Time Window NSGA-II Route Planning Algorithm for Home Care Appointment Scheduling in the Elderly Industry

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***Abstracts*—Given the lack of healthcare resources, the home care sector faces a serious challenge in figuring out how to maximize the effectiveness of healthcare employees' services and raise consumer satisfaction. In this study, a model for healthcare worker scheduling and path planning is built. Fuzzy time window theory is used to discuss how to determine service duration and fuzzy service duration sub-situations. A path-planning algorithm based on a non-dominated ranking genetic algorithm is used to optimize the decision-making process. To analyze the aspects that affect the results of the model runs and use them as a foundation for effective planning recommendations, simulation experiments based on real data were conducted. According to the findings, customer demand under a defined service hour reaches a threshold of 343 before additional man-hour expenses starts to accrue. Decision-makers must therefore make adequate staffing modifications before this happens. The appointment time window has a greater impact on customer satisfaction and can be suitably extended in the customer appointment interface to raise satisfaction. The γ-value, which can be calculated based on the carer's fuzzy service hours, high and low peak demand, and the percentage of urgent tasks, is related to the time cost and satisfaction under fuzzy service hours. The corresponding optimal γ-values are 0.6, 0.3, 0.6, and 0.6, which can balance the time cost and customer satisfaction in this scenario.**

Keywords*—FTWNSGA-II; aging in place; path planning; appointment scheduling; fuzzy time windows

I. Introduction

With economic growth comes a gradual increase in China's population's age, and all facets of society are paying attention to the problem of senior care. Today, home care (HC), senior care and community care are the three main types of care for the elderly. The elderly of today are gradually favoring HC, and the number of HC service institutions is growing [1-2]. This is due to the influence of the traditional notion, the falling capacity of family senior care, and the lack of supply of elderly care institutions. The need for geriatric care has increased, while the rise of healthcare manpower resources among HC service providers has been much slower. One of the main problems the HC sector is dealing with is how to efficiently dispatch healthcare employees to increase service effectiveness and client satisfaction [3–4]. The current HC service scheduling model has the following shortcomings. First, there is a lack of scientific differentiation and scheduling methods for different urgent tasks. Secondly, traditional models are inefficient in dealing with uncertainty and fuzzy time Windows. Finally, it is difficult for existing models to balance service quality and cost-effectiveness. At the same time, most of the previous studies focused on HC service scheduling within the deterministic time window, and failed to fully consider the fuzziness and uncertainty of service time, resulting in poor results in practical applications. Moreover, the traditional algorithm has low efficiency when dealing with multi-objective optimization problems, and it is difficult to take both service quality and cost control into account. To solve these problems, this study introduced the fuzzy time window theory, used the improved NSGA-II to optimize the decision-making process, and verified the effectiveness and feasibility of the model through simulation experiments based on real data.

The innovation of the research is reflected in the following two aspects. First, the fuzzy time window theory is introduced to help HC deal with the uncertainty of service time. Second, the improved NSGA-II optimizes the decision-making process and improves the efficiency and accuracy of the model. The research contribution has the following three points. Firstly, through innovative scheduling and path planning models, the problem of limited medical resources in HC industry is effectively solved, and service efficiency and customer satisfaction are improved. Secondly, the research results provide a scientific basis for HC institutions to make decisions, and help to rationally allocate medical resources and avoid resource waste. Finally, the methods and conclusions of this study are not only applicable to the HC industry in China, but also provide a useful reference for the elderly care services in other countries and regions, and have a wide range of application value and promotion significance.

Section II of the study explains the appointment scheduling (AS) for HC development status, the state of PP research, and suggests a multi-objective optimisation model to address the practical issues with AS for aged services. The creation and path optimization of the scheduling model for both deterministic and fuzzy service duration are thoroughly explained in Section III. Section IV suggests making logical service scheduling decisions based on the model's experimental findings. Section V is the discussion of the results. Section VI summarizes the study procedure, analyzes the flaws, and suggests improvements.

II. Related Works

Since the 1990s, the HC service scheduling issue has increasingly drawn scholarly attention, with more international research findings in this field. In order to connect client services with nearby care service centers using IoT and artificial intelligence, Lam et al. developed an IoT artificial intelligence-based home care service matching system and implemented it into an e-health system. The outcomes show that the strategy can enhance customer happiness and the caliber of service provided [5]. To assign caregivers to home healthcare rooms close to the client's home, Decerle et al. offer a mixed integer planning model for the multi-station home healthcare allocation, routing, and scheduling problem. The approach features a low bias rate and a quick computation time, according to experiments [6]. Grenouilleau et al. looked into an ensemble partitioning heuristic algorithm that incorporates the realistic constraint situation of HC, solves the problem of linear relaxation in the ensemble partitioning model using columns generated by large neighbourhood search, and gets the answer by solving the integer with the heuristic algorithm. Studies revealed that the approach might cut travel time by 37% and boost continuity of service by 16% [7]. Xiang et al. built a bi-objective mixed integer linear programming model based on the goals of minimizing total cost and maximizing satisfaction, and paired a local search method with a genetic algorithm to solve the model. The approach was able to generate a roughly Pareto optimal solution more quickly, according to experiments [8].

The derived branch of the vehicle PP problem includes the AS problem for HC services, which is solvable using the related algorithm. With the use of real-time price signals from the distribution system operator, Wang et al. present a deep reinforcement learning-based distributed scheduling approach for electric vehicle clusters. A deep reinforcement learning technique is used to optimize the EV orderly charging and discharging strategy. The strategy is characterized by a Markov decision process. The technique can cut the cost of user fees by US$133.7 [9]. By optimizing the weighting parameters and deadline miss rate through reinforcement learning and adjusting the reinforcement learning action step size and reward function to improve the learning speed and optimisation capability, Meng et al. enhanced the dynamic priority scheduling algorithm in real-time scheduling strategy for power systems. The strategy can increase scheduling effectiveness and lower operating expenses, according to experiments [10]. Li et al. suggested adding a "distance" clique approach and a circular Jaccard distance metric to an ant colony algorithm for the traveler problem's multi-solution optimization. In order to find the Pareto ideal solution, Tang et al. developed a bi-objective optimisation model based on minimizing both the overall passenger waiting time and the bus company departure time. The model can offer managers of urban rail transit systems logical bus route scheduling solutions, according to experiments [11-12].

In conclusion, it is clear that although multi-objective HCAS models based on variables like caregiver skills, caregiving style, and caregiver starting point are more frequently investigated, they also have drawbacks such difficult mathematics and poor efficiency. Fuzzy time windows (FTW) have been used successfully in vehicle routing issues and have steadily gained attention thanks to literature research. In this study, FTW is first introduced into the HC service scheduling model [13]. Customer satisfaction is calculated under various levels of urgency using an affiliation function, and the optimal value is solved using an improved non-dominated ranking genetic algorithm, which allows HC service businesses to make wise and scientific decisions based on the optimal value.

III. Methods and Materials

In order to carry out reasonable home nursing service scheduling, it is necessary to consider the factors such as labor cost, customer demand and customer satisfaction. In this study, a nursing staff scheduling model was constructed from the perspective of time cost and satisfaction, and an improved non-dominated sorting genetic algorithm (NSGA-II) was designed to solve the model. Firstly, the fuzzy time window theory is used to deal with the uncertainty of service time, and the NSGA-II algorithm is optimized by setting different parameter configurations. Secondly, the triangular fuzzy number is used to represent the customer's service time demand, and the fuzzy confidence level is used for comparative analysis, so as to deal with the time uncertainty in the actual service more accurately.

A. *Construction of HCAS Model and NSGA-IIPP Algorithm under Determined Service Duration*

Given a service agency, the agency has M clients and M dispatchable carers. The origin of the carer is designated as service agency 0, and a client corresponds to a task and a carer, which are classified as urgent task $M_{\mathrm{e}}=(1,2,\cdots,e)$ and general task $M_{\mathrm{g}}=(e+1,\cdots,M)$ according to the degree of urgency. the rated working time of the carer is T, and its path distance is the round trip distance between the service agency and the client's address. The skill level of the carer must match or exceed the task level of the client. Assume that client m has a time window (TW) of $[a_m,b_m]$ and a maximum tolerated TW of $[ast_m,bst_m]$. $[a_m,b_m]$ indicates that the client's desired start time is a_m and the required latest start time is b_m, and the client's satisfaction is 1 if the service is started within this TW. $[ast_m,bst_m]$ indicates that the earliest and latest service start times that the client can tolerate outside of the TW appointment are ast_m and bst_m, and the client's satisfaction beyond this range is 0. Since client satisfaction is directly influenced by the start time of the carer, it can be described using fuzzy constraint theory [14-15], as shown in Eq. (1).

$$u_m(t_m)=\begin{cases}0\ , & t_m<ast_m\\ \dfrac{t_m-ast_m}{a_m-ast_m}\ , & ast_m\le t_m<a_m\\ 1\ , & a_m\le t_m\le b_m\\ \dfrac{bst_m-t_m}{bst_m-b_m}\ , & b_m<t_m\le bst_m\\ 0\ , & t_m>bst_m\end{cases} \tag{1}$$

In Eq. (1) $u_m(t_m)$ is the fuzzy affiliation function of the service start time, indicating user satisfaction; t_m is the time when the carer starts the service. The maximum tolerated TW differs in everyday situations for different urgent types of task clients. Defining this as urgent tasks customers are only allowed to be early and not late, general tasks can be solved for according to Eq. (1) for customer satisfaction. The two definitions can be represented visually by Fig. 1.

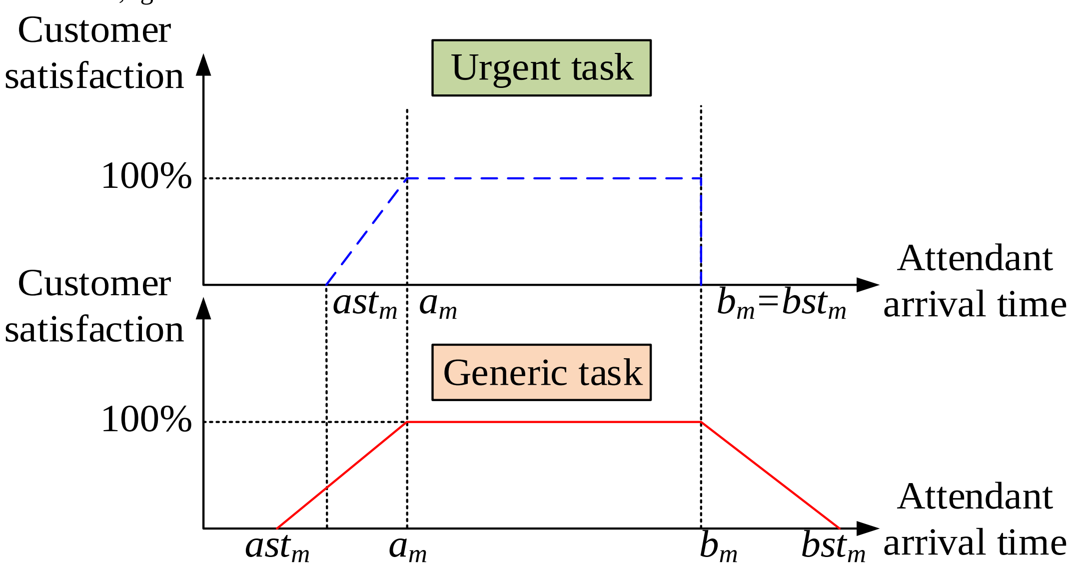

Fig. 1. FTW based on customer satisfaction at different levels of urgency.

Based on the above assumptions, the PP model is constructed using the concept of directed graph, as shown in Eq. (2) [16]. Where V and A denote the set of vertices and the set of arcs respectively; G denotes the planar graph containing all points and arcs.

$$G = (V, A) \tag{2}$$

By labelling the position where the escort departs as 0 and the position where it ends as $m+1$, the calculation of the arc in the directed graph proceeds as shown in Eq. (3).

$$A = \{(m, m', n) | m \in V \setminus \{m+1\}, M \in V\{0\}, n \in N, m \neq m'\} \tag{3}$$

In Eq. (3) n denotes the n th carer; m' is the m' th client, $m \neq m'$ denotes that a carer serves only one client at a time and does not repeat the service for clients already served. As different carers have different skill levels, the total hours of each carer cannot exceed T. Using Q_n to denote the skill level of the n carer, S_m to denote the demand level of user m and t_n to denote the total hours of carer n, the carer and the task need to meet the conditions shown in Eq. (4) in order to be matched.

$$\begin{cases} Q_n \geq S_m \\ t_n \leq T \end{cases} \tag{4}$$

To balance the maximum tolerable TW for general and urgent tasks and to prevent loss of clients due to too early or too late service, a minimum service level factor $u_m(t_m) \geq \alpha_m$ is set and must meet $u_m(t_m) \geq \alpha_m$. This minimum service level factor corresponds to a TW of $[a'_m, b'_m]$, and when an escort arrives early at client m, he/she needs to wait until time a'_m to perform the service, and those arriving after time b'_m incur a penalty time cost. The scheduling optimisation objectives for this study were to minimise working hours and maximise average customer satisfaction within the constraints of a fixed number of people working and TW. Job duration includes point-to-point movement time, early arrival waiting time, late arrival penalty time and service time. Of these, travel time is related to path length, so that time minimisation translates into path minimisation. For the penalty time, the penalty coefficient is calculated by multiplying it with the tardiness time. In summary, the equation for optimising escort scheduling based on task urgency is shown in Eq. (5) when the length of service is determined.

$$\begin{cases} \min D = \sum_{n=0}^{N} t_n + \sum_{n=1}^{N} \sum_{m=0}^{M} \sum_{m'=0}^{M} vt_{n,m,m'} \cdot x_{n,m,m'} + \sum_{n=0}^{N} w_n + C \cdot \sum_{m=0}^{M} \sum_{n=0}^{N} \max_m \{0, st_{m,n} - bst_{m,n}\} \\ \max U = \sum_{m \in M} u_m(t_m) / m \end{cases} \tag{5}$$

$st_{n,m}$ in Eq. (5) indicates the time for carer n to start the task at client m 's home; $x_{n,m,m'}$ is a decision variable indicating the path choice of carer n from client m to client m', with 1 for going and 0 for not going; w_n is the waiting time for the carer to arrive early; $vt_{n,m,m'}$ is the distance from client m to client m'; D, U and C are the working hours, average satisfaction and penalty coefficient respectively. For the solution of the multi-objective optimal scheduling problem of carers, the solution idea of combinatorial optimization can be used. For this type of problem, the current commonly used algorithms include genetic algorithms and particle swarm algorithms [17-18]. In this study, NSGA-II was used to solve the problem. $S = (s_1, s_2, \cdots)$ chromosome A is obtained by using natural numbers to encode the order of the caregiver's moving path, where $s = 0,1,2,\cdots$ indicates the path moved by a certain caregiver and 0 is used to distinguish different caregivers. The initialised population is generated by random matching if the constraints of the scheduling model are satisfied. The end times of the maximum tolerable TW for different clients are extracted and all clients are sorted in order from smallest to largest to form a new set of clients. A client is randomly taken out and placed into the path of the carer, and if the scheduling model constraint is satisfied, it is removed from the original set and placed into the path of that carer, and vice versa, the client is reselected. The cycle ends when the total service time is greater than the rated hours of the carer, and is then repeated for the next carer until the client is empty or all the carers' hours are scheduled. The initialised population is adjusted to the initial position according to the fitness function, i.e. the carer service path is assigned the corresponding client point using fuzzy plausibility theory. Variation operations are applied to duplicate individuals and infeasible individuals are eliminated to ensure that each individual is a feasible solution. The optimisable paths in the feasible paths are treated as objects, and the service start times are adjusted according to the optimal movement shown in Eq. (6) until all feasible solutions are adjusted.

$$G = \min\{(\min(\Delta t_k) | k = m, m+1, \cdots, m'), w_n t_{m'+1}\} \tag{6}$$

In Eq. (6) G denotes the optimal amount of movement; Δt_k denotes the difference between the actual start time of the escort $st_{n,m}$ and a_m, b_m and b'_m. Finally, the optimal PP is obtained by iterating according to the selection, crossover and variation process of NSGA-II. The solution flow of the NSGA-II-based algorithm is shown in Fig. 2.

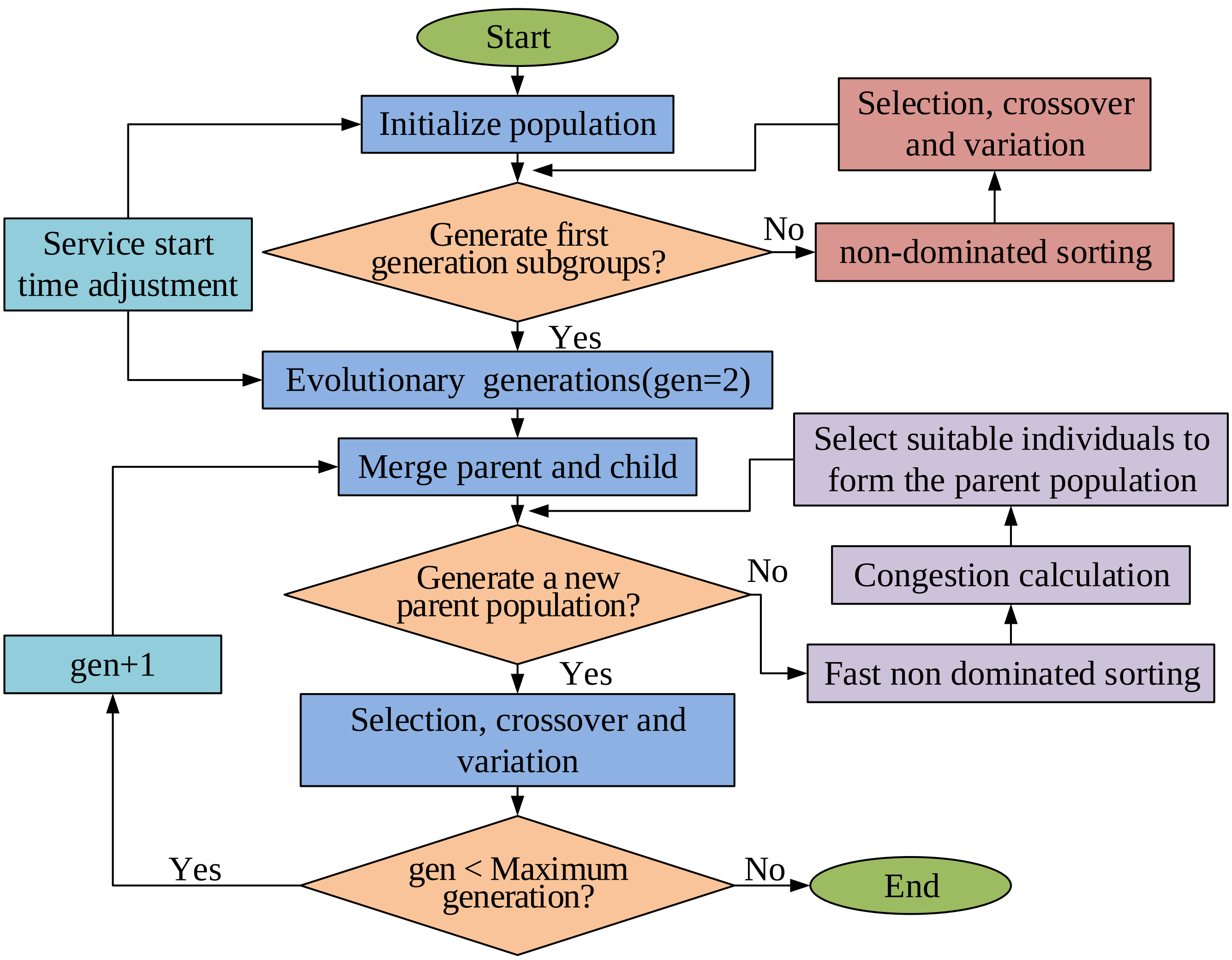

Fig. 2. NSGA-II based algorithm solution flow.

B. HCAS Model and NSGA-IIPP Algorithm Construction under Fuzzy Service Hours

Due to the dynamic nature of client demand in real life HC, there is a high degree of uncertainty about the length of time a carer will be available and when they will end their service. This makes it more difficult to constrain the client's TW appointment and the risk of the carer working beyond the rated working hours. Therefore the issue of scheduling optimisation in the case of fuzzy service lengths needs to be discussed. On the basis of the determined service length, a triangular fuzzy number is created for each client with uncertain service length [19], then for client m, its service length is expressed as $t=(t_{1m},t_{2m},t_{3m})$. When the service of client k is completed, the total working hours of the carer in the current state are calculated in Eq. (7).

$$T_k=\sum_{i=1}^{k}t_i+\sum_{i=1}^{m}\sum_{j=1}^{m}vt_{ij} \tag{7}$$

In Eq. (7), i, j and k are all clients. T_k is a triangular fuzzy number, and the remaining working time of the carer after serving the client is also a fuzzy number, as shown in Eq. (8).

$$\begin{aligned} T'_k &= T-T_k \\ &=\left(T-\sum_{i=1}^{k}t_{3i},T-\sum_{i=1}^{k}t_{2i},T-\sum_{i=1}^{k}t_{1i}\right)-\sum_{i=1}^{m}\sum_{j=1}^{m}vt_{ij} \\ &=(t'_{1k},t'_{2k},t'_{3k}) \end{aligned} \tag{8}$$

According to fuzzy plausibility theory [20], the plausibility Cr that the next client's service hours are less than the remaining hours of that carer is shown in Eq. (9).

$$\begin{aligned} Cr &= Cr(t_{k+1}<T_k) \\ &= Cr\{(t_{1,k+1}-t_{3,k},t_{2,k+1}-t_{2,k},t_{3,k+1}-t_{1,k})\le 0\} \end{aligned} \tag{9}$$

If the client service hours are fuzzy time, the more credibility the carer currently has left, the greater the chance of successfully serving the next client. Expanding Eq. (9) according to the triangular fuzzy number multiplication and division operation gives the result shown in Eq. (10).

$$Cr=\begin{cases} 0\ , & t_{1,k+1}>t'_{3,k} \\ \dfrac{t'_{3,k}-t_{1,k+1}}{2\cdot(t'_{3,k}-t_{1,k+1}+t_{2,k+1}-t'_{2,k})}\ , & t_{1,k+1}\le t'_{3,k},t_{2,k+1}\ge t'_{2,k} \\ \dfrac{t_{3,k+1}-t'_{1,k}-2\cdot(t_{2,k+1}-t'_{2,k})}{2\cdot(t'_{2,k}-t_{2,k+1}+t_{3,k+1}-t'_{1,k})}\ , & t_{2,k+1}\le t'_{2,k},t_{3,k+1}\ge t'_{1,k} \\ 1\ , & t_{3,k+1}>t'_{1,k} \end{cases} \tag{10}$$

A confidence level γ is set so that the next client is only assigned to a carer if the demanded length of time is less than the plausibility that the remaining hours of the carer are greater than that of the carer. The path optimisation calculation under fuzzy service hours is shown in Eq. (11).

$$\begin{cases} \min D=\sum_{n=1}^{N}\sum_{i=0}^{M}\sum_{j=0}^{M}vt_{n,i,j}x_{n,i,j}+\sum_{n=0}^{N}w_n+C\cdot\sum_{m=0}^{M}\sum_{n=0}^{N}\max_m\{0,st_{m,n}-bst_{m,n}\} \\ \max U=\sum_{i\in M}u_m(t_m)/m \\ Cr(T'_k>t_i)>\gamma \end{cases} \tag{11}$$

The confidence level represents the subjective preference of the decision maker. If the decision maker prefers high risk and can bear the risk of time cost of task failure caused by the rated hours of the caregiver being less than the task length, then a smaller γ can be chosen; if the decision maker prefers stability, then a larger γ can be chosen to avoid risk. For the optimal PP under fuzzy service hours, a combination of stochastic simulation and NSGA-II algorithm is used to solve the problem. In the case of fuzzy hours, there may be additional time costs due to insufficient remaining hours when the carer reaches a client by PP, but it is not clear which client to serve will increase the cost risk and what the risk cost is, so the valuation of the additional hours needs to be obtained according to the stochastic simulation algorithm. A value γ is randomly generated in a range of fuzzy service hours for a particular customer, and the value is subjected to an affiliation function according to the triangular fuzzy number, as shown in Eq. (12).

$$u_t(y)=\begin{cases} 0\ , & y<t_1 \\ \dfrac{y-t_1}{t_2-t_1}\ , & t_1\le y<t_2 \\ \dfrac{t_3-y}{t_3-t_2}\ , & t_2\le y\le t_3 \\ 0\ , & y>t_3 \end{cases} \tag{12}$$

An additional random number c is generated to satisfy $c\in[0,1]$. The affiliation function is compared with c and if $u_t(y)>c$, then y is the actual service hours; if not, the process of randomly generating values is repeated and compared again. All actual service hours obtained from the comparison are used to calculate the extra work time present in the escort scheduling. After performing I iterations, the average of the I iterations is obtained based on subjective preference γ and this is used as the valuation of the extra hours worked by the carer. The sequence of feasible carer movement paths is encoded in natural numbers, and one feasible solution, also a chromosome in the genetic algorithm, is shown in Fig. 3. A number represents a client and 0 indicates the carer's movement path. All numbers except 0 are associated with the original position, which is obtained by crossover and mutation operations.

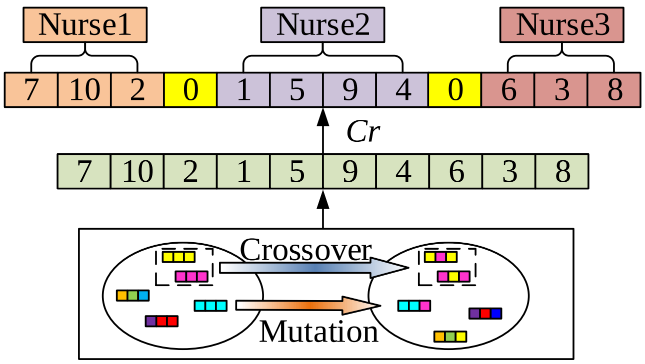

Fig. 3. Chromosome representation of feasible solutions.

Starting from the left of the randomly generated sequence of clients, the values representing the clients are taken out in tu

rn and the corresponding Cr values are calculated by comparing the simulated service hours of the client with the remaining hours of the carer. If $Cr \geq \gamma$, the client is assigned to the current carer; if not, the Cr of the next carer's remaining hours and the simulated service hours of that client is calculated and compared with γ until the condition is met. A chromosome is formed when the last client on the right side of the random sequence is matched with a carer. The above steps are repeated until the chromosome reaches the size of the initialised population. The initial position order is then adjusted according to the fitness function shown in Eq. (13), i.e. the fuzzy plausibility theory is used to assign corresponding client points to the carer service path.

$$FitnV(position) = 2 - \frac{2(position - 1)}{nind - 1} \tag{13}$$

$FitnV$ in Eq. (13) is the fitness function; $position$ denotes the location attribute of each value after the first sorting; and $nind$ denotes the number of individuals in the population. In the NSGA-II selection process, the population is stratified according to the level of individual non-dominance solutions and cycled according to the fitness of the individuals. The crowding degree $crowd_n$ is used to indicate the density of non-dominated individuals at the same level, as shown in Fig. 4.

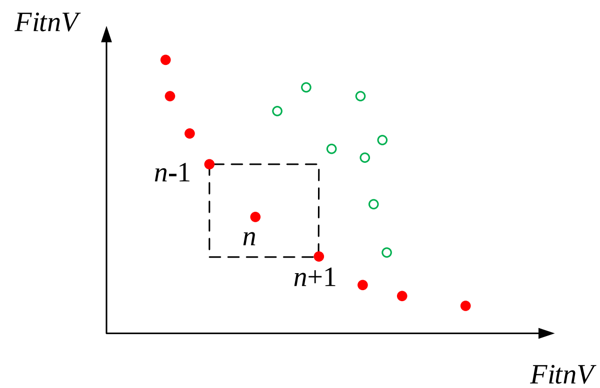

Fig. 4. Graphical representation of the crowding of an individual n.

Crowding is expressed as the sum of the length and width of the rectangle in Fig. 4 with the two individuals adjacent to the non-dominant individual as the diagonal, and is calculated as shown in Eq. (14).

$$crowd_n = crowd_n + FitnV(n+1) - FitnV(n-1) \ , \quad n = 2, 3, \cdots, N \tag{14}$$

The population is sorted according to the value of the objective function, with the first and last two individuals considered to be infinitely crowded. Solutions with smaller crowding are removed according to the value of the fitness function, and the remaining solutions are reordered according to the size of the fitness until the number of solutions meets the requirements. To improve the diversity of the population, crossover and mutation operations are performed. The crossover positions of individuals in the population are randomly set with probability p_c. The crossover positions of the two parent chromosomes are swapped, and the crossover population is then mutated with probability p_m. The new chromosomes obtained by the crossover and mutation operations must meet the full alignment requirements and constraints of the caretaker's movement route, otherwise the crossover and mutation operations will be repeated.

IV. Results

Firstly, the study conducted experiments on minimum total time cost and maximum customer satisfaction by using improved NSGA-II, and analyzed and discussed the influence of different parameter variables on time cost and customer satisfaction in detail. Secondly, the study also discusses the performance of the fuzzy service time scheduling model under different demand and urgent task proportions, so as to further optimize the scheduling scheme and improve the service efficiency and customer satisfaction.

A. Decision Analysis Based on NSGA-IIPP for Determining Service Duration Scenarios

As an example, the staffing of health care workers at home and the volume of client tasks at high and low peaks were collected from an HC service centre in Chengdu. There were 10 general practitioners and 25 nurse practitioners in the home visiting service. To simplify the research questions, all doctor levels were set to 2 and all nurse practitioner levels were set to 1. Client tasks were also divided into two levels, with task levels such as visits and medication injections set to 2 and nursing tasks such as medicine changes and massages and routine checks such as blood pressure and blood glucose set to 1. The centre had 387 client appointments during peak periods and 260 client pre-volumes during low peak periods. Of these, 103 were Level 2 tasks and 284 were Level 1 tasks during the peak period; 59 were Level 2 tasks and 201 were Level 1 tasks during the low peak period. From the peak and low peak tasks, 20% of the data were randomly selected as urgent tasks respectively, and the rest as general tasks. The client's appointment time period was used as the appointment TW, and the maximum tolerable TW was extended 20 min forward for urgent tasks and 20 min backward and forward for general tasks. The client's address was scaled down to the coordinate map of 500×500. The rated service hours for medical care are 8h, starting at 9:00am and stacked in minute increments. For NSGA-II algorithm, when the number of iterations is 800, population size is 200, crossover probability is 0.9, mutation probability is 0.3, the algorithm has the best effect. In addition, the service time is 30 minutes for Level 2 tasks, 20 minutes for Level 1 tasks, the reservation time window range is 30 minutes, the minimum service level coefficient is 0.6, and the penalty coefficient is 2. For the fuzzy service time scheduling model, the triangular fuzzy number is used to represent the customer service time demand, and the fuzzy confidence level is set as 0.5 and 0.6 to compare different experimental scenarios. To explore the effect of different algorithm parameters on the experimental results, parameter test values were set as shown in Table I.

TABLE I. ALGORITHM PARAMETER TEST VALUE SETTINGS

Parameter category	Test category		
	Class 1	Class 2	Class 3
Iterations	500	800	1200
Population size	100	150	200
p_c	0.7	0.8	0.9
p_m	0.1	0.2	0.3

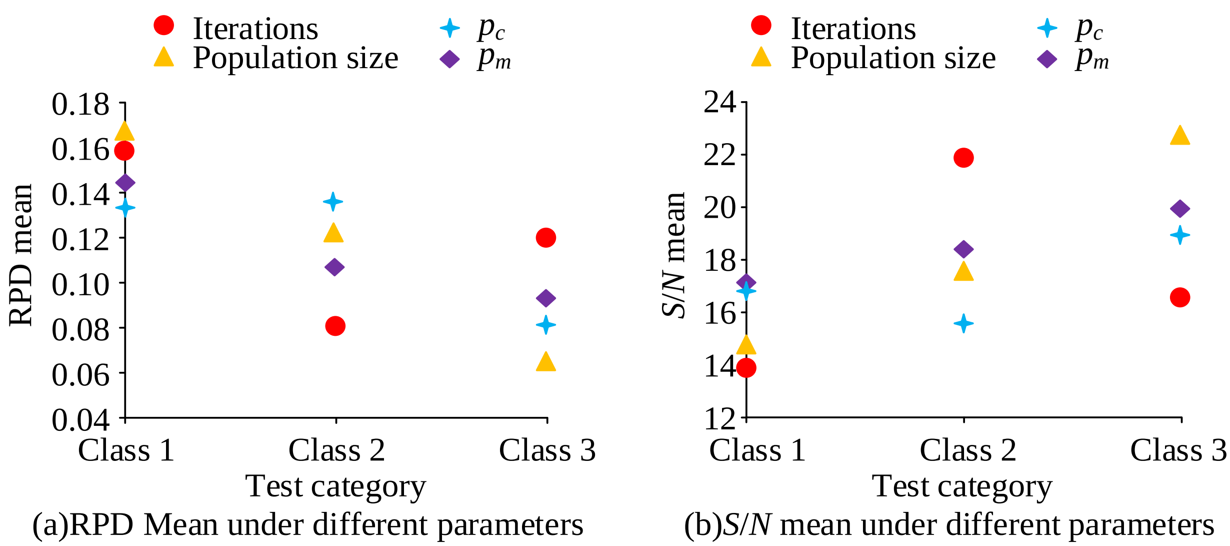

Fig. 5. RPD values and S/N -ratios for different parameters.

The minimum service level coefficient for the experiment was set to 0.6 and the penalty coefficient was set to 2. The relative percentage difference (RPD) and the S/N -ratio solved by the RPD were used as indicators for the experiment, and the results of the experiment were shown in Fig. 5 using the control variable method for each parameter setting in the table.

In Fig. 5, the RPD represents the deviation of the feasible solution from the optimal solution, the smaller the mean value of the RPD the smaller the deviation; the ratio is the negative logarithm of the mean squared RPD, the larger the value the better the feasible solution. As can be seen from Fig. 5, the best results were obtained when the number of iterations was 800, the population size was 200, the probability of crossover operation was 0.9 and the probability of variation operation was 0.3. Therefore, this set of parameters was chosen as the model parameters for the subsequent analysis. Under the determination of service duration, the factors that have a greater impact on time cost and customer satisfaction include demand sensitivity and TW sensitivity. For the demand sensitivity, set the service time for level 2 as 30min, level 1 as 20min, the TW range for booking as 30min, the minimum service level coefficient as 0.6 and the penalty coefficient as 2. Using the peak task volume as the upper limit, the low peak task volume as the lower limit, and 10 as the interval to set 14 groups of demand, the algorithm was tested to observe the impact of demand changes on the time cost of carers. The results are shown in Fig. 6.

Fig. 6 illustrates how the service center has a total rated work time of 16,800 minutes and starts to accrue extra work time charges once the task volume surpasses 343. This shows that the current personnel is unable to satisfy the demand for tasks more than 343 within the allotted work hours. The service center can therefore set customer demand at various times of the day based on historical data and use the scheduling outcomes from the NSGA-II model simulation to adjust the healthcare configuration beforehand, for instance by taking measures to increase the number of nursing staff before the peak period, to prevent a decrease in average customer satisfaction due to a decrease in the ability to meet demand. FTW includes the customer's appointment TW and the potential maximum tolerable TW. To verify the effect of FTW interval settings on waiting/late time and customer satisfaction, the model was used to test three different appointment TW intervals of 30min, 40min, and 50min, with the corresponding maximum tolerable TW for the general task of extending 20min before and after, 30min, and The experimental results are shown in Fig. 7.

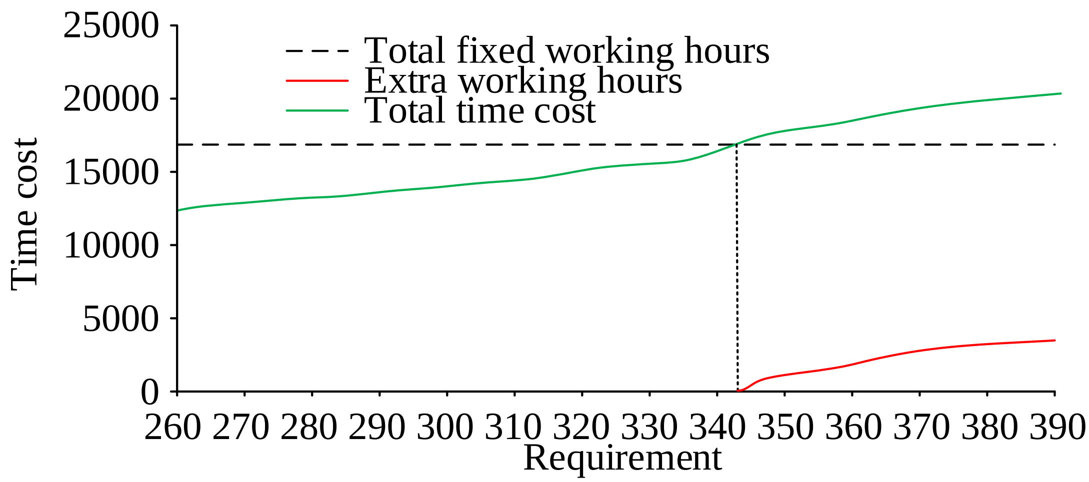

Fig. 6. Impact of low to peak demand changes on time costs.

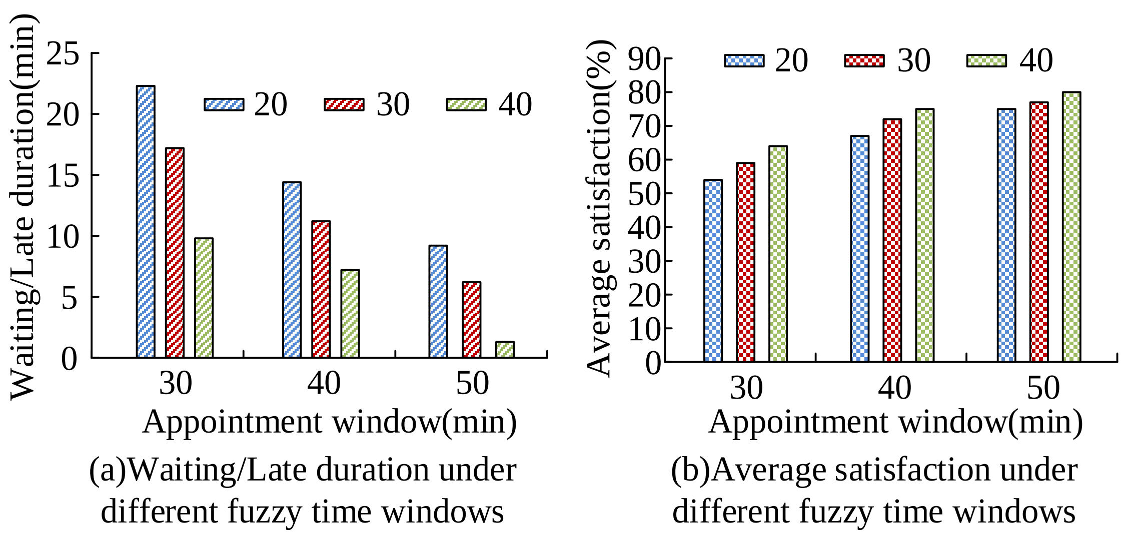

Fig. 7. Waiting/late hours and average satisfaction under different FTW.

As can be seen from Fig. 7, as the TW interval between appointments increases, the average waiting/late time decreases and customer satisfaction increases. The maximum tolerable TW also shows the same trend. This means that the greater the TW interval between appointments, the less likely it is that a healthcare professional will arrive early or be late; the greater the maximum tolerable TW, the longer the wait time acceptable to the customer and the higher the satisfaction level. In comparison, the average increase in customer satisfaction is 31.5% at the TW interval and 12.4% at the maximum tolerable TW, indicating that the TW interval has a greater impact on customer satisfaction. The service centre can therefore consider increasing the length of the appointment TW as much as possible to meet customer needs and collect as much information as possible in terms of customer maintenance to reasonably classify and plan the maximum tolerable TW for customers.

B. NSGA-IIPP-based Decision Analysis for Fuzzy Service Hours Scenarios

In the fuzzy service duration scheduling problem, time cost and customer satisfaction depend on the decision maker's subjective preference γ, which is influenced by demand and task urgency. Therefore, time cost and customer satisfaction are used as indicators to analyse the optimal γ values for different scenarios. Again, using the example of a home healthcare service in an HC service centre in Chengdu, the service time required for Level 1 and Level 2 tasks is set as the triangular fuzzy numbers $(15,25,35)$ and $(20,30,40)$, and tested by the NSGA-II model, the results of the carers' moving/waiting/late time, extra working hours, total time and average satisfaction for different γ values can be obtained as shown in Fig. 8.

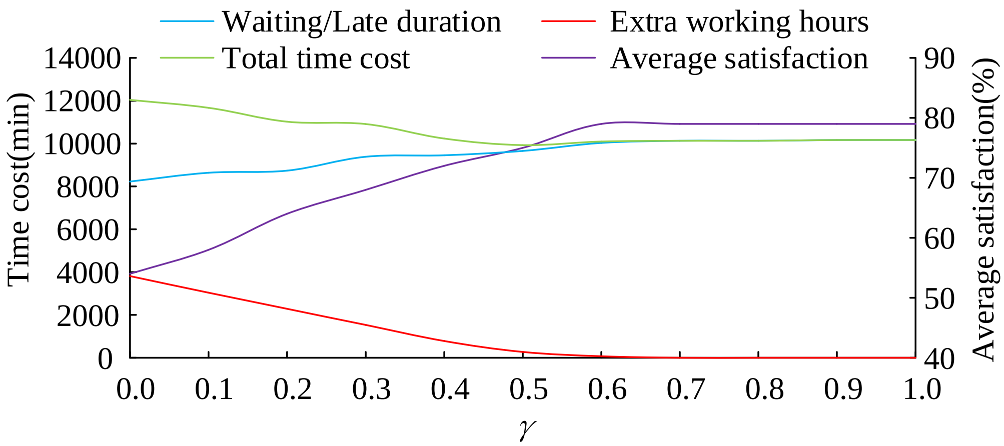

Fig. 8. Cost of time and average satisfaction of carers at different γ values.

As can be seen from Fig. 8, as the decision maker's subjective preference value increases, the cost of moving/waiting/late time is gradually increases and the extra working hours decrease. When the value of γ is less than 0.5, the increment of moving/waiting/late time is lower than the decrease of extra working hours, which makes the total time cost tend to decrease as the value of γ increases. The total time cost reaches a minimum of 9930 min when the γ value is equal to 0.5, and tends to increase from there as the increment of movement/waiting/late time is higher than the decrease of extra hours. Therefore, the subjective preference in the fuzzy service time scheduling for carers is 0.5 in terms of minimising the total time cost, and in terms of average customer satisfaction, customer satisfaction increases for γ values less than 0.6; after γ values reach 0.6 customer satisfaction does not change. Therefore, considering customer satisfaction and total time cost, the value should be set to 0.6 in terms of fuzzy service time scheduling for carers to explore the effect of high and low peak demand on γ-value, experiments were conducted on peak demand of 387 and low peak demand of 260, and the results are shown in Fig. 9.

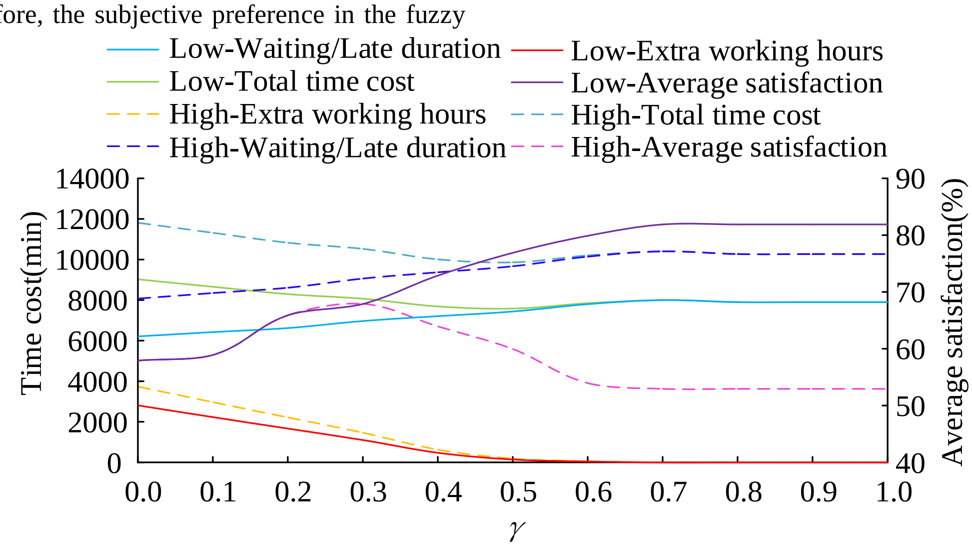

Fig. 9. Time costs and customer satisfaction for different γ values at high and low peak demand levels.

As can be seen from Fig. 9, the trend from a total time cost perspective is the same for peak and low peak periods at different γ values. The optimal γ value for both is 0.5. However, they differ significantly in terms of customer satisfaction. Customer satisfaction during the peak period increases and then decreases with the γ value, and it can be seen that when the γ value increases from 0.3 to 1, the time cost decreases by only 264, while customer satisfaction decreases by 15%. The optimal γ value for the peak period is therefore 0.3. Customer satisfaction increases with the γ value during the low peak period, and after the BBB value reaches 0.7, the satisfaction level stabilizes at 82%, and the optimal γ value, taking into account time cost and satisfaction, is 0.6. As the urgency of the task has a direct impact on the scheduling results, the total time cost and customer satisfaction vary with the value for different levels of urgency. The results are shown in Fig. 10.

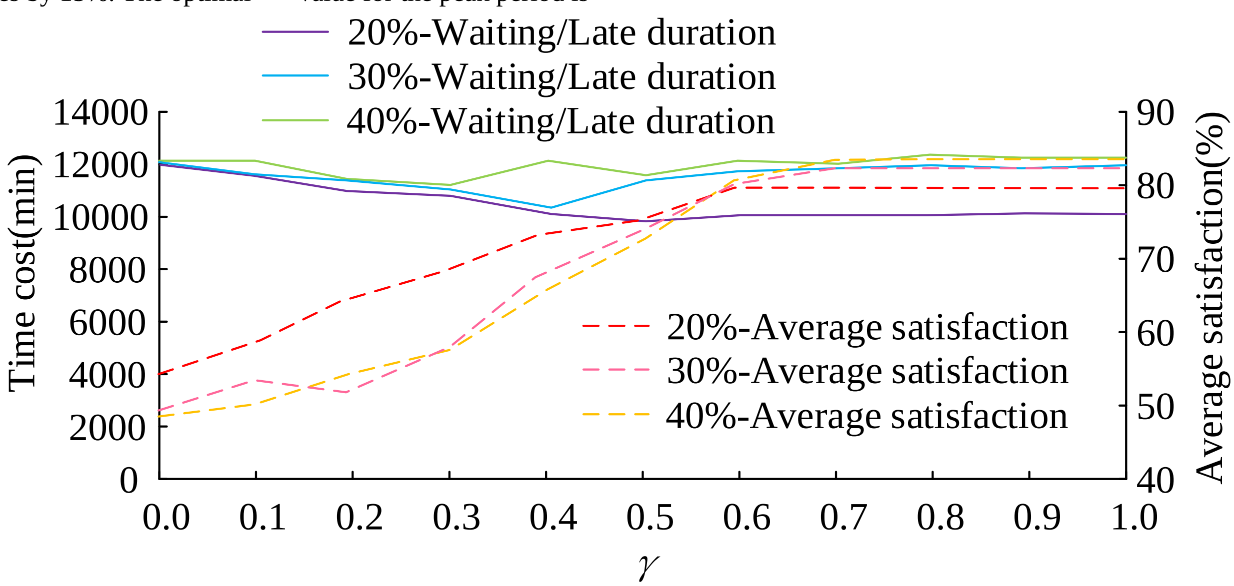

Fig. 10. Variation of total time cost and customer satisfaction with γ-value for different levels of urgency.

As can be seen from Fig. 10, the higher the proportion of urgent tasks, the greater the total time cost at all γ values. The lowest time cost exists for different urgent task ratio situations when the γ-value is between 0.3 and 0.6. In contrast, customer satisfaction varies, with a higher γ-value resulting in higher satisfaction. When the γ-value is less than 0.6, customers with 20% of urgent tasks are more satisfied than those with 30% and 40% of urgent tasks. When the γ-value exceeds 0.6, customer satisfaction is highest at 40% of urgent tasks, followed by 30% and lowest at 20%. On balance, the impact of different urgent task ratios on customer satisfaction is less than the impact on time costs, so the optimal γ-value can be set at 0.6 for different urgent task ratios.

To further verify the effectiveness of the proposed method in home care service scheduling, this study compared it with three recent studies. In the experiment, the same data set was used for scheduling and path planning of the four methods, and the results of each method under different performance indicators were recorded, as shown in Table II.

TABLE II. PERFORMANCE COMPARISON OF DIFFERENT METHODS

Method	Total time cost /min	Average customer satisfaction /%	Total service time /h	Energy consumption /kWh
The method proposed in this paper	9532	96.9	152	486
References [21]	9836	90.5	158	502
References [22]	9775	88.2	165	508
References [23]	9649	85.1	168	512

Table II shows the performance comparison between the latest methods and those proposed in the text under the same conditions. As can be seen from Table II, the proposed method has the best performance in total time cost, which is as low as 9532min, indicating that the method has significant advantages in time optimization. In addition, the average customer satisfaction rate of the method is also excellent, up to 96.9%, indicating that the quality of service is competitive. Finally, the total service time of the method is as low as 152h and the energy consumption is as low as 486kWh. In summary, the proposed method has significant advantages in optimizing total time cost, and service time cost, improving customer satisfaction and reducing energy consumption, which verifies its effectiveness and practicability.

V. Discussion

To verify the validity of the proposed NSGA-II and FTW theories in home care service scheduling, a detailed experiment was conducted and the results were compared with two recent studies. Compared with the multi-objective model proposed in literature [24] for medical resource management and site selection planning during the epidemic, although literature [24] has excellent performance in responding to public health emergencies, it still has shortcomings in dealing with complex time scheduling problems in daily home care services. In contrast, NSGA-II combined with FTW not only performs well in optimizing resource allocation, but also effectively deals with the uncertainty of service time. The results show that the proposed method is significantly better than the methods in the literature [24] in terms of total time cost, with the total time cost as low as 9532 minutes. In addition, the literature [25] performs well in dealing with skill matching and uncertainty, but there is still room for improvement in customer satisfaction and time cost optimization. NSGA-II combined with FTW method has excellent performance in customer satisfaction, with an average customer satisfaction of 96.9%, which is higher than the literature [25]. At the same time, the total service time of NSGA-II combined with FTW method was as low as 152 hours.

In summary, NSGA-II combined with FTW method shows strong ability in home nursing service scheduling, which can provide new technical support and optimization ideas for service organizations. Future research could further optimize the method, including introducing more types of user behavior data, enhancing the algorithm's generalization ability, and testing its performance in other service scenarios to improve its applicability and utility.

VI. Conclusion

The already scarce health care resources look to be even more scarce in light of the rapidly increasing HC demand and the current low planning rate of caregiver scheduling. For two separate scenarios of deterministic and fuzzy service hours, the nurse scheduling and PP models are discussed in this work using the FTW theory. The models are then solved using a PP optimisation technique based on NSGA-II. Real data is used to analyze the impact of various elements on the outcomes of model operation, and a sound planning approach is suggested. The model's 800, 200, 0.9, and 0.3 iterations, population size, crossover operation probability, and variation operation probability were determined via experiments using the RPD and S/N ratio. When the demand exceeded 343, the total time cost exceeded the total fixed man-hours, indicating that the decision-maker needed to make adjustments in advance in accordance with the actual situation. The total time cost calculated by the model under the determined service hours increased with the increase in demand. The average increase in appointment TW is much greater than the maximum tolerable TW, indicating that the appointment TW interval setting has a greater impact on customer satisfaction and that TW can be increased appropriately at the customer appointment interface. Customer satisfaction rises as FTW rises. The γ-value of fuzzy service time scheduling for carers is set to 0.6 under the fuzzy service duration, and the A-values for peak and low peak periods are set to 0.3 and 0.6, respectively. The A-value for the proportion of urgent jobs should be set to 0.6 in order for the model's time cost and customer satisfaction calculations to be more accurate. Overall, this study can help HC service centres make appropriate judgments to a certain extent, although there are still issues with the study's applicability. First, the model still has some challenges in dealing with complexity and uncertainty in practical applications. Although the fuzzy time window theory is introduced, the variable factors and unexpected situations that may be encountered in practice may exceed the preset range of the model. Second, limitations in data sources and experimental Settings may affect the generalizability of the results. This study is based on data from specific regions and time periods, and data from other regions or different time periods may vary, so the broad applicability of the results needs to be further verified.

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References

[1] Franzosa E, Wyte-Lake T, Tsui E K, Reckrey J M, Sterling M R. Essential but Excluded: Building Disaster Preparedness Capacity for Home Health Care Workers and Home Care Agencies. Journal of the American Medical Directors Association, 2022, 23(12): 1990-1996.

[2] Jarling A, Rydstrm I, Bravell M E, Nystrm M, Dalheim-Englund A C. Perceptions of Professional Responsibility When Caring for Older People in Home Care in Sweden. Journal of Community Health Nursing, 2020, 37(3): 141-152.

[3] Xu L, Yang L. Service Quality Evaluation of Medical Caring and Nursing Combined Institutions for the Aged Based on IVPFS-DEMATEL and Two-Stage Decision Model with Grey Synthetic Measures. The Journal of grey system, 2022, 34(1): 154-172.

[4] Hui-Min L, Yue L, Ai-Chun L I, Xiang L, Ting Y E, Wang J. Construction of the institutional care service needs index system for the disabled elderly of combination of medical and health care. Journal of Nursing Administration, 2018, 99(2): 249-260.

[5] Lam H Y, Ho G T S, Mo D Y, Tang V. Enhancing data-driven elderly appointment services in domestic care communities under COVID-19. Industrial Management & Data Systems, 2021, 121(7): 1552-1576.

[6] Decerle J, Grunder O, Hassani A H E, Barakat O. A matheuristic-based approach for the multi-depot home health care assignment, routing and scheduling problem. RAIRO - Operations Research, 2021, 55(z1): 1013-1036.

[7] Grenouilleau F, Legrain A, Lahrichi N, Rousseau L M. A set partitioning heuristic for the home health care routing and scheduling problem. European Journal of Operational Research, 2018, 275(1): 295-303.

[8] Xiang T, Li Y, Szeto W Y. The daily routing and scheduling problem of home health care: based on costs and participants' preference satisfaction. International Transactions in Operational Research, 2023, 30(1): 39-69.

[9] Wang K, Wang H, Yang J, Feng J, Li Y, Zhang S, Okoye M O. Electric vehicle clusters scheduling strategy considering real-time electricity prices based on deep reinforcement learning. Energy Reports, 2022, 8: 695-703.

[10] Meng S, Zhu Q, Xia F, Lu J. Research on parameter optimisation of dynamic priority scheduling algorithm based on improved reinforcement learning. IET Generation, Transmission & Distribution, 2020, 14(16): 3171-3178.

[11] Li H, Zhang M, Zeng C. Circular Jaccard distance based multi-solution optimization for traveling salesman problems. Mathematical Biosciences and Engineering: MBE, 2022, 19(5): 4458-4480.

[12] Tang J, Yang Y, Hao W, Liu F, Wang Y. A Data-Driven Timetable Optimization of Urban Bus Line Based on Multi-Objective Genetic Algorithm. IEEE Transactions on Intelligent Transportation Systems, 2021, 22(4): 2417-2429.

[13] Tang V, Choy K L, Ho G T S, Lam H Y, Tsang Y P. An IoMT-based geriatric care management system for achieving smart health in nursing homes. Industrial management & data systems, 2019, 119(8): 1819-1840. DOI: 10. 1108/IMDS-01-2019-0024.

[14] Saeed M, Ahmad M R, & Rahman A U. Refined Pythagorean Fuzzy Sets: Properties, Set-Theoretic Operations and Axiomatic Results. Journal of Computational and Cognitive Engineering, 2022, 2(1), 10–16.

[15] Ejegwa P A, Agbetayo J M. Similarity-distance decision-making technique and its applications via intuitionistic fuzzy pairs. Journal of Computational and Cognitive Engineering, 2023, 2(1): 68-74.

[16] Wu Z, Chen H, Zhang J, Liu S, Huang R, Pei Y. A directed link prediction method using graph convolutional network based on social ranking theory. Intelligent data analysis, 2021, 25(3): 739-757.

[17] Mallipeddi R R, Kumar S, Sriskandarajah C,et al. A Framework for Analyzing Influencer Marketing in Social Networks: Selection and Scheduling of Influencers. Management Science, 2021, 68(1): 75-104.

[18] Zhang C, Yang T. Optimal maintenance planning and resource allocation for wind farms based on non-dominated sorting genetic algorithm-II. Renewable Energy, 2021, 164(3): 1540-1549.

[19] Dong J, Wan S, Chen S. Fuzzy best-worst method based on triangular fuzzy numbers for multi-criteria decision-making. Information Sciences, 2021, 547(2): 1080-1104.

[20] Dey P, Jana D K. Evaluation of the convincing ability through presentation skills of pre-service management wizards using AI via T2 linguistic fuzzy logic. Journal of Computational and Cognitive Engineering, 2022, 2(2): 133–142.

[21] Ma X, Fu Y, Gao K, Zhu L, Sadollah A. A multi-objective scheduling and routing problem for home health care services via brain storm optimization. Complex System Modeling and Simulation, 2023, 3(1): 32-46.

[22] Xiang T, Li Y, Szeto W Y. The daily routing and scheduling problem of home health care: based on costs and participants' preference satisfaction. International Transactions in Operational Research, 2023, 30(1): 39-69.

[23] Jafari V, Rezvani M H. Joint optimization of energy consumption and time delay in IoT-fog-cloud computing environments using NSGA-II metaheuristic algorithm. Journal of Ambient Intelligence and Humanized Computing, 2023, 14(3): 1675-1698.

[24] Eriskin L, Karatas M, Zheng Y J. A robust multi-objective model for healthcare resource management and location planning during pandemics. Annals of Operations Research, 2024, 335(3): 1471-1518.

[25] Fu Y, Ding F, Mu Z, Sun C, Gao K. Integrating scheduling and routing decisions into home health care operation with skill requirements and uncertainties. Journal of Simulation, 2024, 18(3): 259-282.