staff, their work patterns and a strategy for accuracy checks, with an objective of maximising patient safety and satisfaction while minimising the cost.

3.2 Decision variables and their state space

In this paper three decision variables are defined:

1. The number of dispensers, *d*
2. The number of pharmacists, *p*
3. The working pattern, *w*.

The third decision variable, the working pattern, *w*, is used to model whether a pharmacist contributes (*w*=1) or not (*w*=2) to the primary tasks of dispensing.

Figure 2 shows a set of nodes that represent the state space of the decision variables within the ACO framework.

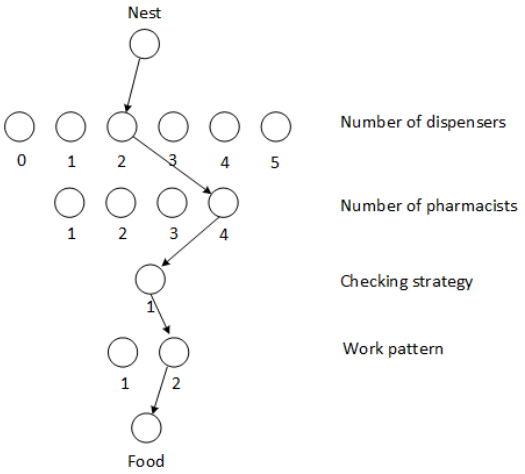

Fig. 2. State space of the community pharmacy optimisation problem with an example solution.

The graph consists of layers of nodes for each decision variable and directed arcs exist between the layers but not within. In the algorithm ants must choose one node from each layer to create a path from their nest to the source of food. For example, the path in Figure 2 represents a pharmacy with 2 dispensers and 4 pharmacists using the work pattern 2, i.e. the pharmacists focus on secondary tasks only.

Note that in this paper a particular checking strategy is assumed: if a prescription fails the accuracy check (the fifth stage of the process), performed by a pharmacist, the prescription is

sent back to the stage of generating labels (the second stage) to be dispensed again.

3.3 The method of initial and local search

During the initial search, a number of ants find and evaluate a number of solutions. After this step the best solution is sent to a local search, where other solutions in the vicinity of the best solution are also evaluated.

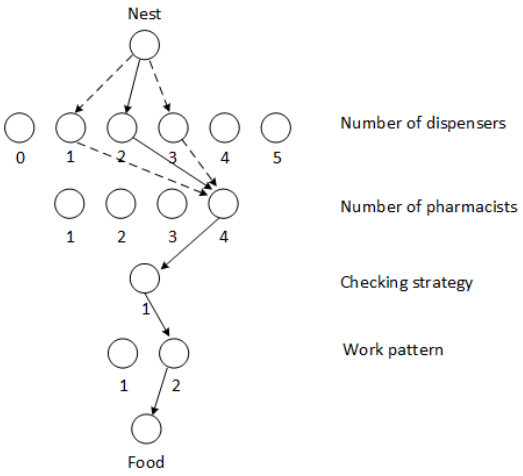

Fig. 3. Local search procedure

An example in Figure 3 shows that whilst most of the path is kept the same, one of the layers (for the number of dispensers in this example) is investigated using a node to the left and to the right of the chosen node in that layer (paths with 1 dispenser and with 3 dispensers respectively). This process is used to improve the best solution from the initial search. The pheromone updates, described in 2.3, were controlled using a cycle of 3. This means that every 3rd update was carried out by the global best ant's path, and every other update used the best path from the iteration.

3.2 Cost parameter

The cost of staff wages is considered in the optimisation, using the data from the Office of National Statistics in the UK (ONS, 2015). The median earning of UK pharmacists and dispensers were £41500 (C_p) and £21134 (C_d) respectively, therefore the total cost is calculated as shown in Eq. (8).

$$Cost = C_p \times p + C_d \times d \qquad (8)$$

3.3 Utility function

In order to evaluate the suitability of each solution, three parameters are considered: the number of completed prescriptions, ($X_{completed}$), the average of patient waiting time, ($X_{waiting}$), and the number of process errors, (X_{error}). These parameters are outputs from the CPN simulations which are then used within the optimisation framework. In order to transform this multi-objective optimisation problem into a single objective optimisation problem, a utility function, U, is proposed in Eq. (9), which has these three parameters:

$$U = \lambda_1 X_{waiting} + \lambda_2 X_{errors} - \lambda_3 X_{completed} + \gamma \qquad (9)$$

where the weightings are such that $\lambda_1, \lambda_2, \lambda_3 > 0$. The chosen values are λ_1=0.1, λ_2=60 and λ_3=0.1. In this paper it is assumed that all the three parameters are of equal importance to the decision maker. Therefore, the three chosen weightings mean, for example, that a reduction of 5 minutes in the average waiting time has an equivalent benefit of a reduction of 0.3 number of errors and an increase of 300 in the number of completed prescriptions. The constant of γ=30 in Eq. 9 is chosen for these specific weightings to ensure that the value of the utility function is positive for the evaluation of any combination of values for the decision variables.

4. Pharmacy process data collection and analysis

4.1 Data collection

As a part of this study, process duration data has been collected in 4 UK pharmacies. Some previous data collection schemes that focussed on pharmacy process duration were relying on small sample sizes (Afolabi & Erhun, 2003) or the process stages were not clearly defined (Cavaye et al., 2018), and both of these studies were not in the UK. Pharmacy 1 and Pharmacy 2 in this study were large multiple pharmacies, which belonged to a community pharmacy chain. Pharmacy 3 and Pharmacy 4 were two single stores, run independently by pharmacists. Since Pharmacy 1 and 2 were from the same chain, they used the same set of operating procedures. Therefore, due to clear similarities in the dispensing process, the data from these two pharmacies was placed in a single group to have a larger data set. For brevity, data collected in Pharmacy 3 and 4 is not presented and analysed in this paper.

At the time of data collection, Pharmacy 1 and 2 had between 4 to 8 staff working in the store, whereas Pharmacy 3 had between 4 and 7 and Pharmacy 4 – between 3 and 5. Each pharmacy

Table 1. Results of data collection study

Task	Number of Items	Number of Observations	Mean, *sec*	Distribution	Parameter 1	Parameter 2
Reception	N/a	160	17.9	Gamma(α, β)	2.46	7.25
Labels	1	150	27.2	Lognormal(μ, σ)	3.14	0.549
	2	57	38.0	Lognormal(μ, σ)	3.53	0.454
	3	33	54.6	Lognormal(μ, σ)	3.88	0.487
	4	36	59.5	Lognormal(μ, σ)	3.96	0.515
	Medium	34	90.8	Gamma(α, β)	5.41	16.8
	Large	10	177.7	Gamma(α, β)	4.48	39.7
Picking	1	138	18.7	Lognormal(μ, σ)	2.58	0.851
	2	65	20.0	Lognormal(μ, σ)	2.79	0.635
	3	38	27.0	Gamma(α, β)	3.99	6.76
	4	27	45.7	Lognormal(μ, σ)	3.42	0.540
	Medium	43	56.0	Gamma(α, β)	3.06	18.2
	Large	5	131.2	Gamma(α, β)	4.00	32.8
Applying	1	113	19.2	Lognormal(μ, σ)	2.63	0.787
	2	68	32.3	Lognormal(μ, σ)	3.24	0.673
	3	30	40.8	Lognormal(μ, σ)	3.47	0.658
	4	30	50.8	Lognormal(μ, σ)	3.75	0.599
	Medium	61	91.5	Lognormal(μ, σ)	4.32	0.615
	Large	18	176.7	Gamma(α, β)	2.59	68.5
Checking	1	133	32.2	Lognormal(μ, σ)	3.35	0.486
	2	68	45.2	Lognormal(μ, σ)	3.65	0.539
	3	34	59.0	Lognormal(μ, σ)	3.96	0.484
	4	34	47.9	Gamma(α, β)	8.66	0.181
	Medium	50	83.4	Lognormal(μ, σ)	4.34	0.409
	Large	12	175.8	Lognormal(μ, σ)	4.97	0.629
Handover	N/a	160	34.2	Lognormal(μ, σ)	3.15	0.874

had one pharmacist working per shift, except for Pharmacy 3 which occasionally had two.

Durations of the six stages of the dispensing process, shown in Figure 1, were collected for each individual prescription. Through discussions with a group of pharmacists from these pharmacies, it was assumed that the first and the final stage of the process, i.e. prescription reception and handover, do not depend on the number of items in a prescription. When recording durations of other stages, the number of items was assumed to be relevant and was recorded.

The data collection method used was researcher observation using a stopwatch, and the total number of prescriptions observed in Pharmacy 1 and 2 was 160 prescriptions for each stage, i.e. 320 observations for most stages.

Note that no data was collected for the first and last stages at Pharmacy 2 due to the layout of the store (the desk for receiving and handing out prescriptions was not visible from the pharmacy floor where the observations took place). It took between 3 to 5 days to complete data collection in each pharmacy.

4.2 Data analysis

Durations of each stage were grouped into six categories: prescriptions containing 1 item, 2 items, 3 items, 4 items, between 5 to 8 items (medium) and more than 9 items (large). A statistical package in R was used to test the fit of multiple distributions, using the maximum likelihood estimation method for the parameters. Table 1 shows the number of observations, the best fitting probability distributions of time to

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complete, their parameters, the mean value for each process stage, and the prescription category in terms of the number of items.

For example, there were 160 prescriptions that were completed in the prescription reception stage, with the mean of 17.9 seconds: the time to complete this stage is distributed according to Gamma distribution with the two parameters α=2.46 and β=7.25. It can be observed that the mean value for the duration of each stage increases as the number of items increases (apart from in the accuracy checking stage where the mean time for 3 items is greater than for 4 items). This may have been due to the way that items were counted. A prescription containing 3 items may be made up of 3 boxes (1 for each item), although it is also possible that it could contain many more, since doctors may prescribe multiple boxes for the same patient, which will then take longer to check. It may have been that more of the three item prescriptions were made up of multiple boxes than the 4 item prescriptions.

For the category of large prescriptions, very few observations were collected in most stages, such as label generation, picking and accuracy checking. Due to a small sample size, the distribution type is assumed to be identical to the category of medium prescriptions, and the parameters were estimated using the distribution fitting analysis on any data that was collected in this category.

4.3 Data usage in the CPN model

The distributions and the estimations of their parameters shown in Table 1 are used in the pharmacy CPN model, to sample the duration to complete each stage of the process. For example, in the label generation stage, the lognormal distribution is applied to model the duration when a prescription contains no more than 4 items, and the specific parameters are used for the case of 1 item, 2 items, etc. given in the rows from 2 till 5 in Table 1. When medium or large prescriptions are being dispensed, Gamma distribution is selected with the specific parameters for medium and large prescriptions respectively.

5. Results

5.1 Parameters and algorithm initialisation

Each iteration of the algorithm was run using two search phases, as described in 3.3. During the initial search four ants built solutions in the state space, and evaluated the solution 500 times to produce an objective value. The best ant out of the four is passed to the local search, where the path is used to find suitable solutions nearby. The local search evaluated the objective of the best search ant an additional 500 times, and then it tested two nearby local optimisation paths using 1000 simulations each. The lowest value returned from the three local searches represents best solution of the iteration.

Table 2 shows the algorithm parameters.

Table 2. Algorithm parameters

Parameters	Values
α	1
β	0
ρ	0.98
τ_0	151.0

The value of α = 1 indicates that pheromone trails are used to guide solution construction, and β = 0 indicates that no heuristic information is used. The value of ρ = 0.98 has been used before in applications of the MMAS algorithm (Stutzle & Hoos, 2000). The initial value of pheromone trails placed onto all paths was τ_0 = 151.0, which was the lowest value of the utility function returned after 1 iteration of the algorithm. A small ant colony of size 4 was used, since the state space of the problem is relatively small and it represents the lower end of possible colony sizes. The MMAS algorithm was run for 50 iterations, with a stopping condition such that if the same iterations best path was returned 3 times consecutively, the algorithm would end.

5.2 Analysis

The objective values obtained by ants at the local search stage throughout the algorithm are plotted in Figure 4. Set-ups using the flexible work pattern (where pharmacists may contribute to stages 1-4, w=1) are marked with crosses, and solutions which used the non-flexible work pattern (w=2) are marked with circles.

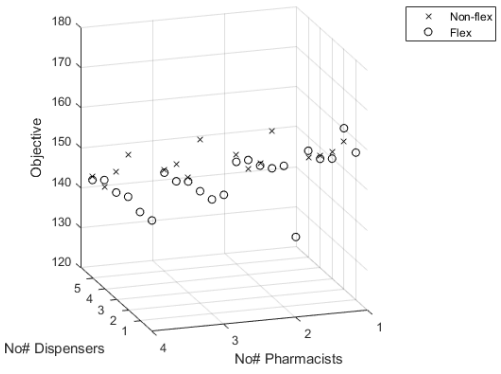

Fig. 4. Aggregated objective state space for local ants

Each discrete point in the *x*-*y* plane of Figure 4 corresponds to a choice of the number of dispensers and pharmacists in a team. Solutions which were tried more than once at the local search stage were aggregated to produce a single result. The results form a layer of points, where solutions with fewer staff have higher objective values are located in the front right hand corner; and solutions containing more members of staff have lower objective values and are located in the back left hand corner of the graph. Many of the worst performing solutions used the non-flexible work pattern, although for most set-ups, the difference between the two work patterns, while using the same team, was small. The optimal solution used two pharmacists and no dispensers with a flexible work pattern.

Every solution tested at the local stage was assigned a cost using Eq. 8, and Figure 5 shows the 2-D plot of the utility function values against cost.

Pareto optimal solutions (solutions which are better than all other cheaper solutions), are marked with red markers. The Pareto front, where the first solution from Table 3 is discounted, is marked with black markers.

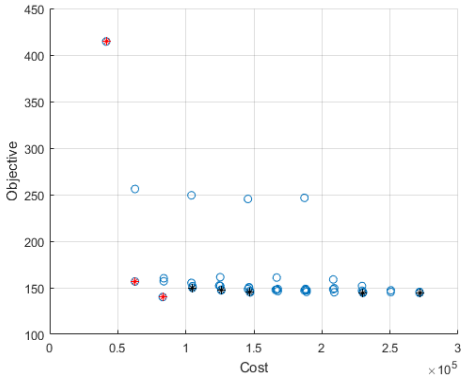

Fig. 5. Utility function values against cost

Table 3. Best solutions to the optimisation problem

Solution	Setup			Performance indicators				
	Number of dispensers	Number of pharmacists	Flexible or non-flexible	Dispensing errors	Completed prescriptions	Waiting time (sec)	Cost (£ per year)	Objective
1	0	2	1	1.2	170	522	83000	140.07
2	5	4	1	1.8	252	292	271670	144.56
3	5	3	1	1.8	252	295	230170	144.62
4	5	1	1	1.6	224	400	147170	144.95
5	4	1	1	1.6	223	412	126036	147.23
6	3	1	1	1.6	223	448	104902	149.93
7	1	1	1	1.1	162	773	62634	157.74
8	0	1	1	0.6	81	3561	41500	414.49

Table 3 shows a set of best solutions to the optimisation problem. As shown in Figure 5, the Pareto front contains 3 solutions (solutions 1, 7 and 8 in Table 3), all containing relatively few members of staff, 1 or 2. These set-ups are very cheap (see the cost column in Table 3), but consequently fewer prescriptions are completed and the waiting times are long (see the completed prescriptions and waiting time columns respectively). If the first solution was to be discounted, 5 other solutions (from 2 till 6) become Pareto optimal. These set-ups contain a higher number of staff (and therefore they cost more), a number of completed prescriptions is higher and waiting times are lower. The first solution may be outperforming more expensive set-ups, because in this optimisation framework a lot of emphasis is placed on reducing dispensing errors. Using the set-ups with more staff, more prescriptions are completed, which also means that more errors are made. Since larger teams are capable of dispensing a higher volume of prescriptions, for example, over 200 prescriptions, then the solutions from 2 till 6 would be the most suitable ones. They would also be most appropriate if the waiting time could not exceed 8 min (480sec), for example.

6. Conclusions and future work

This paper has demonstrated that a Max-Min Ant System (MMAS) is a suitable method for optimising community pharmacy dispensing

processes, modelled using a CPN method. In-field data from two UK pharmacies was used in the CPN model. An example utility function was proposed in order to look for a trade-off between the number of dispensing errors, the waiting time, the number of completed prescriptions and staff cost. A set of Pareto optimal solutions were found, and discussed.

Future work could extend through including other strategies for accuracy checking. For example, additional accuracy checks could be introduced before the final accuracy check, and prescriptions could be rectified as soon as they fail the accuracy check before reaching a more time consuming final accuracy check.

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