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Empirical Study on How to Set Prices for Cruise Cabins Based on Improved Quantum Particle Swarm Optimization

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Abstract

This essay puts forward a cruise pricing model based on improved quantum particle swarm optimization, aiming at optimizing the pricing strategy and realizing the maximum sales income expected. Firstly, we combine the two factors – actual booking records and expected booking records in the process of cruises pricing – and improve the dynamic price-setting model based on demand learning put forward earlier. Then we improve the Dynamically Changing Weight's Quantum-behaved Particle Swarm Optimization (DCWQPSO) based on multistage punish function, in order to faster the converging speed and avoid the problem of local optimum. Lastly, we use the improved DCWQPSO to find the best expected sales income in the improved pricing model. The instance analysis of cruise pricing shows that the process of constructing this model is reliable and logical. Also this model could better higher the maximum expected sales inc ome and better perform in future application.

Keyswords: cruise pricing, improved pricing model, multistage punish function, improved DCWQPSO, maximum expected sales income

1. Introduction

Regarded as *the gold industry floating on the gold waterway*, the cruise industry has now become one of the fastest developing industries in modern tourism business, and has reached 8% increment in recent years (Sun, 2011). With new cruises' being put in operation and new ports' being constructed, the cruise business is developing rapidly, showing tremendous life power and development potential (Liu, 2011). However, the China's cruise business is just setting off and immature, also lacking any theoretical studies of the cruise' profit management. In recent years, the China's cruise tourism business is in a strong developing trend and become the new form and new field of China's economy development, due to the influence of international cruise industry markets. Therefore, it has become an important issue that worth studying how to rationally increases the cruise industries' profit.

In the process of cruise business operation, the companies emphasize on three aspects mostly: demand precast, storage distribution and cabin pricing, so the pricing of the cruise directly influence the business' sales income, which could be a key problem of the study. As for the pricing of the cruise, many experts and scholars had made a great amount of studies on it. For example, Sun *et al.* (2015) made a comparison analysis on the cabin distribution of cruise profit management based on the EMS R-a and EMS R-b. Sun *et al.* (2013) put forward a dynamic pricing adjustment strategy especially for the north-American market based on demand learning, and further discusses the implementing process of this new strategy using actually statistics of American cruise companies. The study results shows that this strategy could higher cruise companies' total profit in some extent. Shen (2015) made a study on cruises' dynamic stock control and dynamic pricing of different types of cabins in different periods based mostly on profit management theory. However, he did not make transformation on the extant model, also he put in his essay that it was a difficult problem to restrictedly optimize the pricing of cruise to achieve maximum expected income.

When dealing with the optimizing problem, the Particle Swarm Optimization, PS (Kennedy J, 1995) algorithm stands out with easy understandability and access among other global optimization algorithms, which attracted scholars' attention, generated many applications (Kuok K K, 2010). But there are some aspects that remain to be improved as shown in the actual practice. For example, the easily resulted premature convergence, lack of global optimization abilities and slow convergence speed, etc.(Zhou, 2011). Sun (2004) came up with a new particle evolution model from the quantum mechanics point of view, which is based on the delta (δ) potential and the hypothesis that the particles would feature quantal behaviors. He later put forward the algorithm- Quantum Particle Swarm Optimization, QPSO based on the model. Because of the differences appeared in the particles' agglomeration state in the quantum space, the algorithm could manage to do search within the whole feasible region, since its ability at global searching is far better than the standard particle swarm algorithm. However in the actual application, the QPSO still needs to be improved to better suit the specific circumstances. At present, there are plenty of studies about improving the quantum particle swarm optimization in order to better solve the multi-object optimization problem. For example: Zhang *et al.*(2008) improved the particle swarm optimization based on multi-stage punish function; Wen *et al.*(2015) dynamically reconfigured the distribution network based on integer coded quantum particles warm optimization algorithm; Huang *et al.*(2012) studied about the quantum-behaved particle swarm algorithm with self-adapting adjustment of inertia weight; Cao *et al.*(2012) applied the Improved quantum particle swarm optimization into power network planning considering geography factor; Li *et al.*(2014) applied the adaptive parameter into adjusting the research on quantum-behaved particle swarm optimization.

This essay puts forward a cruise pricing model based on improved quantum particle swarm optimization, with improvement made in the dynamic pricing theory according to the actual circumstances, also using the multistage punish function to optimize the DCWQPSO algorithm and lastly improving the problem of optimization with the improved algorithm's restriction. We use *the eighth electrical and mathematical modeling contest* type B's statistics to prove the pricing model put forward in this essay, and the results show that this model works well with excellent precision and applicability.

2. Cruise Pricing Model

Focusing on the cruise pricing problem, this essay firstly puts the idea of improving the previously made dynamic pricing model based on demand learning by studying the actual booking records and expected booking records in cruise pricing, which would make the model more realistic. Secondly, the improving of DCWQPSO using the multistage punish function, which would help avoid local optimum and faster the convergence speed. Lastly, find the global optimized sales profit expectation, using the improved quantum particle swarm optimization.

2.1 Improved Dynamic Pricing Model

Sun et al. (2013) put forward a dynamic pricing model based on demand learning, which could not only set dynamic prices, but also dynamically dig out the information of customers' maximum reserved prices.

However, the model did not take the relations between the actual booking records and expected booking records into consideration. In reality, the expected records are in some kind of relation with the prices, which we could fit by comparing the hash maps. Also the actual records are in some kind of relation with the expected records. According to this, in this section the improvement of this dynamic pricing model based on demand learning will be discussed. With the new voyage statistics imported, the demand function will be re-evaluated, and the best prices of different future voyage could be set by using the following non-linear model.

Actual booking records (demand function) and the expected booking records function:

$$\begin{cases} D_n = f(W_n) \\ W_n = f_0(p_t) \end{cases}$$

Where, D_n stands for the actual booking records in the n-th circle, W_n stands for the expected booking records in the n-th circle.

The weekly prices p_t (t=1,2…,n) obey the uniform distribution between the interval of $[p_{\min}, p_{\max}]$.

Thus, in the demand function $D_n = f(W(p_t)) = f(p_t)$

Then, $R_n = p_n \cdot D_n$

Where, R_n stands for the total profit during the n-th circle of every cruise voyage.

From above, the improved model of maximum expected profit is presented below:

Subject function: $\max R = \sum_{t=1}^{n} p_t D(p_t)$

Restriction requirement:

$$s.t.\begin{cases} \left| \dfrac{p_{t+1} - p}{p_{t+1}} \right| < 0.2 \qquad (t = 1, 2, ..., n) \\ \sum_{t=1}^{n} D(p_t) \le M \\ p_t > 0 \qquad (t = 1, 2, ..., n) \\ p_{\min} \le p_t \le p_{\max} \end{cases}$$

Where, R stands for the total profit of each cruise voyage, M stands for the maximum capacity of each level's cruise cabins, p_t stands for the cabin price of the t-th circle in the same level.

By using the data of different voyages, layout the demand function $D(p_t)$, substitute the data to calculate the specific function of R, and lastly calculate the value of R then we have the profit expectation of the cruise company.

2.2 Improved QPSO Based on Multistage Punish Function

2.2.1 Dynamically Changing Weight's Quantum-Behaved Particle Swarm Optimization (DCWQPSO)

Choosing the inertia weight β of the QPSO is crucial, because it's related to the whole algorithm's convergence ability. The bigger the value of β is, the better it is the quality of global searching and the faster the convergence speed is but the less precise result is; the smaller the value of β is, the more precise result is and the slower the convergence speed is. In order to improve the convergence ability of the QPSO, Huang *et al.*(2012) came up with an algorithm DCWQPSO.

During the iterative process of the QPSO, the global optimal position value in the current iterative always excels or at least equals to that of last iterative as a result of the calculating of the particle swarm's position.

$$s_d = \frac{F(x_g(t-1))}{F(x_g(t))}$$

If the optimization object is to search for the minimal value, the define

$$s_d = \frac{F(x_g(t))}{F(x_g(t-1))}$$

Another factor that affect the QPSO's performance is the particle aggregation. Particle swarm's global optimal position value's fitness value $F(x_g(t))$ always excels that of every particle's current optimal position value. If every particle's current optimal position value's fitness value's average is

$$M_t = \frac{1}{N}\sum_{i=1}^{N} F(x_i(t))$$

During the process of optimizing the minimal value, $F(x_g(t)) \le M_t$ defines the particle aggregation degree factor:

$$j_d = \frac{F(x_g(t))}{M_t}$$

During the process of optimizing the maximal value, $F(x_g(t)) \geq M_t$, defines:

$$j_d = \frac{M_t}{F(x_g(t))}$$

This improved algorithm could dynamically adjust β according to the evolution speed factor s_d and the aggregation degree factor j_d during operation, which is

$$\beta = f(s_d, j_d) = \beta_0 - s_d\beta_1 + j_d\beta_2$$

Where, β_0 is β initial value, commonly $\beta_0 = 1$; β_1 is the weight influenced by s_d; β_2 is the weight influenced by j_d. Since $0 \leq s_d \leq 1$, $0 \leq j_d \leq 1$ $0 < j_d \leq 1$, the $\beta_0 - \beta_1 \leq \beta \leq \beta_0 + \beta_2$. Commonly in the initial state, make $s_d = 0, j_d = 0$.

2.2.2 The Punish Function

The punish function is commonly defined as (Zhang *et al.*, 2008)::

$$F(x) = f(x) + h(k)H(x), x \in S \subset R^n$$

Where, $f(x)$ is the initial object function for the constrained optimization problem, $h(x)$ is the punish function's factor, k is the iterations of the particle swarm algorithm, which means that the constrained optimization method's punish function value increases with the increase of the iteration. $H(x)$ is the multistage punish function, and is defined as:

$$H(x) = \sum_{i=1}^{m} \theta(q_i(x)) q_i(x)^{\gamma(q_i(x))}$$

$$q_i(x) = \max\{0, g_i(x)\}, i = 1, ..., m$$

Where, m is the number of the constraint conditions, $q_i(x)$ is the corresponding constraint violation function, $g_i(x)$ is the constraint function, $\theta(q_i(x))$ is the multistage distribution function, $\gamma(q_i(x))$ is the series of the punish function. $q_i(x)$, $\theta(q_i(x))$ and $\gamma(q_i(x))$ is based on the constrained optimization problem, and the value is set based on the following rules.

(1)If $q_i(x) < 1$, then the series $\gamma(q_i(x)) = 1$;

(2)If $q_i(x) \geq 1$, then the series $\gamma(q_i(x)) = 2$;

(3)If $q_i(x) < 0.001$, then $\theta(q_i(x)) = 10$;

(4)If $0.001 < q_i(x) < 0.1$, then $\theta(q_i(x)) = 20$;

(5)If $0.1 < q_i(x) < 1$, then $\theta(q_i(x)) = 100$;

(6)If $q_i(x) \geq 1$, then $\theta(q_i(x)) = 300$.

2.2.3 Improved DCWQPSO Based on Multistage Punish Function

There are many studies on expanding the QPSO in order to operate the constrained optimization, helping optimization with all kinds of constrained operation technology. Also, it's possible to transform the constrained optimization problem into non-constrained optimization problem by adding the multistage distribution punish function.

In this section, an improved algorithm DCWQPSO based on multistage punish function will be put forward, in order to further improved the DCWQPSO, and add the restrictions as a punish function form into the object function to make it a single object optimization problem. Here are the calculation steps of the DCWQPSO using the multistage punish function:

Step 1: Find the initial position of all the particles in the object space and at the same time initialize the inertial factor initial value β_0, the evolution speed factor weight β_1 and the aggregation degree factor weight β_2;

Step 2: Update the average optimal position of the particle swarm according to the particles' average optimal position;

Step 3: Calculate each particle's current adaptive value and compare it to that of the previous iteration. If the current value is smaller, then set that particles' position as the current position;

Step 4: Calculate the swarm's current global optimal position;

Step 5: Compare the current and previous global optimal position adaptive value. If the current value is smaller, then set the particle swarm's global optimal position as the current position;

Step 6: Update all the particles' position according to the position update formula;

Step 7: Update the evolution speed factor s_d and the aggregation degree factor j_d;

Step 8: Update the inertial factor value β;

Step 9: Repeat **Step 2 to 8** till the end loop condition is met.

This improved algorithm could find the global optimal solution in the fastest way and would not easily fall into local optimum.

Lastly, we use this improved DCWQPSO algorithm to calculate the solution of the improved dynamic pricing model in order to find the global optimal expected ticket sales income.

3. Instance Analysis

In this section, the cruise pricing model based on the improved particle swarm algorithm will be proved by using *the eighth electrical and mathematical modeling contest* type B's statistics (website :http://shumo.nedu.edu.cn/).

3.1 Demand Function Solving

The statistics of the first seven voyage's first class cabin picked out form the type B could be seen in the Tab.1 and 2. In the Tab.1, 4 of the first 7 circles' historic pricing data including the expected booking records, the actual booking records and the pre-set prices are shown, while in the Tab.2 different circle's pre-set prices' restriction intervals are shown. In order to make the fit result better, logic regression forecasting method was used to complete all the seven voyage's statistics. Due to the limited length of this article, we would just calculate the solution of the model using the data of the first class cabin.

Table 1. Statistics of the first 8 voyages

Expected booking records							
Circle	Voyage 1	Voyage 2	Voyage 3	Voyage 4	Voyage 5	Voyage 6	Voyage 7
12	31	136	49	96	148	39	54
13	10	40	32	35	83	24	10
14	2	9	36	25	11	7	6
15	1	0	5	4	10	5	3
Pre-set prices							
Circle	Voyage 1	Voyage 2	Voyage 3	Voyage 4	Voyage 5	Voyage 6	Voyage 7
12	1770	1900	1800	1860	1900	1760	1760
13	1730	1820	1720	1760	1810	1710	1831
14	1660	1720	1800	1810	1720	1846	1831
15	1610	1650	1680	1690	1750	1766	1720
Actual booking records							

Circle	Voyage 1	Voyage 2	Voyage 3	Voyage 4	Voyage 5	Voyage 6	Voyage 7
12	28	34	37	43	37	37	51
13	8	8	28	21	22	22	12
14	2	6	9	5	7	8	6
15	1	0	3	2	5	4	4

Table 2. Pre-set prices intervals

Circle	Prices intervals	
12	1750	1950
13	1700	1850
14	1650	1850
15	1600	1800

By observing the booking records and pricing's scatter diagram's trend, this article would talk about the exponential fitting of the 12-th circle's expected booking records and pricing, you could see the fitting graph in Figure 1. Meanwhile, and by observing the 12-th circle actual booking records and expected booking records' scatter diagram's trend, this article would talk about the linear fitting of the actual booking and expected booking records, you could see the fitting graph in Figure 2.

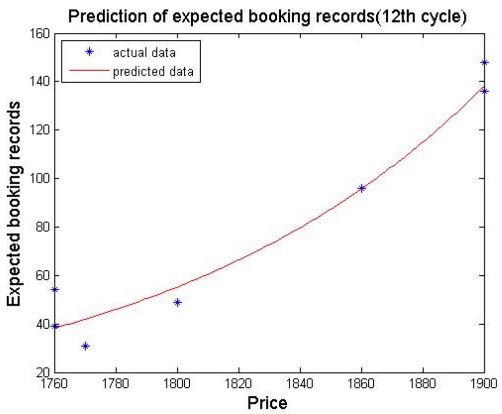

Figure 1. The fitting diagram of the expected and pricing(12th)

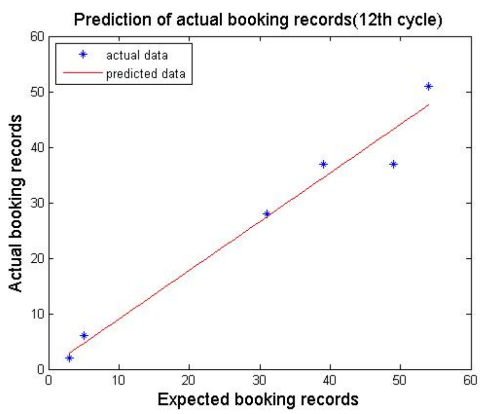

Figure 2. The fitting diagram of the actual and expected booking records(12th)

The 12th circle's expected booking records and pricing's fitting equation $W_n = e^{0.0092 p_t - 12.5}$

The 12th circle's actual and expected booking records and actual booking records' fitting equation

$$D_n = 0.8769W_n + 0.2360$$

Then the 12th circle's demand function is $D_n = 0.8769(e^{0.0092p_t - 12.5}) + 0.2360$

Thus, the 13th to 15th circles' demand function could also be calculated:

Then the 13th circle's demand function is $D_n = 0.8806(e^{0.0099p_t - 14}) + 0.5069$

Then the 14th circle's demand function is $D_n = 0.7203(e^{0.0171p_t - 27.4}) + 0.4537$

Then the 15th circle's demand function is $D_n = 0.8598(e^{0.0211p_t - 34}) + 0.3232$

3.2 Optimization Model Solving

By substituting the demand function from the 3.1 section into the maximal expected profit's optimization model then using the Matlab, we could find the solution of the improved DCWQPSO. In order to better represent the advantages of the improved algorithm, we would respectively using the DCWQPSO and the QPSO to solve the improved model, you could see the convergence comparison in Figure 3 (the red line describes the improved DCWQPSO's convergence, while the blue line describe that of the ordinary QPSO) and the solution in Tab.3.

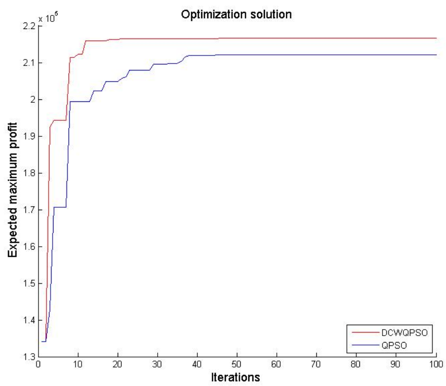

Figure 3. Convergence Comparison

Table 3. Improved model's solving result

DCWQPSO solution			QPSO solution		
Circle	Price	Booking records forecast	Circle	Price	Booking records forecast
12	1860.18	84.3	12	1799.27	48.31
13	1761.56	28.72	13	1777.49	33.55
14	1718.42	5.85	14	1650.62	2.14
15	1607.66	0.96	15	1799.41	35.98
Maximal expected income:		216599.43	Maximal expected income: 212168.02		

3.3 Discussion

As shown in the Figure 3, compared with the ordinary QPSO, the improved DCWQPSO has faster convergence speed and bigger expected profit, which further proves that the improved DCWQPSO would not easily fall into local optimal problem and has better optimization and application. As for the result of the Tab.3, DCWQPSO's maximal expected profit is 216,599.43, which is a 2.09% increment compared to that of 212,168.02 of the ordinary QPSO. Also calculating the average voyage profit, which is 105,795, proves that the improved algorithm has much bigger maximal expected income than previous. Thus, the cruise-pricing model put forward in this essay is of significance and bound to make more profit to the actual cruise business.

4. Conclusion

This essay puts forward a cruise pricing model based on the improved quantum particle swarm optimization, basing on the dynamic pricing theory and the improved particle swarm algorithm, with the aim at optimizing the pricing strategy and achieving maximal sales income.

The innovation of this essay lies at two points. First, we improved Sun *et al.*(2013)'s dynamic pricing model by combining the actual situation of cruise pricing's actual and expected booking records, which proves the practicality of the improved model. Second, we put forward a improved algorithm by combining the multistage punish function and the DCWQPSO, in order to faster the finding of the global optimal solution and avoid local optimal. The examples show that, the improved algorithm has better application advantages. All in all, the model in this essay is countable and logical, and the pricing model would work well in improving the maximal expected sales income.

As for the model's application, this essay's case analysis takes relatively less statistics types, which need to be more in real cruise pricing. However, as long as there are better parameters and index for this improved model, it could work just fine.

This particle swam algorithm has a wide academic use, other than the pricing model put forward in this essay, other fields of science or business also uses this algorithm, such as the distribution network's dynamic reconstitution (Wen *et al.*, 2015) and the red wine's quality classification(Qiu *et al.*, 2015).

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